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Enhancing risk-based engineering design: a hybrid fuzzy failure analysis with empirical validation

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Introduction: Precise risk-based design is essential for accurately identifying and assessing threats, improving reliability, and ensuring the overall safety of safety-critical systems. Failure Mode and Effect Analysis (FMEA) is a widely employed technique for the evaluation of risk of components, systems, services, and processes. To address subjectivity and ambiguity in decision-makers' judgments in traditional FMEA, several methodological improvements have been proposed; however, a state-of-the-art review shows that several research avenues are still open in this domain. Reducing the variation in priority ranking within failure analysis remains a mostly underexplored area. This significant gap serves as the main motivation for investigating whether the synergy between different aggregation methods and normalization techniques, when combined with a fuzzy reference-based approach, can effectively decrease the distinct rankings.

Methodology: This study proposes an improved FMEA methodology that combines the Fuzzy Analytic Hierarchy Process (Fuzzy AHP), Fuzzy Elimination Et Choix Traduisant la REalité (Fuzzy ELECTRE III), and Entropy methods to derive a logical ranking of FMEA failure modes, thereby enhancing the effectiveness of FMEA. The proposed approach employs linguistic variables to set S, O, and D weights, FMEA using the Entropy and Fuzzy AHP methods, integrates these weights using Fuzzy ELECTRE III, and finally analyzes the priority of the options. To validate the practical applicability of the proposed framework, a real-world case study on a safety-critical machine component, the clutch system, which is a suitable case for risk-based engineering design, is conducted.

Results and discussion: The results are compared with those obtained by the integration of TOPSIS and VIKOR with FMEA, showing that the proposed method provides fewer priority rankings while delivering more effective results. Such clustering provides a more realistic representation of risk, acknowledging that minor distinctions between failure modes are often statistically insignificant. This ensures that resources are not diverted to minor issues at the expense of catastrophic but rare failure modes.

KEYWORDS

automotive industry, decision support system, failure mode and effects analysis (FMEA), fuzzy logic, hybrid method, multi-criteria decision analysis (MCDA), multi-criteria decision-making (MCDM), reliability

1 Introduction

The car clutch is a critical component in passenger safety, allowing the driver to quickly disengage power in emergencies, preventing unintended movement and reducing kickback (Acko, 2024b; Moore and Rennell, 1991; Media Q, 2023; Acko, 2024a). A neglected clutch can cause issues such as slippage or sticking, increasing the risk of accidents. Ensuring its reliability is crucial for overall vehicle safety, making risk assessment and system improvement essential. The safety criticality of this system is detailed in Section 4.1.

Today's competitive markets require proactive design during the development and continuous improvement of existing safety critical systems such as the clutch system. Failure Mode and Effects Analysis (FMEA) is a solution that addresses both. By systematically analyzing potential weaknesses early on, engineers can identify problems before they impact customers. Additionally, FMEA allows for periodic reevaluation of existing systems, helping identify areas susceptible to new problems or those with hidden weaknesses. The engineering mission of FMEA is to identify and avoid potential failures in systems or processes before they impact customers (Stamatis, 2003; Liu et al., 2015). To this end, FMEA assigns three factors to each failure mode: severity (S), occurrence (O), and detection (D). These factors represent the intensity of the impact, the probability of occurrence, and the ease of detecting the failure, respectively. In a typical FMEA assessment, the risk priority numbers (RPNs) of the failure modes are ranked by the risk factors (O, S, and D).

Although FMEA is a simple and valuable tool, its traditional approach using a single RPN score can mask important distinctions between failures (Ibarra et al., 2024). This is why various variations are systematically analyzed and implemented to improve the effectiveness of FMEA, leading to a more nuanced assessment, a more informed prioritization, and ultimately to more robust and reliable systems.

To identify which failure mode has a critical role, Wang et al. (2009) evaluated the risk factors of FMEA using fuzzy linguistic variables and proposed fuzzy RPN to identify the most critical failure modes for FMEA problems. However, limitations were observed across the Multiple Criteria Decision Making (MCDM) approaches. The traditional prioritization of failure modes for risk reduction is criticized based on methodological drawbacks, critical ones being: the identical relative weights of risk factors (Ouyang et al., 2022), dissimilarity of different sets of risk factors (Liu et al., 2016), complicated fuzziness of FMEA phenomena by using numerical values (Resende et al., 2024), and the mathematical formula for obtaining RPNs is too simple and lacks a solid scientific foundation as there is no rationale about why O, S and D should be multiplied to calculate the RPN (Gargama and Chaturvedi, 2011). This disability in facing FMEA problems shows its weakness doubly when faced with MCDM methods. MCDM can be explained as the evaluation of the alternatives to select or rank, using a number of criteria, expressed in qualitative and/or quantitative measurement units.

Despite the advancements in risk assessment, traditional FMEA remains hindered by the limitations of the RPN, specifically its equal treatment of risk factors and its inability to distinguish between high-severity and high-occurrence risks effectively. While various MCDM methods have been introduced to mitigate these issues, many existing hybrid approaches rely solely on either subjective expert judgments or objective data. They often fail to capture the full spectrum of uncertainty. Moreover, widely used compensatory methods, such as TOPSIS and VIKOR, tend to generate highly dispersed rankings that can obscure the true criticality of failure modes by allowing low-risk factors to offset severe ones. To address these issues, the objective of this study is to develop a robust hybrid methodology that integrates several MCDM methods, aiming to minimize the variation in priority ranking and ensure a more logical, stable, and safety-critical categorization of failure modes.

In this study, an integrated method is proposed, which combines the rational approaches of two different MCDM methods, namely, Fuzzy AHP and Fuzzy ELECTRE III, to enhance the robustness of FMEA decision-making. The Fuzzy AHP method captures expert judgments with imprecision and is used to determine the risk factors' weights, and Fuzzy ELECTRE III provides a robust outranking approach for prioritizing failure modes under uncertainty. This integrated approach aims to address traditional FMEA limitations by improving accuracy, reliability, and decision support in failure mode prioritization and to enhance FMEA effectiveness by making the following contributions:

1. Contribution 1. Proposing an integrated MCDM method using the AHP, Entropy, and ELECTRE methods to employ FMEA.
2. Contribution 2. Incorporating the fuzzy numbers in the integrated method to address subjectivity and imprecision in decision-making
3. Contribution 3. Reducing the number of failure mode prioritization levels to facilitate risk management strategic planning.

The following Section delves into conventional FMEA's theoretical foundation, limitations, and the state of the art on variations of FMEA methods. In Section 3, the theoretical foundations of the new method are introduced. In Section 4, the proposed method is implemented in a case study to validate its functionality using a real-world example, and in Section 5, the limitations and future research paths are reported, and finally, in Section 6, a comprehensive conclusion is provided.

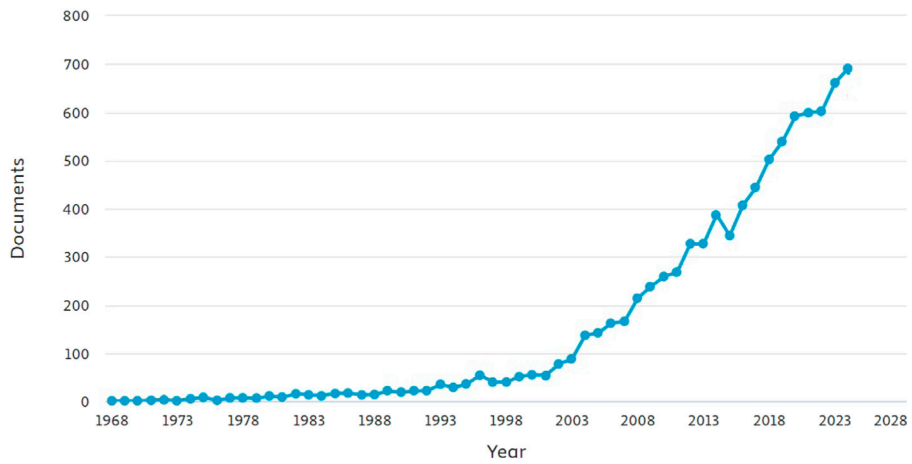

FIGURE 1
Document results per year for each search string in December 2024 in SCOPUS. Results of search string: (fmea OR 'Failure Mode and Effects Analysis').

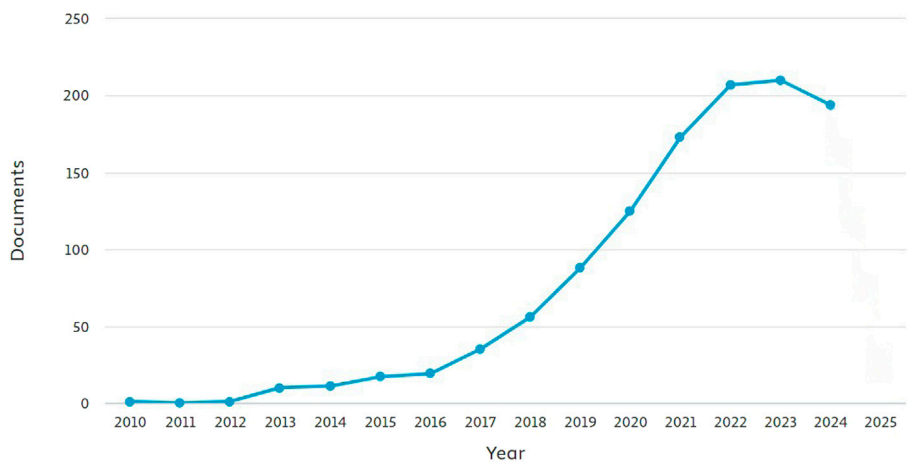

FIGURE 2
Document results per year for each search string in December 2024 in SCOPUS. Results of search string: fmea OR 'Failure Mode and Effects Analysis' AND Fuzzy.

2 Literature review

In order to perform a preliminary analysis of the literature to illuminate the overall research landscape of the field, several Scopus queries were conducted in December 2024. The preliminary analysis reveals the distribution and integration of methodologies within the field of FMEA. The first search string, (FMEA OR 'Failure mode and effects analysis'), produced 8,812 documents (Figure 1), establishing a baseline for the conventional implementation of FMEA. Introducing fuzzy logic in the search with string (FMEA OR 'Failure Mode and Effect Analysis') AND fuzzy reduced the results to 1,086 documents (Figure 2), representing approximately 12.89% of the total FMEA documents. Further refinement of the search to include MCDM methods alongside fuzzy logic, using string (FMEA OR 'Failure Mode and Effects Analysis') AND Fuzzy AND (mcdm OR Fuzzy AHP OR topsis OR vikor OR Fuzzy ELECTRE III OR promethee OR maut OR anp OR dematel OR moora), yielded 290 articles (Figure 3). This subset represents 3.44% of the fuzzy-enhanced FMEA documents. These figures indicate a growing interest in integrating fuzzy logic and MCDM methods with FMEA.

Members of FMEA teams usually originate from a variety of backgrounds, and as a result, their perspectives may differ significantly. They may also differ in terms of their levels of evaluation, practical experience, and knowledge structures. Because individual rationality and cognition differ, as does the impact of social ties, experts in the FMEA may have varying effects on the decision-making process. Furthermore, it is essential to capture the fuzziness of the experts' evaluations by using partial weights of risk factors (Sabripoor et al., 2024).

