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NEW APPROACH FOR FAILURE MODE AND EFFECT ANALYSIS BASED ON INTERVAL-VALUED INTUITIONISTIC FUZZY CLOUD THEORY AND SOCIAL NETWORK CONSENSUS ANALYSIS

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Failure mode and effect analysis (FMEA) is a proactive risk assessment methodology extensively used across industries to enhance the safety and reliability of systems, products, and services. Classical FMEA predominantly relies on experts' subjective judgments, which inherently involve multiple types of uncertainty, including vagueness, hesitation, and randomness. However, existing FMEA studies seldom consider these types of uncertainty simultaneously. Moreover, experts' heterogeneous backgrounds and experiences can lead to divergent and inconsistent risk assessments. Few FMEA studies have investigated consensus-reaching mechanisms to address such an issue. Therefore, this paper presents a new FMEA framework integrating interval-valued intuitionistic fuzzy cloud (IVIFC) theory with social network consensus analysis to further enhance the performance of risk assessments. First, the IVIFC is adopted to describe experts' linguistic assessments. It blends the strength of interval-valued intuitionistic fuzzy sets in manipulating vagueness and hesitation with the advantage of the cloud model in reflecting the randomness of assessment information. Then, a social network consensus analysis model with maximum expert consensus is introduced to assist FMEA experts in reaching an agreement. Additionally, a hybrid method combining techniques for ordering preferences for similarity to ideal solutions and grey relational analysis is developed to derive the risk order of failure modes. Eventually, an empirical case in the robot-aided rehabilitation setting is presented to illustrate the developed FMEA model, with its effectiveness further substantiated through simulation and comparative analysis. The results show that the proposed model resolves major deficiencies of classical FMEA and offers a reliable solution for practical FMEA applications.

Keywords: FMEA; Cloud model; Interval-valued intuitionistic fuzzy set; Expert consensus; Risk assessment; Robot-aided rehabilitation.

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1. INTRODUCTION

Failure mode and effect analysis (FMEA) is an important risk assessment methodology extensively used for recognizing failure modes of products, systems, or processes (Huang *et al*., 2020; Zhang *et al*., 2023). It was originally developed in the 1960s by the United States aerospace industry for evaluating system safety and reliability (Liu *et al*., 2024). Different from other risk analysis techniques, FMEA identifies critical failure modes in advance and takes precautions to reduce the risk of those failure modes. Additionally, proper application of FMEA might improve product quality, reduce product development cycles, and improve user experience (Ilbahar *et al*., 2022). Currently, the FMEA has found widespread application across various fields, including automotive (Nahavandi & Tavakoli, 2022; Liu *et al*., 2023c), construction (Chen *et al*., 2023; Li *et al*., 2025), and healthcare industries (Liu *et al*., 2020; Liu *et al*., 2023b; Liu *et al*., 2024). The traditional FMEA requires participants to assign risk ratings to occurrence (O), severity (S), and detection (D) of each possible failure mode on a

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numerical scale varying between 1 and 10 (Stamatis, 2003). Failure modes are prioritized by employing their risk priority number (RPN), whose values are derived by multiplying O, S, and D values. Higher RPNs reflect more critical failure modes and tend to result in greater system risks. Finally, critical failure modes are determined, for which precautions are subsequently taken to mitigate their overall risk. Although the traditional RPN method is simple and convenient, it has multiple inherent deficiencies in real-world implementation (Huang *et al*., 2021; Huang *et al*., 2023; Zhang *et al*., 2024a; Zhang *et al*., 2024b; Chen *et al*., 2025).

FMEA experts often utilize linguistic terms to express their risk evaluations as they align with people's expression habits (Liu *et al*., 2019b; Liu *et al*., 2024; Daas & Innal, 2023b; Daas & Innal, 2024a). However, experts' linguistic assessment information of FMEA usually involves different types of uncertainty, such as vagueness, hesitation, and randomness (Huang & Xiao, 2021; Liu *et al*., 2022; Daas & Innal, 2023a). To describe experts' linguistic assessment information, researchers have developed a variety of modified FMEA approaches based on different linguistic representation methods, e.g., fuzzy set (Li, 2024; Daas & Innal, 2023a; Rahnamay Bonab & Osgooei, 2025, intuitionistic fuzzy set (Carnero, 2026; Daas & Innal, 2024b), interval-valued intuitionistic fuzzy set (IVIFS) (Wang *et al*., 2016; Wu *et al*., 2024b), and cloud model (Akhtar *et al*., 2024; Liu *et al*., 2023a). While these methodological enhancements show improved performance over the conventional FMEA, several limitations persist. Specifically, those fuzzy set theory-based methods can describe fuzziness but not hesitation and randomness in the risk assessment information (Huang & Xiao, 2021; Liu *et al*., 2024). The IVIFS-based methods can deal with fuzziness and hesitation, but lack the mechanism of dealing with randomness. In contrast, the cloud model could consider both fuzziness and randomness, but not the hesitation of qualitative concepts. As a result, these limitations might adversely influence the accuracy of reflecting the real preferences of decision-makers. As such, it is meaningful to find a suitable linguistic representation model that is able to simultaneously address the multiple types of uncertainty in FMEA team members' linguistic risk assessments.