In order to investigate how the fuzzy process can cope with uncertainties, including subjective expert evaluations due to

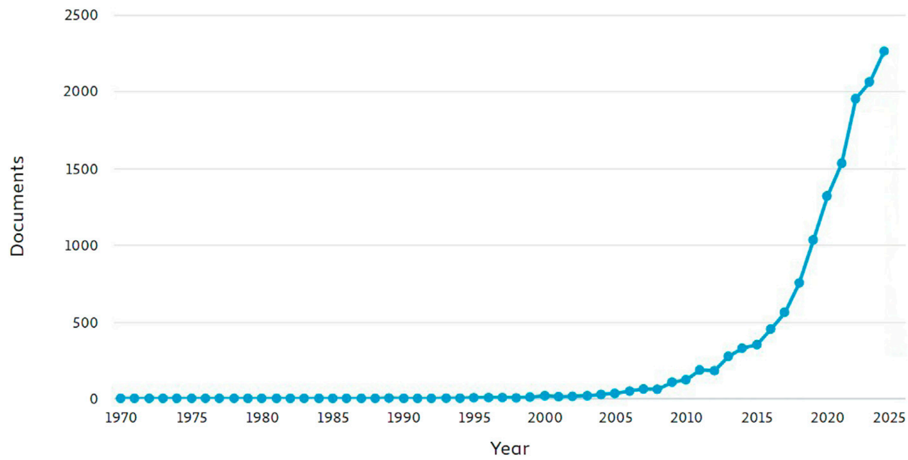

FIGURE 3
Document results per year for each search string in December 2024 in SCOPUS. Results of search string: (fmea OR 'Failure Mode and Effects Analysis') AND Fuzzy AND (mcdm OR Fuzzy AHP OR topsis OR vikor OR Fuzzy ELECTRE III OR promethee OR maut OR anp OR dematel OR moora).

subjective perspectives, incomplete information, and linguistic assessments of decision-makers through the FMEA, this study evaluates a large number of methodologies that have been reported to model the uncertainties in the decision data collected from FMEA team members. This study explores how the fuzzy process can address uncertainties, such as subjective expert evaluations, incomplete information, and linguistic evaluations of decision-makers in FMEA. To achieve this, it reviews various approaches and methodologies used to model these uncertainties in the decision data provided by the FMEA team members (Bowles and Peláez, 1995) originally developed a fuzzy logic-based FMEA for analyzing the structures, reliability and assessment of system criticality based on the severity of the failure and the probability of its occurrence to discover the relationships between risk factors and risk of failure.

Based on the literature review on decision making techniques and the objective of this research, the widely used MCDM methods include multi-attribute utility methods (MAUT) (e.g., AHP and ANP), outranking methods (e.g., ELECTRE) and compromise methods (e.g., TOPSIS and VIKOR). In addition, Saaty (2008) uses expert judgment to determine priority scales and suggests AHP for measurement through pairwise comparisons. Pairwise comparisons of criteria in the AHP method, a structured approach to handle complicated decision-making problems, offer a precise, reliable and practical means to accommodate real-life circumstances, making it superior to other MCDM methods. AHP models the decision problem into a hierarchy with a goal, decision criteria, and alternatives. In contrast, the ANP forms a network structure that is a more general form of the AHP used in multi-criteria decision analysis (Saaty, 2005).

He et al. (2012) presented an integrated approach with the objective of maximizing the level of customer service and minimizing logistics costs by using a fuzzy AHP-based integer linear programming model for the multi-criteria transshipment problem. Kaya and Kahraman (2010) employed a combination of fuzzy VIKOR and AHP to determine the most suitable renewable energy policy and select the optimal production site in Istanbul. Similarly, Fouladgar et al. (2012) used fuzzy AHP and VIKOR to propose a decision-making method for the selection of the project portfolio in investment decisions. They stated that their proposed method addressed qualitative assessment information without the need for a numerical conversion. Liu et al. (2016) reported an integrated multi-attribute decision-making model to classify failure modes under uncertainty. Mohsen and Fereshteh (2017) proposed an extension of VIKOR based on entropy measures for the risk assessment of failure modes. The entropy of measurements quantifies the average level of uncertainty, which measures the expected amount of information needed to describe the state of the variable, considering the distribution of probabilities across all potential states (Gray, 2011). Furthermore, Wang et al. (2017) presented an FMEA method employing a house-of-reliability-based rough VIKOR approach.

The Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE), developed in the early 1980s, is widely employed in decision making in diverse fields, including business, governmental institutions, transportation, healthcare, and education. Rather than prescribing a definitive 'right' decision, PROMETHEE helps decision makers identify the alternative that best aligns with their goals. It allows structuring the decision-making process to identify and quantify conflicts and synergies between alternatives (Behzadian et al., 2010). Another influential approach in multi-criteria decision-making is the ELECTRE method, developed by Roy (1968). Unlike PROMETHEE, which ranks alternatives based on preference, ELECTRE compares alternatives in pairs to establish dominance. This method suitably addresses uncertainty and is especially effective in cases that involve both qualitative and quantitative criteria. ELECTRE III, in particular, employs a fuzzy-based outranking approach. Chen et al. (2021) proposed an approach for bid evaluation, called "ELECTRE III-based Multi-Criteria Group Decision-Making (MCGDM)", which manages uncertainty through "Generalized Comparative Linguistic Expressions (GCLEs)" for qualitative assessments. Their model improves expert consensus and integrates subjective and objective weighting.

TABLE 1 Improvements in FMEA through Fuzzy logic and MCDM Approaches integration.

Improvement	Reference	Explanation
Enhanced decision-making	Wang et al. (2009)	MCDM approaches such as fuzzy AHP (analytic hierarchy process), TOPSIS (technique for order of preference by similarity to ideal solution), and VIKOR (VIšekriterijumsko KOmpromisno Rangiranje) offer systematic methods to enhance decision-making by integrating multiple criteria and handling uncertainty in FMEA.
Handling subjectivity and ambiguity	Sharma et al. (2005)	MCDM techniques introduce rigor by quantifying and prioritizing criteria (e.g., FMEA risk factors). This helps mitigate the subjective judgments that can influence traditional FMEA results
Integration of expert knowledge	Braglia and Bevilacqua (2000)	A decision-making support system incorporating fuzzy logic and AHP assists maintenance staff in assessing failure mode criticality. By using triangular fuzzy numbers (TFNs) instead of crisp inputs in fuzzy models, the methodology evaluates expert opinions effectively, reducing subjectivity in FMEA.
Optimization of prioritization	Liu et al. (2015)	By combining different MCDM approaches, FMEA can achieve optimized prioritization of failure modes based on comprehensive analyses that consider various perspectives and criteria simultaneously
Enhanced effectiveness	Certa et al. (2017)	Studies have demonstrated that integrating MCDM techniques like fuzzy ELECTRE III (Elimination and choice expressing reality) with FMEA results in more effective identification and mitigation of critical failure modes compared to using FMEA alone

Beyond implementing fuzzy logic, hybrid methods have gained significant traction in operations research due to their ability to combine the strengths of multiple techniques, thus improving the precision and robustness of decision making (Akhtar et al., 2024; Boral et al., 2020; Dabous et al., 2021; Ervural and Ayaz, 2023; Xiao et al., 2011). For example, hybrid methods are commonly used in problems with a large number of criteria (Liu et al., 2015), effectively handling uncertainty (Pelissari et al., 2021; Yang et al., 2011), reducing the number of criteria (Pawlak and Słowinski, 1994), and handling constraints under the value-at-risk measure (Hooshmand et al., 2023), and offer the solution of gray stochastic MCDM problems (Zhou et al., 2019; Zhou et al., 2019). However, a significant gap remains when comparing the prevalence of these hybrid methods with the conventional FMEA approach. This gap highlights the ongoing challenges of ambiguity and inaccuracy associated with traditional FMEA, as discussed in Section 2.

2.1 Problem statement and proposed solution

Although FMEA is an effective risk assessment tool (Brown, 2007), it has limitations. In some cases, the RPN may not adequately differentiate between failure modes. For instance, consider two failure modes through the typical RPN (Formula 1).

$$RPN = S \times O \times D \tag{1}$$

Failure mode 1: $(S = 4, O = 3, D = 3)$

$$RPN_1 = S_1 \times O_1 \times D_1 = 4 \times 3 \times 3 = 36$$

Failure mode 2: $(S = 9, O = 1, D = 4)$

$$RPN_2 = S_2 \times O_2 \times D_2 = 9 \times 1 \times 4 = 36$$

Although both failure modes have the same RPN, failure mode 2 has a high severity (9) and a low occurrence (1). This distinction is not captured by the traditional RPN calculation.

Fattahi and Khalilzadeh (2018) introduced a fuzzy hybrid method to address this limitation. Their approach replaced traditional RPNs with "Fuzzy Weighted Risk Priority Numbers" (FWRPNs). Furthermore, previous research has explored the use of Vikor and Fuzzy AHP as weighting factors in FMEA (Liu et al., 2015; Safari et al., 2016; Jianxing et al., 2021). The integration of MCDM approaches with FMEA has shown significant potential to enhance the accuracy of FMEA results. Table 1 shows the approved improvements gained from the integration of FMEA with fuzzy logic and MCDM approaches. This is the main motive for investigating alternative hybrid methods to achieve more improvements. Therefore, a general research question arises: Does the combination of other MCDM approaches improve the FMEA results?

The proposed approach in this article uses fuzzy logic combined with Fuzzy AHP and entropy methods to weight factors, followed by the Fuzzy ELECTRE III method for ranking failure modes. However, several other MCDM methods can be employed to enhance the FMEA process. Each method has unique strengths that can address different aspects of decision-making and risk assessment. Future research will involve studying these combinations and comparing their effectiveness in various industrial contexts. The goal of future studies with several alternative methods implemented in various domains is to develop a versatile and adaptive FMEA framework that can be tailored to different types of systems and operational conditions, ensuring a more comprehensive risk assessment and mitigation strategy.

2.2 Theoretical foundation of conventional FMEA

Failure mode and effects analysis is the most common tool in the broad area of failure effects analysis. This tool follows a process aimed at the systematic and logical study of how a system reacts to failures (Rausand and Hoyland, 2003). Sometimes, this process includes criticality analysis, and the name extends to Failure Mode, Effects, and Criticality Analysis.

Given the wide variety of FMEA-based methods, standardizing this widely used tool is essential to ensure consistency and reliability in risk assessment (Booker et al., 2020). The first published standard

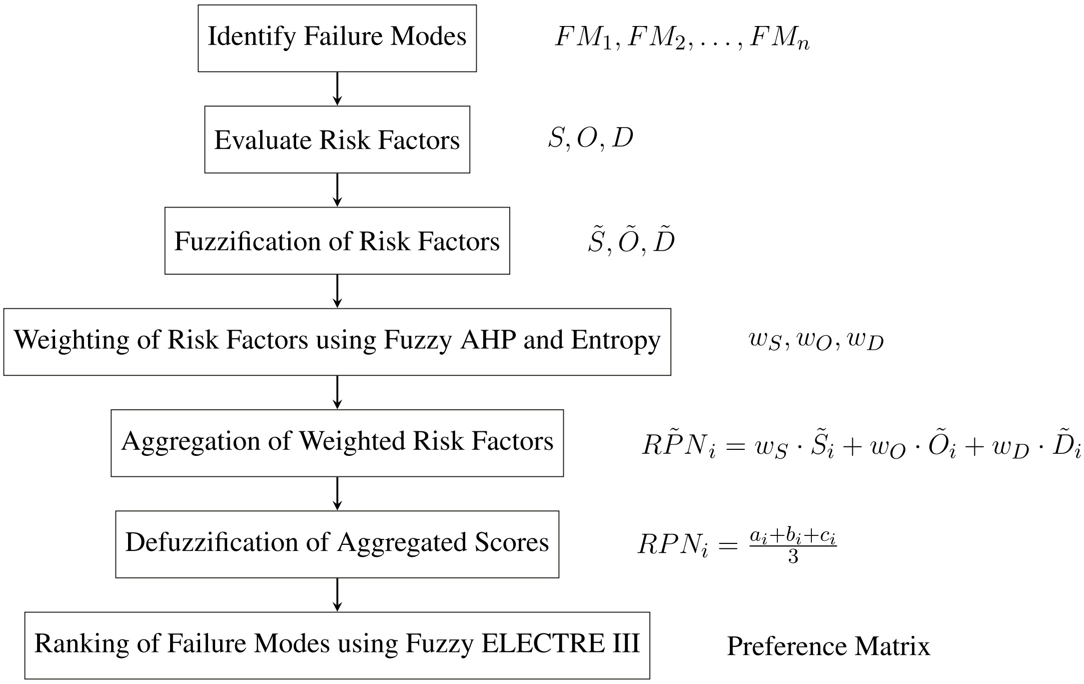

FIGURE 4
Flowchart of the Fuzzy FMEA and Entropy process.

that describes the detailed approach of the FMEA method was demonstrated in the US Armed Forces Military Procedures document MIL-P-1629 (Military, 1949). The revised version of this standard is MIL-STD-1629A, which was introduced in 1980 and is widely used to systematically evaluate failures by item failure mode analysis. It assesses the potential impact of failures on mission success, personnel and system safety, system performance, maintainability, and maintenance requirements (Agarwala, 1990; Baig and Prasanthi, 2013). The current study employs fuzzy logic due to the inherent subjectivity and ambiguity associated with FMEA assessments. Fuzzy logic allows experts to incorporate their knowledge and experience when evaluating failure modes (Pelissari et al., 2021; Radojevic and Petrovic, 1997).

Traditional FMEA relies on a multiplication operation to calculate the RPN; the approach is sensitive to changes in factor assessments and can lead to similar RPN values for significantly different failure modes. This is why Fuzzy FMEA's popularity has sharply increased. Fuzzy logic, introduced by (Zadeh, 1965), is a mathematical framework to represent uncertainty and partial truth. In contrast with traditional logic, where variables are true or false, fuzzy logic allows for degrees of truth between 0 (completely false) and 1 (completely true). Fuzzy set theory utilizes membership functions (MFs) to represent these degrees of membership. Triangular MFs are commonly used in Fuzzy FMEA applications (Zha et al., 2023).

Fuzzy FMEA offers several advantages. Fuzzy logic aligns well with human language, making it easier for experts to provide FMEA input (Burduk et al., 2024). In addition, fuzzy FMEA can handle both quantitative data and qualitative information, providing a more comprehensive evaluation of failure modes (Sabripoor et al., 2024).

Figure 4 outlines the step-by-step process of Fuzzy FMEA, which consists of failure mode identification, risk factor evaluation, fuzzification, weighting, aggregation, defuzzification, and final ranking.

The process starts with identifying potential failure modes (FM_1, FM_2, . . ., FM_n) and evaluating their risk factors: Severity (S), Occurrence (O), and Detection (D). In the fuzzification step, these crisp risk factor values are converted into fuzzy numbers ($\tilde{S}$, $\tilde{O}$, $\tilde{D}$) using appropriate membership functions. In the Fuzzy FMEA process shown in Figure 4, the failure modes (FM1, FM2, … , FMn) are identified, leading to a risk assessment based on risk factors S, O and D. In the next step (fuzzification), they are transformed into fuzzy numbers (w_S, w_O, w_D) which are obtained using fuzzy AHP and entropy, which balance the subjectivity of expert judgments with an objective weighting mechanism. Next, in the aggregation step, the risk factors are combined into a fuzzy Risk Priority Number (RPN) using the weighted sum (Equation 2) (Liu et al., 2011):

$$R\tilde{P}N_i = w_S \cdot \tilde{S}_i + w_O \cdot \tilde{O}_i + w_D \cdot \tilde{D}_i \tag{2}$$

Since $R\tilde{P}N_i$ is still a fuzzy number, the defuzzification step converts it into a single crisp value to enable ranking. The centroid method is commonly used, defined in Equation 3 (Sodenkamp et al., 2018).

$$RPN_i = \frac{a_i + b_i + c_i}{3} \tag{3}$$

Finally, the ranking of failure modes is determined using Fuzzy ELECTRE III, which constructs a preference matrix based on the defuzzified RPN values. This ensures a more robust ranking compared to conventional FMEA, which often suffers from ambiguity and inconsistent prioritization.

In the last decade, various efforts have been made to improve FMEA. Different MCDM methods, FVIKOR, FCOPRAS, FMOORA, FMABAC, FTOPSIS, FMAIRCA, and Fuzzy AHP, are widely used to address the drawbacks of simply multiplying the three RPNs. Some specific improvements are gained by integrating MCDM with FMEA, which is reported in Table 1. However, there are other variations of FMEA that, in general, improve the results, such as:

1. Gupta et al. (2021) proposed a fuzzy FMECA model utilizing Dempster-Shafer theory and a linear equation to aggregate expert opinions and calculate risk. However, their approach relies on a compensatory linear formula that fails to prevent high-severity risks from being overshadowed by other factors, and it lacks an objective weighting component (such as Entropy) to mitigate the subjectivity of expert judgments.
2. Boral et al. (2020) proposed an integrated MCDM approach combining Fuzzy AHP for weighting and Fuzzy MAIRCA for ranking failure modes. However, they rely solely on subjective expert judgment (Fuzzy AHP) for weighting without validating it against objective data (Entropy), and they utilize MAIRCA, a compensatory method that, unlike Fuzzy ELECTRE III, may allow low-risk factors to offset critical high-severity failures.
3. Zhu et al. (2020a) proposed a hybrid risk ranking model using linguistic neutrosophic numbers, regret theory, and PROMETHEE, with weights derived from a maximizing deviation model and TOPSIS. However, while they address psychological behavior, their weighting method lacks the specific synergy of combining subjective hierarchical structure (AHP) with objective data (Entropy), and their approach adds significant computational complexity (neutrosophic sets) without explicitly addressing the reduction of ranking variation.
4. Wang et al. (2020) proposed a novel FMEA method using an extended matter-element model for ranking and AHP for deriving risk factor weights. However, their reliance on AHP alone introduces purely subjective bias into the weights, and the matter-element model is a correlation-based approach that lacks the non-compensatory "veto" thresholds provided by Fuzzy ELECTRE III to ensure safety-critical failures are not downplayed.
5. Huang et al. (2022) proposed a reliability model integrating probabilistic linguistic term sets with the TODIM method, utilizing TOPSIS to derive objective weights. However, by using TOPSIS for weights, they ignore the structural expert intuition provided by AHP (relying only on objective data), and the TODIM method focuses on gain/loss psychology rather than the strict outranking relationships necessary to distinctively separate close priority rankings.
6. Liu et al. (2019) proposed an integrated risk prioritization approach using interval-valued intuitionistic fuzzy sets and the MABAC method, with a linear programming model for optimal weights. However, their method uses MABAC, which aggregates distances linearly (compensatory), and their weighting optimization is mathematical rather than a hybrid approach that balances the decision-makers' intent (Subjective AHP) with the data's information content (Objective Entropy).
7. Bian et al. (2018) proposed a risk priority model utilizing D numbers to handle uncertainty and TOPSIS to rank failure modes. However, TOPSIS is a compensatory distance-based method that can hide severe risks if other factors are favorable, and the study fails to incorporate a hybrid weighting mechanism, leaving the relative importance of risk factors potentially unbalanced or ill-defined.
8. Grunske et al. (2007) proposed a method using probabilistic fault injection and model checking to identify if failure modes exceed tolerable hazard rates. However, this is a formal verification technique rather than an MCDM framework, meaning it lacks the ability to rank failures based on the trade-offs of subjective criteria (severity, detection) using hybrid weights and linguistic variables.
9. Liu et al. (2012) proposed a fuzzy FMEA model using linguistic variables and the extended VIKOR method to determine risk priorities. However, VIKOR creates a "compromise" solution that is inherently compensatory, whereas the Fuzzy ELECTRE III method in this study uses non-compensatory outranking to ensure that high-severity failures retain a high priority regardless of other factors.
10. Shi and Yang (2009) proposed an evaluation framework for software trustworthiness using Fuzzy AHP for weights and Fuzzy TOPSIS for ranking. However, their approach suffers from the same limitations as traditional fuzzy FMEA improvements. It relies exclusively on subjective weights (FAHP) without an objective Entropy check, and uses TOPSIS, which fails to provide the granular, non-compensatory differentiation of rankings offered by Fuzzy ELECTRE III.

The articles listed above present various methods for calculating risk priority. However, the novelty of this paper lies in the integration of FMEA with Fuzzy AHP and Fuzzy ELECTRE III. This new approach limits the results to the most feasible answers. In the next section, the proposed method is systematically presented.

3 Methodology

This section explains the process of combining the implementation of fuzzy logic with MCDM within the proposed hybrid FMEA approach, and then, in detail, the outline of the steps of the proposed method is explained.

3.1 Methods and tools

To overcome the ambiguity and subjectivity often present in conventional FMEA, this study combines four distinct mathematical tools: Fuzzy Logic, Fuzzy Analytic Hierarchy Process (AHP), Shannon Entropy, and Fuzzy ELECTRE III. The rationale for selecting these specific methods and their role in the overall structure is outlined below.

TABLE 2 Fuzzy evaluation scores for alternative.

Linguistic terms	Fuzzy score
Very poor (VP)	(0,0,1)
Poor (P)	(0,1,3)
Medium poor (MP)	(1,3,5)
Fair (F)	(3,5,7)
Medium good (MG)	(5,7,9)
Good (G)	(7,9,10)
Very good (VG)	(9,10,10)

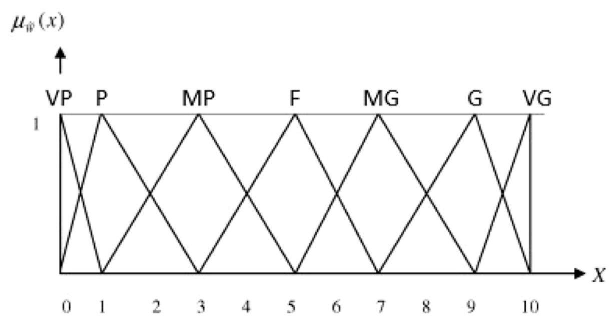

FIGURE 5
Linguistic terms and corresponding triangular fuzzy numbers used in the study.

3.1.1 Fuzzy logic

In engineering risk assessment, precise numerical data is often unavailable, and expert judgments are frequently expressed in linguistic terms (e.g., "High," "Low"). To handle this inherent uncertainty by using degrees of truth rather than rigid binary sets, Fuzzy logic is employed based on a spectrum of data derived from Fuzzy set theory.

Unlike traditional binary sets (where the variables must be 0 or 1), fuzzy logic variables may have a truth value between 0 and 1 (Zadeh, 1965). This approach enables the modeling of concepts that are inherently vague or ambiguous, such as 'tallness'. Fuzzy logic provides a robust framework for handling the uncertainty and imprecision found in many real-world problems. It has been widely applied in fields such as control systems (Ferdaus et al., 2020), artificial intelligence (Bakhtavar et al., 2021), and decision-making processes where human-like reasoning is advantageous (Mardani et al., 2019).

The study implements Triangular Fuzzy Numbers (TFNs) due to their computational efficiency and ability to represent the linear uncertainty typical in risk estimation (Klir and Yuan, 1995). In order to implement triangular fuzzy logic, the steps derived from several sources (e.g., Klir and Yuan, 1995; Kutlu and Ekmekçioğlu, 2012; Lai et al., 1992; Zadeh, 1965) can be followed. The process begins with the input TFN (a1, a2, a3), followed by Fuzzification, where the membership function in Equation 4 is applied.

$$\mu_{\tilde{A}}(X) = \begin{cases} 0, & x < a_1 \\ \dfrac{x - a_1}{a_2 - a_1}, & a_1 \leq x \leq a_2 \\ \dfrac{a_3 - x}{a_3 - a_2}, & a_2 \leq x \leq a_3 \\ 0, & x > a_3 \end{cases} \tag{4}$$

The Fuzzy Evaluation Scores Table is conducted based on fuzzy numbers. A fuzzy number is a special fuzzy set in the universe of discourse X whose membership function is convex and normal. Several methods are used to express imprecision by means of fuzzy numbers. Among these methods, TFNs are more popular compared to the others because of their simplicity and features. They are useful in promoting representation and information processing in a fuzzy environment. Linguistic variables are generated during the aggregation step and provide the basis for the final ranking and decision-making process. The sample linguistic variables used for rating the failure modes are shown in Table 2 and Figure 5.

Finally, defuzzification (Tseng and Tzeng, 2002; Zhang et al., 1999) converts the aggregated fuzzy values into a crisp output. Defuzzification uses predefined fuzzy rules to process fuzzified inputs. In this study, the center of area (COA) method is used for defuzzification. It is a simple and practical method that finds the best non-fuzzy performance (BNP) value. The BNP value of the TFN $\tilde{a} = (a_1, a_2, a_3)$ is the defuzzied value of $\tilde{x}_0(\tilde{a})$ and is calculated using Equation 5.

$$\tilde{x}_0(\tilde{a}) = \frac{1}{3}[(a_3 - a_1) + (a_2 - a_1)] + a_1 \tag{5}$$

This final step leads to the Output Result, providing a crisp ranking of failure modes. Each formula is displayed outside the corresponding process block for clarity.

3.1.2 Fuzzy AHP method

While traditional FMEA treats risk factors (Severity, Occurrence, Detection) as equally important, scientific reality dictates that different systems prioritize these factors differently based on operational context. Fuzzy AHP is selected to capture the subjective engineering knowledge required to weight these factors. This approach, which was originally developed by Saaty (1990), is a structured technique for organizing and analyzing complex decisions, based on mathematics and psychology (Saaty, 2008; Sankar and Prabhu, 2001; Vaidya and Kumar, 2006). Fuzzy AHP facilitates decision making by structuring a hierarchy of criteria, comparing them pairwise, and calculating weightings that reflect the relative importance of each criterion (Ahmed and Kilic, 2024; Ghodsi et al., 2022). The implementation of Fuzzy AHP is increasing sharply due to the advantages highlighted by researchers and practitioners (Chan et al., 2008; Wu et al., 2023; Gonzalez-Urango et al., 2024; Zhu et al., 2021).

The flow chart in Figure 6 illustrates the steps involved in the Fuzzy AHP method (Buckley et al., 2001). The process begins by identifying and defining the criteria and sub-criteria. Each formula used in this process is shown to the right of the corresponding step in the flow chart.

To evaluate failure modes in fuzzy AHP methods, first, the fuzzy numbers representing performance scores $\lambda_k > 0$ (for decision makers) should be determined, satisfying the constraint

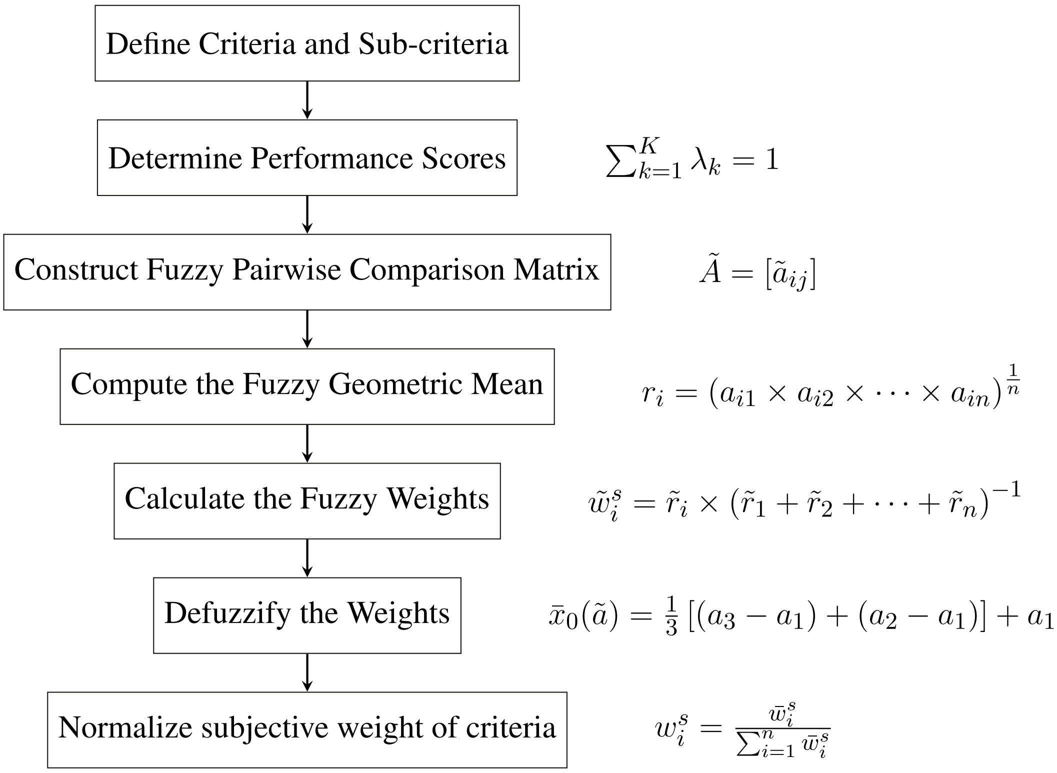

FIGURE 6
Flowchart of the fuzzy AHP method.

$\sum_{k=1}^{K} \lambda_k = 1$. Next, the results of the pairwise comparison are combined to construct the fuzzy pairwise comparison matrix $(\tilde{A})$, as shown in Equation 6.

$$\tilde{a}_{ij} = \left(a_{ij1}, a_{ij2}, a_{ij3}\right), \quad i = 1, 2, \ldots, n-1, \quad j = 2, 3, \ldots, n,$$
$$\text{where } a_{ij1} = \sum_{k=1}^{K} \lambda_k a_{ij1}^k, \quad a_{ij2} = \sum_{k=1}^{K} \lambda_k a_{ij2}^k, \quad a_{ij3} = \sum_{k=1}^{K} \lambda_k a_{ij3}^k. \tag{6}$$

Then construct the fuzzy pairwise comparison matrix $(\tilde{A})$ (Equation 7).

$$\tilde{A} = \left[\tilde{a}_{ij}\right] = \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \tilde{a}_{21} & \tilde{a}_{22} & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \cdots & \tilde{a}_{nn} \end{bmatrix} = \begin{bmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ 1/\tilde{a}_{12} & 1 & \cdots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/\tilde{a}_{1n} & 1/\tilde{a}_{2n} & \cdots & 1 \end{bmatrix}. \tag{7}$$

Next, the fuzzy geometric mean is calculated for each criterion by employing the geometric technique. To obtain the fuzzy geometric mean r_i of the fuzzy comparison values between criteria, Equation 8 is used.

$$\tilde{r}_i = (\tilde{a}_{i1} \times \tilde{a}_{i2} \times \cdots \times \tilde{a}_{in})^{\frac{1}{n}} \tag{8}$$

The next step involves synthesizing the pairwise comparisons to derive fuzzy weights for each criterion. These fuzzy weights are calculated using the average of the fuzzy comparison values Equation 9. Subsequently, the fuzzy weights are defuzzified using Equation 10 where $\tilde{w}_i^s$ can be indicated by the TFN $\tilde{w}_i^s = (w_{i1}^s, w_{i2}^s, w_{i3}^s)$. Then the subjective weight of criterion i (wis) can be first defuzzified and normalized using Equation 11.

$$\tilde{w}_i^s = \tilde{r}_i \times (\tilde{r}_1 + \tilde{r}_2 + \cdots + \tilde{r}_n)^{-1} \tag{9}$$

$$\bar{x}_0(\tilde{a}) = \frac{1}{3}[(a_3 - a_1) + (a_2 - a_1)] + a_1 \tag{10}$$

$$w_i^s = \frac{\bar{w}_i^s}{\sum_{i=1}^{n} \bar{w}_i^s} \tag{11}$$

By structuring the decision problem hierarchically and using pairwise comparisons (Equation 6), Fuzzy AHP allows the engineering team to express relative importance based on their experience. This step is crucial for incorporating the "human element" of engineering expertise into the mathematical model (Figure 6).

3.1.3 Entropy method

Relying solely on expert judgment (AHP) can introduce cognitive bias. To counterbalance this, the Entropy method is integrated to provide objective weights as a decision-making technique. The entropy method for decision making is a technique used to evaluate and rank alternatives by measuring the level of uncertainty or disorder in the decision matrix (Zeleny and Cochrane, 1982; Zhu Y. et al., 2020). It assigns weights to criteria based on their entropy values, reflecting their importance in the decision process (Yoon and Hwang, 1995). In the current article, the Shannon Entropy (Shannon, 1948) is used. Figure 7 illustrates the step-by-step outline of this method.

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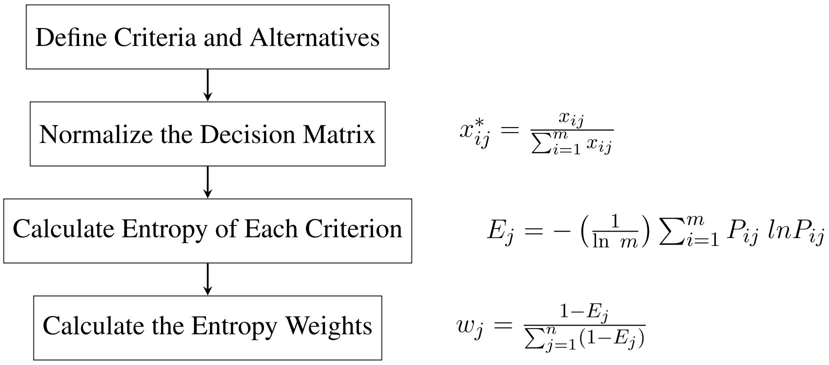

FIGURE 7
Flowchart of the entropy method.

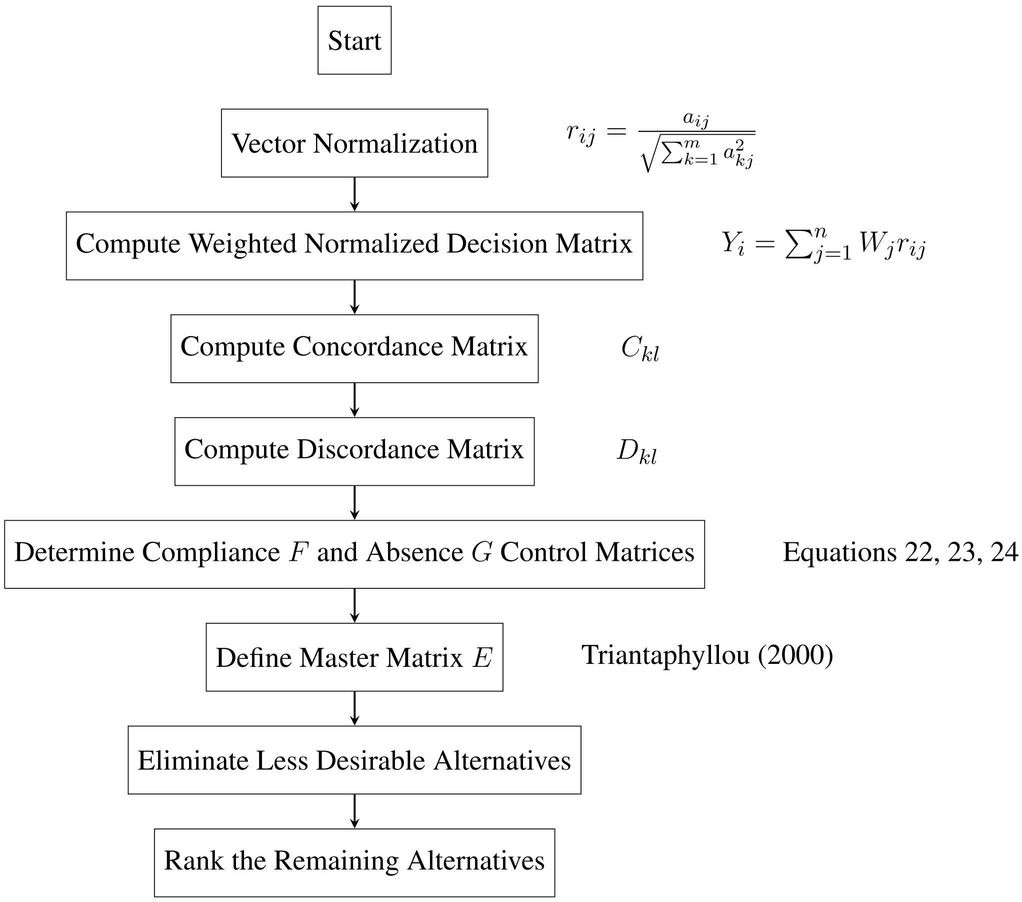

FIGURE 8
Updated flowchart of the fuzzy ELECTRE III method.

After identifying the decision criteria and the available alternatives in the 'Defining Criteria and Alternatives Step', the decision matrix should be normalized to ensure that all criteria are comparable. Normalization is performed by Equation 12, where p_j^i indicates the projected outcomes of criterion j.

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{12}$$

Then the entropy value of each criterion, which indicates the degree of disorder or uncertainty in the data, is computed using Equation 13, which calculares the entropy E_j of the set of projected outcomes of criterion j that the result stays between 0 and 1. The entropy value indicates the degree of disorder or uncertainty in the data.

$$E_j = -\left(\frac{1}{\ln\ m}\right)\sum_{i=1}^{m} P_{ij}\cdot \ln P_{ij} \tag{13}$$

In the 'Calculate the Entropy Weights' step, which assigns greater importance to criteria with lower entropy (higher information content), the weights of the criteria are determined using the entropy values in Equation 14.

$$w_j = \frac{1-E_j}{\sum_{j=1}^{n}\left(1-E_j\right)} \tag{14}$$

Figure 7 illustrates the step-by-step outline of the Shannon Entropy method.

3.1.4 Fuzzy ELECTRE III method

The choice of the ranking method is critical for safety analysis. Traditional RPN and distance-based MCDM methods are "compensatory," allowing high performance in one factor to offset dangerously low performance in another critical systems, where catastrophic severity must never be diluted by other scores. To ensure a non-compensatory and more reliable assessment, this study employs the Fuzzy ELECTRE III (Elimination and Choice Expressing Reality) method. The Fuzzy ELECTRE III in this article is taken from (Bayyurt, 2013; Triantaphyllou, 2000) and follows the following steps as also shown in Figure 8.

First, a vector normalization is performed using the Equation 15 and the weighted normalized decision matrix is constructed using Equation 16 where $\sum_{j=1}^{n} W_j = 1, \quad \text{for } j = 1,\ldots,n$.

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{k=1}^{m} a_{kj}^2}} \tag{15}$$

$$Y_i = \sum_{j=1}^{n} W_j r_{ij} \tag{16}$$

The Concordance Matrix C and the Discordance Matrix D are calculated in the next step. To obtain the concordance matrix C, we first define the matching set. For any pair of alternatives A_k and A_l ($k,\quad l = 1,\ldots,m$ and $k \neq l$), the set of decision criteria j ($j = 1,2,\ldots,n$) is divided into two subsets (Equation 17):

$$C_{kl} = \left\{ j \mid Y_{kj} \geq Y_{lj} \right\} \tag{17}$$

Then the concordance matrix C is structured as follows in matrix (Equation 18).

$$C = \begin{bmatrix} - & C_{12} & \ldots & C_{1n} \\ C_{21} & - & \ldots & C_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ C_{m1} & C_{m2} & \ldots & - \end{bmatrix} \tag{18}$$

To measure the relative compliance with the matching index, the concordance index C_{kl} between the alternatives A_k and A_l is calculated with Equation 19 where W_j indicates the weight of the criterion j and C_{kl} is the concordance index that measures the degree to which alternative A_k is at least as good as alternative A_l in the matching criteria.

$$C_{kl} = \sum_{j\in C_{kl}} W_j \tag{19}$$

The discordance matrix D is formed using the discordance indices d_{kl} obtained from the decision matrix Y. It is defined by Equation 20.

$$D_{kl} = \frac{\max_{j\in D_{kl}} |Y_{kj} - Y_{lj}|}{\max_{j} |Y_{kj} - Y_{lj}|} \tag{20}$$

The discordance index (Equation 21) is constrained by:

$$0 < D_{kl} < 1 \tag{21}$$

The next step is to obtain the Compliance F and Absence G Control Matrix.

In the decision-making process, matrix control is performed by adjusting a threshold value. This ensures that an alternative A_k qualifies on the basis of its matching index only if it meets a predefined threshold. For example, an alternative A_k is considered to have successfully passed the matching index requirement *if and only if* its concordance index C_k exceeds a predefined threshold value C_{th}.

The elements of the membership matrix F (denoted as F_{kl}) take values of 0 or 1. There are no diagonal elements in the matrix, which means that there is no element in the cases where $k = l$ (Equation 22).

$$F_{kl} = \begin{cases} 1, & \text{if } C_{kl} \geq C_{\text{th}} \\ 0, & \text{otherwise} \end{cases} \tag{22}$$

The threshold value C_{th} can be defined as the average compliance index, calculated with Equation 23 and, similarly, for the Absence G Control Matrix the threshold value D_{th} is calculated by Equation 24.

$$C = \frac{1}{m(m-1)}\sum_{k=1}^{m}\sum_{l=1}^{m} C_{kl} \tag{23}$$

$$D = \frac{1}{m(m-1)}\sum_{k=1}^{m}\sum_{l=1}^{m} D_{kl} \tag{24}$$

In the next step, the master matrix E (dominance matrix) will be defined. According to Triantaphyllou (2000) the values of E are also 0 or 1 (Equation 25). Finally, the less desirable alternatives will be eliminated.

$$E_{kl} = \begin{cases} 1 & \text{if } \tilde{C}_{kl} \geq C^{*} \text{ and } \tilde{D}_{kl} \leq D^{*} \\ 0 & \text{otherwise} \end{cases} \tag{25}$$

It establishes dominance relationships using concordance (agreement) and discordance (disagreement) indices. Crucially, it utilizes "veto thresholds" scientific boundaries that prevent a failure mode from being ranked favorably if a specific risk factor exceeds a safety limit. This aligns the mathematical ranking process with the strict safety protocols required in automotive engineering (Figure 8).

3.2 Proposed hybrid approach

Previous studies have highlighted that FMEA is not a reliable method of assessing risk factors because it does not account for their

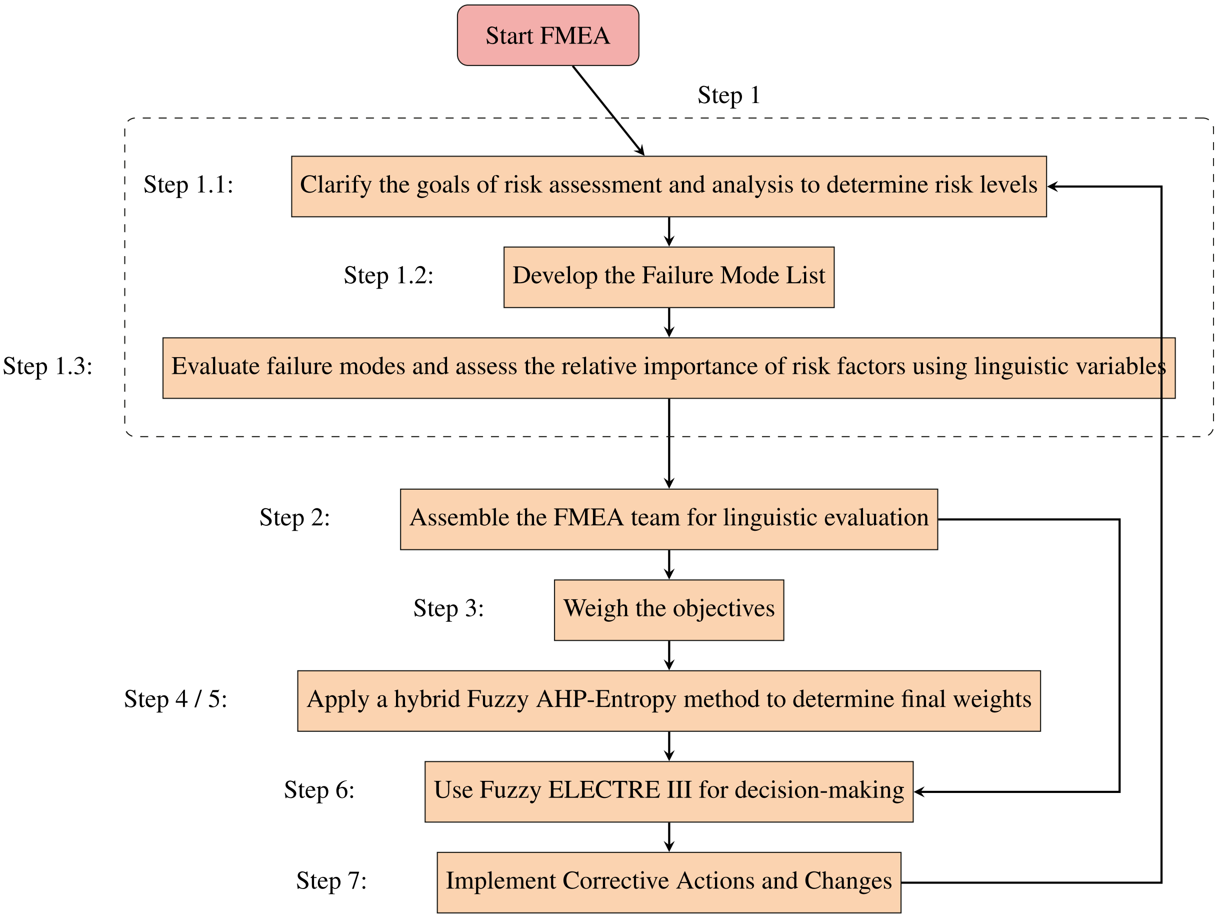

FIGURE 9
Flow chart of the proposed FMEA approach integrated with Fuzzy AHP, Entropy, and Fuzzy ELECTRE III.

relative importance and treat them equally; in addition, previous approaches often consider only subjective or objective weights of risk factors independently, each having its limitations (Section 2). To address these shortcomings, this study employs a hybrid weighting mechanism that integrates Fuzzy AHP with the Entropy method. The reliance on a single source for weighting often leads to skewed risk assessments. Expert-based methods alone are prone to cognitive bias, while data-driven methods can lack engineering context. Fuzzy AHP is utilized to capture the subjective experience of the engineering team, allowing for the hierarchical structuring of risk factors and handling the ambiguity inherent in linguistic judgments. However, to prevent potential bias or inconsistency in human judgment, the Entropy method is introduced as an objective counterweight. By calculating weights based on the probabilistic distribution and information content of the data itself, Entropy reduces the uncertainty associated with purely subjective assessments. Consequently, the synergy of these two methods ensures a balanced weighting scheme that incorporates expert intuition while being mathematically validated by the data structure. Decision makers' opinions are elicited as linguistic variables within a group MCDM framework using FMEA. These linguistic variables are then translated into TFNs. Subsequently, a systematic approach combining weighting and the Fuzzy ELECTRE III method is utilized to prioritize the risks associated with failure modes. Actually, the rationale for this hybrid structure is twofold:

- Balanced Weighting Mechanism: By integrating Fuzzy AHP with Entropy, the model captures the experiential knowledge of the engineering team (Subjective) while cross-validating it against the statistical information content of the data (Objective). This synergy prevents skewed risk assessments that might arise from dominant opinions or statistical anomalies.
- Non-Compensatory Prioritization: Safety-critical systems require a "safety-first" logic. The use of Fuzzy ELECTRE III ensures that high-risk failure modes (e.g., those with catastrophic severity) are not mathematically masked by favorable scores in other categories, a common flaw in compensatory methods like RPN or TOPSIS.

The flow chart in Figure 9 presents a systematic approach divided into several sequential steps, each addressing a crucial aspect of the analysis. The flowchart details the structured process, each step contributing to the overall methodology. The steps and their progression in the figure are outlined as follows.

Start FMEA This is the initiation point of the FMEA Step 1: Risk Assessment and Analysis.

- Clarify the Goals: Define the objectives of the risk assessment to accurately determine the levels of risk.
- Develop Failure Mode List: Create a comprehensive list of potential failure modes that could affect the system.
- Evaluate Failure Modes: Assess the failure modes and determine their relative importance using linguistic variables.
- Box: The dashed box groups these nodes together, indicating they are part of the same phase (Step 1) in the process.

Step 2: Team Assembly.

- Node: Assemble the FMEA Team
- Description: Form a team to perform the linguistic evaluation of failure modes. This team will help ensure the accuracy and comprehensiveness of the FMEA.

Step 3: Objective Weighing.

- Node: Weigh the Objectives
- Description: Assign weights to the different objectives based on their importance to the analysis.

Step 4: Hybrid Method Application.

- Node: Apply Hybrid Fuzzy AHP-Entropy Method
- Description: Use a combination of Fuzzy AHP and Entropy methods to determine the final weights of the objectives. This hybrid method helps in effectively evaluating and prioritizing criteria.

Step 5: Decision Making.

- Node: Use Fuzzy ELECTRE
- Description: Apply the Fuzzy ELECTRE III method for decision-making. This technique is used to handle uncertainty and provide a final evaluation of the alternatives.

Step 6: Corrective Actions.

- Node: Implement Corrective Actions
- Description: Based on the findings and decisions made in the previous steps, implement corrective actions and changes to address identified issues.

Return arrow description: After completing the final step, there is a return arrow from Implement Corrective Actions to Clarify the Goals. This indicates that the results and actions taken might require a review of the initial goals or other steps to refine the analysis and actions.

In summary, the flow chart integrates various methods to improve the analysis and decision-making process, ensuring a robust approach to identifying and addressing potential failures in a system.

4 Case study

In this section, the implementation of the proposed approach is presented, and the method is validated by analyzing the Fuzzy ELECTRE III method and comparing it with other methods of MCDM in FMEA.

4.1 Real-life case and condition

The case study focuses on a car manufacturer, founded in 1965 and located in Iran. Operations research methods and MCDM and, in particular, FMEA are widely used in car manufacturing to optimize production and decision making (Fan et al., 2022; Yousaf et al., 2023; Deulgaonkar et al., 2021; 2019; Moreno and Espejo, 2015). Techniques like linear programming streamline schedules (Wan and Zhan, 2021), reduce waste or emission (Zhang et al., 2024), and inventory and distribution (Ramos et al., 2022).

The target of this study is a component of the economy sedan model, the clutch system of the car (Figure 10). This essential system is positioned between the engine and the gearbox and is actuated through the clutch pedal. Therefore, it is an integral part of the car's operation, in that it allows the driver to connect the engine to the gearbox and disconnect while changing gears smoothly, in such a way that the power is transferred without a single beat missed.

Since the clutch system has this very critical function in relation to car performance (Pourgol-Mohammad et al., 2017) and safety (Cho and Han, 2011), its failure or malfunction can result in serious operational problems or safety hazards. One of the key functions of a car's clutch is to enhance safety, as it can serve as a crucial feature in emergencies. By depressing the clutch pedal, the driver can quickly disconnect the power from the wheels, helping to regain control or prevent unintended forward movement in critical situations. In addition, in the case of mechanical jams, it reduces the risk of kickback. However, a neglected clutch system can cause serious problems such as slipping, sticking, or difficulty in engaging the gears, resulting in reduced efficiency and potential accidents. Therefore, the presence of a clutch inherently contributes to vehicle safety (Matthes, 2005). Moreover, the clutch is a crucial component in ensuring the safety of the vehicle, especially when driving on mountainous areas or on other curvy roads (Wu et al., 2022). Recent studies focused on designing specific safety–critical clutch systems to avoid some types of accidents (Kumar et al., 2022). Finally, Trieu Minh (2012) unveiled the criticality of the clutch system in a hybrid electric vehicle for vibration reduction. Given its significance, it is essential to analyze potential failure risks and improve system reliability to enhance overall safety.

This system requires a risk analysis to identify probable modes of failure, estimate their impacts, and finally resolve them to improve the reliability and safety of the system (Lijesh et al., 2016). It prevents unexpected failure, assures smoothness in car operation, and hence is crucial to driver safety and satisfaction (Godina et al., 2021; Yousaf et al., 2023).

The technical design details associated with this study are confidential, as the technology owner has restricted the

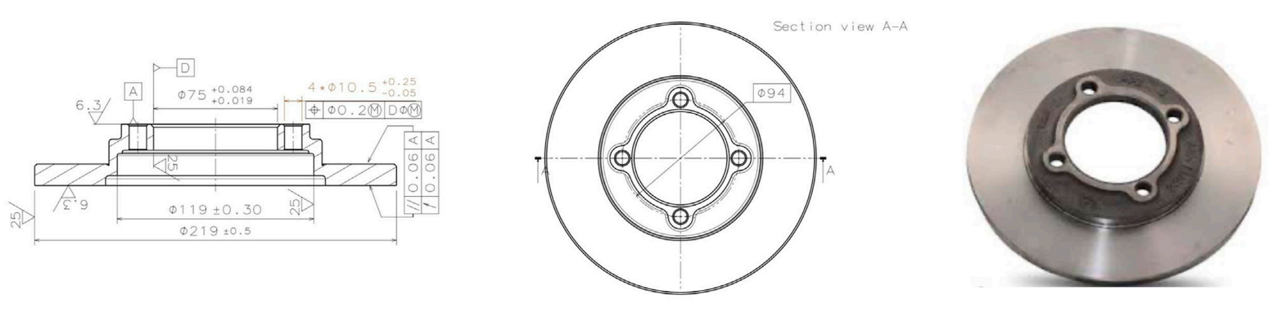

FIGURE 10
Clutch Disk Under Study (Originally designed by Kia Motors but modified several times by the Iranian company). The figures on the left and center depict the critical design parameters under investigation, complete with their respective tolerances. The figure on the right showcases an actual post-manufacture machine part.

TABLE 3 Failure modes linguistic scores according to the risk factors assigned by the FMEA team.

Critical mode	Occurrence					Severity					Detection				
	GM1	GM2	GM3	GM4	GM5	GM1	GM2	GM3	GM4	GM5	GM1	GM2	GM3	GM4	GM5
CM1	MG	G	F	MG	F	G	G	G	G	G	P	F	P	P	P
CM2	MP	P	MP	MP	MP	VG	G	G	VG	G	VP	VP	VP	P	VP
CM3	G	MG	G	MG	MG	G	MG	G	G	G	F	F	MP	F	F
CM4	F	F	P	F	F	F	F	MP	F	F	VP	MP	VP	MP	VP
CM5	F	MP	F	F	F	F	MG	MG	F	F	P	MP	P	P	P
CM6	VG	MG	VG	VG	VG	MG	MG	MG	MG	MG	MG	F	MG	MG	F
CM7	F	F	F	MG	F	MP	MP	MP	F	F	F	MP	MP	MP	MP

publication of details about the design parameters. Consequently, throughout the remainder of this article, all technical parameters will be referenced using labels only, without a detailed explanation. This approach is satisfactory for the research project because the objective of the case study is to implement and validate the proposed process while ensuring that the focus remains on the process itself and its performance, rather than on the particular characteristics of the machine part under consideration.

4.2 Implementation and results

To conduct the case study, the initial steps involve defining the objectives of the risk assessment to accurately determine the levels of risk. This includes clarifying the goals, developing a comprehensive list of failure modes, and evaluating these failure modes to determine their relative importance using linguistic variables. These activities, grouped together in Step 1, are carried out within the engineering department.

Following this, the process moves to Step 2, which focuses on team assembly. In this phase, a team is formed to perform the linguistic evaluation of failure modes, ensuring the accuracy and comprehensiveness of the FMEA. Once the team assembly is completed, the weighting phase begins. The group is made up of five experts, which are named GM1, GM2, GM3, GM4 and GM5. Table 3 shows the ranking results (Figure 9) used as input to the Subjective Weighting using Fuzzy AHP. The parameters in Table 3 are: CM1: Appearance. CM2: Parallel—It specifies the allowable deviation from parallelism between two surfaces. CM3: Limp—State of weakness or instability, often associated with physical rotation of the wheel. CM4: Internal diameter CM5: Surface finish CM6: Hole diameter CM7: External diameter.

Accordingly, in Table 3, experts are asked to express their assessments qualitatively using linguistic variables. These 7 linguistic terms for O, S, and D are assigned mathematical numbers for the fuzzy process. Thus, the meanings of these variables are VG (Very Good), G (Good), MG (Medium Good), MP (Medium Poor), P (Poor), VP (Very Poor), F (Fair).

TABLE 4 Pairwise comparison matrix.

Risk factor	O			S			D		
O	1.000	1.000	1.000	0.182	0.288	0.588	0.294	0.480	1.667
S	1.701	3.472	5.495	1.000	1.000	1.000	3.500	1.500	2.083
D	0.600	2.083	3.401	0.480	0.667	0.286	1.000	1.000	1.000

TABLE 5 Fuzzy geometric mean matrix.

Risk factor	O			S			D		
O	1.000	1.000	1.000	0.567	0.660	0.838	0.665	0.783	1.186
S	1.194	1.514	1.765	1.000	1.000	1.000	1.518	1.145	1.277
D	0.843	1.277	1.504	0.783	0.874	0.659	1.000	1.000	1.000

TABLE 6 Calculation of T.

Risk factor	O	S	D
O	0.377	0.517	0.993
S	1.812	1.733	2.254
D	0.660	1.116	0.991
T	2.850	3.366	4.237

TABLE 7 Obtained weights and defuzzification.

Risk factor	O	S	D	
W1	0.089	0.154	0.349	
W2	0.428	0.515	0.791	
W3	0.156	0.331	0.348	
DeFuzzy	0.197	0.578	0.278	1.053

4.2.1 Subjective weighting using fuzzy AHP

The subjective weighting process begins with collecting evaluations from team members and constructing a fuzzy pairwise comparison matrix for risk factors (Table 4).

The weights are obtained using the following process. The evaluations of the team members are collected and a fuzzy pairwise comparison matrix is constructed to calculate the AHP weights for O, S, and D. Table 4 represents the pairwise comparison matrix for the three risk factors. This matrix was derived from five experts who compared these factors relative to each other in terms of importance and representation of how much more important one factor is compared to another, and the T row is the sum of each column (total for each criterion), used for normalization and weight calculation. The fuzzy values come from linguistic terms (such as “More important,” “Less important,” etc.), which are then transformed into fuzzy numbers for mathematical processing.

Next, compute the fuzzy geometric mean according to the formulas, exponent each of the elements to 1/3 and calculate $r_{ij} = (a_{ij})^{\frac{1}{3}}$ and shown in Table 5.

In Table 6, the COA method is applied to defuzzify fuzzy numbers using the formula $T_i = a_{i1}^{\frac{1}{3}} a_{i2}^{\frac{1}{3}} + a_{i1}^{-\frac{1}{3}} a_{i3}^{\frac{1}{3}} + a_{i2}^{-\frac{1}{3}} a_{i3}^{-\frac{1}{3}}$ and these defuzzified values are normalized in Table 7 to obtain subjective weights for each risk factor, which W1, W2 and W3 represent as fuzzy weights of criteria.

TABLE 8 Goal weight of risk factors with Fuzzy AHP method.

WJS1	0.187
WJS2	0.549
WJS3	0.264

TABLE 9 Aggregated fuzzy failure modes data for O, S, and D.

O			S			D		
4.600	6.600	8.400	7.000	9.000	10.000	0.600	1.800	3.800
0.800	2.600	4.600	7.800	9.400	10.000	0.000	0.200	1.400
5.800	7.800	9.400	6.600	8.600	9.800	2.600	4.600	6.600
2.400	4.200	6.200	2.600	4.600	6.600	0.600	1.800	3.400
2.600	4.600	6.600	3.800	5.800	7.800	0.200	1.400	3.400
8.200	9.400	9.800	5.000	7.000	9.000	4.200	6.200	8.200
3.400	5.400	7.400	1.800	3.800	5.800	1.400	3.400	5.400

TABLE 10 Defuzzified Failure Mode values.

O	S	D
6.533	8.667	2.067
2.667	9.067	0.533
7.667	8.333	4.600
4.267	4.600	1.933
4.600	5.800	1.667
9.133	7.000	6.200
5.400	3.800	3.400

Furthermore, Table 8 shows the final normalized subjective weights for each of the three risk factors (WJS1, WJS2, WJS3) for the risk factors (O, S, D) after applying Fuzzy AHP.

4.2.2 Formation of total rank fuzzy weighted matrix

A fuzzy weighted matrix is then formed based on the evaluations provided by five experts on seven criteria. The evaluations are summed across seven options for each of the criteria (O, S, and D), resulting in a matrix that includes seven items and three options (see Table 9, and fuzzy failure modes of fuzzy total rank in Table 10).

4.2.3 Objective weighting using entropy method

The objective weights of the risk factors are determined using the Entropy method. In the entropy method, objective weights for risk factors (Occurrence, Severity, and Detection) are determined by quantifying the amount of uncertainty to avoid bias when dealing with subjective data from experts (Table 11). In Table 11 Ej represents the entropy for each risk factor, ‘1-Ej’ gives the complement of the entropy, showing the degree of certainty or

TABLE 11 Objective weight of risk factors with entropy method.

Risk factor	O	S	D
E_j	0.967	0.978	0.900
$1-E_j$	0.033	0.022	0.100
W_j	0.212	0.141	0.647

TABLE 12 Final weight gain.

Risk factor	ϕ	ϕ	ϕ
	0.500	1.000	0.000
O	0.199	0.187	0.212
S	0.345	0.549	0.141
D	0.456	0.264	0.647

TABLE 13 Weighted matrix with ϕ = 0.5 to adjust the relative importance of the subjective and objective weights.

Risk factor	O	S	D
1	1.300	2.990	0.942
2	0.531	3.128	0.243
3	1.526	2.875	2.098
4	0.849	1.587	0.882
5	0.915	2.001	0.760
6	1.818	2.415	2.827
7	1.075	1.311	1.550

consensus in expert judgments, and Wj represents the final weight for each risk factor, which is used in subsequent analyzes.

4.2.4 Combined weight calculation

This step entails the synergistic aggregation of subjective weights derived from Fuzzy AHP and objective weights calculated via the Entropy method to determine the final comprehensive weights for each risk factor. The justification for this composite approach lies in its ability to mitigate the inherent limitations of using a single weighting source. While Fuzzy AHP captures the experiential knowledge of the engineering team, it remains susceptible to cognitive bias. Conversely, the Entropy method provides a purely mathematical assessment of data variation but lacks engineering context. By combining these two distinct inputs using a linear weighting formula, the methodology ensures that the final importance of S, O, and D is not solely dictated by human preference nor blindly driven by data dispersion. The coefficient ϕ is introduced to govern this trade-off. In this study, a value of $\phi = 0.5$ is selected to establish an equilibrium, treating expert intuition and objective information content as equally critical components of the risk assessment. The resulting weights are presented in Table 12.

TABLE 14 The effective coordination of the inconsistent matrix multiplication.

Critical mode	CM1	CM2	CM3	CM4	CM5	CM6	CM7
CM1	-	1	0	1	1	0	1
CM2	0	-	0	0	0	0	0
CM3	1	1	-	1	1	0	1
CM4	0	0	0	-	0	0	0
CM5	0	0	0	1	-	0	0
CM6	1	1	1	1	1	-	1
CM7	0	0	0	1	0	0	-

4.2.5 Application of fuzzy ELECTRE III method

In this stage, the Fuzzy ELECTRE III method is applied to rank the failure modes based on their weighted evaluations. The process consists of multiple steps following the process explained in Section 3.1.4.

First, the weights obtained from Table 12 are multiplied by the values in Table 10 (Defuzzy Total Rank Fuzzy Failure Modes) to calculate the weighted matrix. Where w_j^c values are the combination weights of criteria, and $\varphi \in [0,1]$, showing the relative importance between subjective and objective weight (Table 13). In this paper, weights are assumed to be equally important using $\varphi = 0.5$ (Liu et al., 2015). However, in future studies, the impact of using $\varphi = 1$ *and* 0 can be studied by means of sensitivity analysis.

The results of the remaining stages of the ELECTRE method are obtained through the following steps:.

1. Determine coordinated and uncoordinated sets using the Fuzzy ELECTRE III method (Equation 26).

$$C_{kl} = \{j \mid y_{kj} \geq y_{lj}\}, \quad D_{kl} = \{j \mid y_{kj} \leq y_{lj}\} \tag{26}$$

2. Form the coordinated matrix I based on the weights from C.
3. Construct the uncoordinated matrix using Equation 27.

$$d_{kl} = \frac{\max_{j \in D_{kl}} |y_{kj} - y_{lj}|}{\max_j |y_{kj} - y_{lj}|} \tag{27}$$

4. Calculate the effective coordinated and uncoordinated matrices. Effective coordinated matrix: $\sum$ each item divided by 1; otherwise, set to 0. Effective uncoordinated matrix: Sum all items divided by the number of items; set to 0 for each.
5. Multiply the effective coordinated matrix by the effective uncoordinated matrix (Table 14).
6. Prioritize based on Fuzzy ELECTRE III principles.

As a result of the ELECTRE III analysis, the seven failure mode options are ranked into five priority levels:

1. The first priority is assigned to CM6.
2. The second priority is shared by CM1 and CM3, which have equal values.

TABLE 15 Priority options on the FMEA with a variety of MCDM methods including Fuzzy AHP. ENTROPY, and ELECTRE III. (ϕ = 0.5).

Priority	Ranking with fuzzy ELECTRE	Ranking with fuzzy VIKOR	Ranking with fuzzy TOPSIS
Priority 1	FM3, FM2	FM6	FM6
Priority 2	FM7, FM6	FM3	FM3
Priority 3	FM5, FM1	FM1	FM7
Priority 4	FM4	FM2	FM1
Priority 5	–	FM7	FM5
Priority 6	–	FM5	FM4
Priority 7	–	FM4	FM2

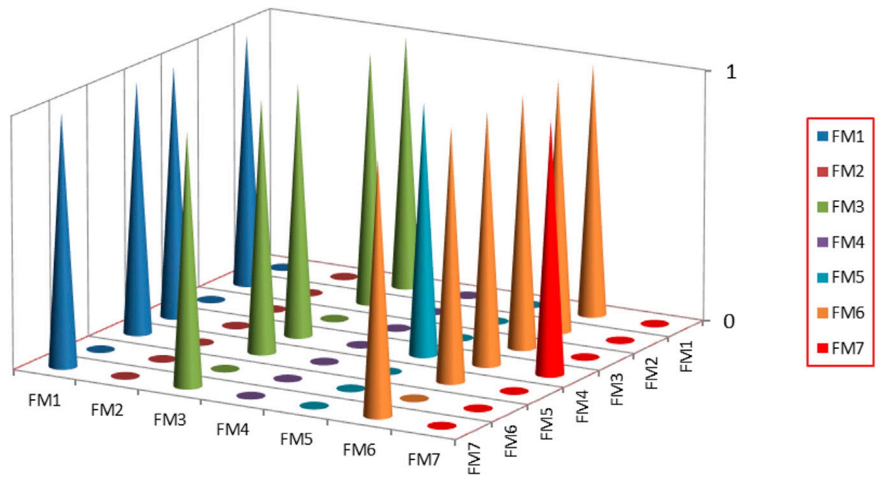

FIGURE 11
Relationship diagram obtained by Fuzzy ELECTRE III method. The chart provides a graphical illustration of the results of Table 14.

3. The third priority is shared by CM2, CM5, and CM7, which also have equal values.
4. The fourth priority is assigned to CM4, which has the lowest rank.

This ranking provides valuable information for decision makers about prioritizing failure modes and implementing corrective actions accordingly.

4.3 Validation of implementation feasibility

To assess the effectiveness of the proposed method, the results are compared with those obtained using alternative techniques, specifically Fuzzy TOPSIS and Fuzzy VIKOR. These alternative approaches are applied to rank the car component under study (Figure 10), using the same input data as in this article (Table 3) but alternative techniques proposed by Liu et al. (2015). The results are compared to those generated by the Fuzzy ELECTRE III method (Table 15; Figure 11).

Table 16 presents the priority rankings calculated using Fuzzy TOPSIS and Fuzzy VIKOR methods, as presented in Behzadian et al. (2012), while Table 17 displays the corresponding results derived from the Fuzzy VIKOR method, as presented in Opricovic and Tzeng (2007); the measures S, R and Q of the VIKOR method are detailed in Table 18.

The comparison highlights how effective coordination of the inconsistent multiplication of matrices in our proposal compared to the TOPSIS and VIKOR methodologies. The results of this comparison are presented in Table 15.

4.3.1 Discussion

The comparative analysis highlights a fundamental divergence in how risk is prioritized. While traditional MCDM methods (TOPSIS, VIKOR) rely on "net distance" or "compromise" calculations, the proposed hybrid ELECTRE III method relies on "outranking" relations with veto thresholds. As detailed below, this leads to a superior risk assessment profile by eliminating the 'illusion of precision' often seen in linear rankings and preventing the masking of high-severity risks.

4.3.1.1 Sensitivity and instability in fuzzy TOPSIS

The results in Table 16 reveal that Fuzzy TOPSIS is highly sensitive to the weight restriction parameter (ϕ). For instance, FM6 jumps from Rank 3 to Rank 1 simply by adjusting the

TABLE 16 Ranking with a combination of Fuzzy TOPSIS and VIKOR.

Failure mode	Proposed approach (ϕ = 1)		Proposed approach (ϕ = 0.5)		Proposed approach (ϕ = 0)		Traditional FMEA					Fuzzy TOPSIS		Final results
	Q	Rank	Q	Rank	Q	Rank	O	S	D	RPN	Rank	Rc	Rank	Ranking
FM1	0.859	2	0.656	3	0.224	4	7	9	2	126	3	0.853	4	FM6
FM2	0.745	4	0.527	4	0.026	6	3	10	1	30	6	0.914	7	FM3
FM3	0.905	1	0.759	2	0.660	2	8	9	4	288	2	0.786	2	FM7
FM4	0.000	7	0.000	7	0.018	7	4	4	1	16	7	0.903	6	FM1
FM5	0.309	5	0.216	6	0.104	5	5	6	1	30	5	0.883	5	FM5
FM6	0.835	3	1.000	1	1.000	1	9	7	6	378	1	0.734	1	FM4
FM7	0.162	6	0.300	5	0.362	3	6	4	3	72	4	0.848	3	FM2

The ranking is shown under the 'Final Results' column from the top (Highest rank) to down (Lowest).

TABLE 17 Ranking the conventional alternative approach for FMEA using Fuzzy VIKOR.

Failure mode	FM1	FM2	FM3	FM4	FM5	FM6	FM7
BY S	5	4	6	1	2	7	3
BY R	6	4	5	1	2	7	3
BY Q	5	4	6	1	2	7	3
Result							
Ranking from right (highest rank) to left (lowest)	FM6	FM3	FM1	FM2	FM7	FM5	FM4

The ranking is shown under the results row from the right (Highest rank) to the left (Lowest). The S, R, and Q measures are detailed in Table 18.

TABLE 18 Interpretation and ranking impact of VIKOR measures.

Name	Ranking measures for alternatives	Interpretation	Ranking impact
S	Group utility measure	Measures the overall deviation of each failure mode from the ideal solution across all criteria. Lower S means the failure mode is closer to the best possible performance	Failure modes with lower S values rank higher (better)
R	Regret measure	Focuses on the worst performance of each failure mode across all criteria. Lower R indicates a failure mode with more balanced performance	Failure modes with lower R values rank higher (more stable risk profile)
Q	Final VIKOR index	Combines S and R to provide a compromise ranking, balancing overall utility and worst-case performance. Lower Q means a failure mode is more critical	Failure modes with lower Q values rank highest in the final ranking

balance between subjective and objective weights. This volatility is a significant drawback in safety-critical engineering; it suggests that the ranking is driven more by mathematical assumptions than by the inherent risk of the component. Furthermore, TOPSIS assigns a unique rank to every failure mode based on Euclidean distance. This creates artificial distinctions between failure modes that are practically identical in risk profile, potentially leading to misallocated maintenance resources.

4.3.1.2 Inconsistency in fuzzy VIKOR measures

The analysis of Fuzzy VIKOR (Table 17) reveals a limitation regarding ranking stability across its internal measures. While FM6 is identified as the highest risk, the method produces inconsistent rankings for secondary risks (FM1 and FM3) depending on whether the Group Utility (S) or Individual Regret (R) is prioritized. This ambiguity compels decision-makers to rely on the composite index (Q), which attempts a mathematical compromise but may obscure the specific nature of the risk (e.g., high severity vs. high occurrence). Unlike the proposed ELECTRE III method, which establishes clear dominance, VIKOR's compromise approach forces a trade-off that may not always align with the strict "safety-first" constraints required for critical automotive components.

4.3.1.3 Logical clustering via fuzzy AHP-entropy-fuzzy ELECTRE III

The results obtained by the proposed hybrid method (Table 15) demonstrate a superior logical structure compared to the comparative methods. While TOPSIS and VIKOR force a strict linear ranking (1 through 7) based on minute decimal differences, the Fuzzy ELECTRE III method clusters the failure modes into four distinct priority levels. For instance, FM3 and FM2 are grouped together in the highest priority level. This "clustered ranking" is methodologically more robust for risk assessment because it acknowledges the inherent uncertainty of expert inputs; distinguishing between a "Rank 2" and "Rank 3" risk often implies a precision that simply does not exist in linguistic data. Furthermore, the method demonstrates distinct safety advantages through its non-compensatory nature. Unlike TOPSIS, which allows high detection scores to mask severe risks, ELECTRE III utilizes veto thresholds to ensure critical failure modes are not demoted. Additionally, the method validates its accuracy by converging with other methods on low-risk items; like VIKOR and TOPSIS, it correctly identifies FM4 as the lowest priority (Priority 4), confirming that the model is calibrated correctly while providing more actionable, safety-critical insights at the top of the ranking order.

The proposed Hybrid Fuzzy ELECTRE III method sorted the FMs into four distinct priorities (see the first column and rows from Priority 1 to 4 in Table 15; Figure 11). Instead, the two other methods identify seven distinct priorities. This reduction in the number of distinct priorities and the formation of equal priority classes can simplify strategies needed to enhance the reliability of the final products. However, this inference requires validation through additional case studies to test the hypothesis in future research.

The differences in priority rankings highlight how the choice of the MCDM method impacts the outcome. Different methodologies lead to different prioritization, which can influence the risk management activities that follow.

Methodological differences have a crucial impact on the results of different approaches. For example, the impact on aggregation and normalization is as follows:

- The different aggregation methods and normalization techniques used by VIKOR (linear normalization) and TOPSIS (vector normalization) contribute to the variations in rankings.
- ELECTRE's preference-based approach further differentiates its results from those obtained using VIKOR and TOPSIS.

4.3.1.4 Comparison of variations

The result of the comparative analysis suggests the importance of selecting an appropriate MCDM method based on the specific needs and characteristics of the risk evaluation context. Each method provides a unique perspective on prioritizing failure modes, with Fuzzy ELECTRE III, Fuzzy VIKOR, and Fuzzy TOPSIS each offering distinct advantages and insights into risk assessment. However, according to Table 15 the Fuzzy ELECTRE III method is beneficial in FMEA, as it enables analysis based on relevant parameters and helps to reduce priorities. For instance, in our case study with seven options, Fuzzy ELECTRE III identifies four distinct priorities 11. This allows for a more focused analysis and a better understanding of the sensitivity of the parameters.

4.3.1.5 Differences in the MCDM methods

The MCDM methods argued in this paper (i.e., Fuzzy TOPSIS, Fuzzy VIKOR, Fuzzy ELECTRE III) have different approaches in raking failure modes. Fuzzy TOPSIS is generally sensitive to distances from the Positive and Negative Ideal Solutions. Lower distance values from the former and greater distance values from the latter lead to higher ranks. This feature makes TOPSIS suitable for ranking failure modes that are clearly distinguishable and well-separated. Instead, Fuzzy VIKOR focuses on finding a compromise solution by achieving a balance between the Utility Measure and the Regret Measure, which in turn leads to the final ranking of failure modes. This approach makes fuzzy VIKOR sensitive to the worst-performing criterion, i.e., if a failure mode performs poorly in one criterion, it will be ranked lower even if it performs very well in other criteria. Consequently, this perspective makes Fuzzy VIKOR suitable for cases where an acceptable trade-off is preferred to selecting the absolute best option. Unlike the two mentioned methods, ELECTRE III puts the failure modes in pairwise comparisons and uses concordance (agreement) and discordance (disagreement) indices to determine the dominance relationships between them. Relying on this outranking approach makes ELECTRE III less sensitive to small differences and suitable for situations where there are multiple trade-offs and strong interactions among criteria.

4.3.1.6 Advantages of the proposed hybrid approach

The proposed hybrid framework offers three distinct advantages over prevalent Fuzzy MCDM approaches such as Fuzzy TOPSIS and Fuzzy VIKOR. First, the synergistic weighting mechanism solves the dilemma of "Expert Bias" vs. "Data Blindness." While most existing methods rely on a single source of weights, this approach cross-validates subjective expert intuition (Fuzzy AHP) with objective information content (Entropy), ensuring a risk profile that is both practically grounded and mathematically rigorous. Second, and most critically for safety engineering, the use of Fuzzy ELECTRE III introduces non-compensatory logic. In standard distance-based methods (TOPSIS) or compromise methods (VIKOR), a failure mode with catastrophic severity can be downgraded if it has a very low occurrence rate (mathematical compensation). The proposed method employs "veto thresholds," ensuring that high-severity risks retain their critical status regardless of other mitigating factors. Finally, the method avoids the "fallacy of hyper-precision." Instead of forcing a strict ordinal ranking (e.g., Rank 1 to Rank 7) based on negligible decimal differences, this approach sorts failure modes into logical priority clusters (e.g., Priority Level 1, 2, 3). This categorization provides a more realistic representation of uncertain data and facilitates clearer resource allocation strategies for maintenance teams.

4.3.1.7 Disadvantages of proposed hybrid approach

Despite its methodological robustness, the proposed hybrid approach introduces a higher degree of operational complexity compared to traditional RPN or distance-based methods

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(TOPSIS). The primary disadvantage lies in the cognitive load required for parameter calibration. Unlike direct linear calculations, Fuzzy ELECTRE III requires the precise definition of preference, indifference, and veto thresholds. These thresholds are sensitive; incorrect calibration by the decision-maker can lead to incoherent rankings or an inability to distinguish between options (too many "indifferent" relations). Furthermore, the method relies on pairwise comparisons, which creates a non-linear increase in computational effort as the number of failure modes grows. Consequently, while this approach is superior for critical components (like the clutch system), it may require specialized software automation to be scalable for system-wide analyses involving hundreds of failure modes.

5 Limitations and future studies

While the proposed hybrid framework offers significant improvements in handling uncertainty and risk prioritization, three key limitations must be acknowledged to guide future research.

First, regarding scalability and computational intensity, the reliance on Fuzzy ELECTRE III requires complex pairwise comparisons. As the number of failure modes (n) increases, the number of comparisons grows structurally ($n \times n$), potentially making manual calculation unfeasible for complex systems with hundreds of failure modes. Future research should focus on developing automated decision support software or integrating Machine Learning (ML) algorithms to learn from expert inputs and automate the generation of preference and veto thresholds, thereby reducing the cognitive load on the engineering team.

Second, the method assumes static risk behaviors. The current model treats the failure modes as fixed snapshots in time. However, in real-world automotive manufacturing, risk profiles change dynamically based on machine wear, supplier quality, and environmental conditions. A promising avenue for future research is the development of a Dynamic FMEA (D-FMEA) framework, potentially integrated with Digital Twin technology, where the Entropy weights are updated in real-time based on live sensor data from the production line.

Third, the sensitivity of threshold parameters in ELECTRE III remains a critical factor. While this study utilized expert consensus to define indifference and veto thresholds, these values are inherently subjective. Future studies could employ Data Envelopment Analysis (DEA) or evolutionary algorithms to mathematically optimize these thresholds, ensuring the most robust ranking separation without excessive manual trial-and-error.

6 Conclusion

Precise risk-based design is the cornerstone of safety-critical engineering. This study addressed the fundamental deficiencies of the traditional RPN and conventional fuzzy approaches—specifically their inability to manage conflicting risk factors and their tendency to allow high-detection scores to mask high-severity risks.

The primary contribution of this work is the development of a robust hybrid methodology that synergizes Subjective (Fuzzy AHP) and Objective (Entropy) weighting with a Non-Compensatory (Fuzzy ELECTRE III) ranking engine. By moving away from simple multiplicative formulas and distance-based methods (e.g., TOPSIS), this approach introduces a safety-first logic: it prevents the compensation of critical severity risks by other factors, a feature that is indispensable for automotive safety components like the clutch system.

The empirical validation on the clutch system demonstrated that the proposed method reduces the noise inherent in traditional rankings. While comparative methods (TOPSIS and VIKOR) produced highly dispersed, linear rankings (Ranks 1–7) based on mathematical minutiae, the proposed method successfully grouped failure modes into four logical priority clusters. This clustering provides a more realistic representation of risk, acknowledging that minor distinctions between failure modes are often statistically insignificant.

For engineering managers, this framework offers a strategic tool for resource allocation. By reducing the number of priority levels, decision-makers can focus maintenance efforts on the "Priority 1" cluster with greater confidence, knowing that these risks have been vetted against strict safety thresholds. The transition from a "Compensatory" model to an "Outranking" model ensures that resources are not diverted to minor issues at the expense of catastrophic but rare failure modes, ultimately supporting a "Zero Defect" manufacturing philosophy.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

AA: Methodology, Project administration, Writing – original draft, Writing – review and editing. AS: Conceptualization, Data curation, Formal Analysis, Validation, Writing – review and editing. MP: Investigation, Validation, Writing – review and editing. MG: Investigation, Validation, Writing – review and editing. EP: Supervision, Validation, Writing – review and editing. MB: Supervision, Validation, Writing – review and editing.

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