In addition, FMEA is often conducted by a multidisciplinary team of experts representing various functional areas (Huang *et al*., 2021; Huang *et al*., 2023; Zhang *et al*., 2023). These experts typically possess differing levels of accumulated experience, academic backgrounds, and cognitive perspectives. Thus, they often present different risk assessments on failure modes, and even these assessments are sometimes controversial. This will result in a lower consensus among experts and affect risk ranking results for failure modes. Achieving a consensus over experts' risk assessments requires a consensus-reaching mechanism in the FMEA process (Zhang *et al*., 2023; Zhang *et al*., 2024a). Besides, individual participants in an FMEA team are susceptible to influence originating from their social relationships (e.g., friendships or trust) with other team members. Therefore, the impact of social relationships among risk experts plays a critical role in achieving consensus among FMEA experts. However, few FMEA studies have investigated the influence of social networks on experts' assessment revisions and consensus achievement.

To enhance FMEA's effectiveness, a variety of multi-criteria decision-making (MCDM) methods are incorporated into the risk determination process of failure modes. The most frequently used MCDM methods are techniques for ordering preferences for similarity to ideal solutions (TOPSIS) (Gul & Ak, 2021; Nahavandi & Tavakoli, 2022; Shi *et al*., 2023) and grey relational analysis (GRA) (Hua *et al*., 2023; Li, 2024; Li *et al*., 2025). In addition, the literature survey by Liu *et al*. (2019a) has demonstrated the competitiveness and effectiveness of the TOPSIS and GRA methods, revealing that both are the most preferred approaches for risk ranking in FMEA. The TOPSIS method determines the risk ranking of failure modes by calculating the distance between the evaluation sequence and the positive and negative ideal solution sequences. The TOPSIS is utilized in this paper for the following reasons: (1) it is rational and easily understandable; (2) its computational process is straightforward and fast; and (3) it allows us to choose the best alternatives for each criterion represented in a simple mathematical form. Although the TOPSIS is applied in many fields, it fails to account for the correlation between attributes and can suffer from rank reversal when alternatives are added or removed (Dong *et al*., 2022; Wu *et al*., 2024a; Yan *et al*., 2023). Meanwhile, if the total distance is the same, the risk of failure modes cannot be distinguished. Fortunately, the limitations of TOPSIS can be mitigated by the GRA method. Specifically, the GRA determines the risk ranking of failure modes by calculating the correlation degree between the comparison of failure modes and the reference failure mode. Therefore, this paper will develop a hybrid MCDM model combining TOPSIS and GRA to ensure reliable risk rankings of failure modes, which benefits from the advantages of both methods.

In this study, we aim to present a new FMEA framework based on a linguistic computational method, social network consensus analysis, and a hybrid MCDM model. Specifically, our contributions are summarized as follows: (1) A novel linguistic computational method, i.e., interval-valued intuitionistic fuzzy clouds (IVIFCs), is adopted to adequately capture multiple uncertainties of experts' risk judgements. (2) Social network consensus analysis, maximizing expert consensus, is utilized to enable FMEA experts to reach a consensus. (3) A hybrid method of TOPSIS and GRA is presented to derive the risk priority of failure modes. Finally, the effectiveness of the proposed FMEA framework is illustrated by an empirical case in the robot-aided rehabilitation setting.

The rest of this paper proceeds below. The next section performs a literature review on recent advances in FMEA. Section 3 introduces the linguistic representation method. Section 4 introduces the new proposed FMEA framework. In

Section 5, an empirical case is provided to demonstrate the developed FMEA model, accompanied by simulation analysis and comparative analysis. Finally, Section 6 summarizes this research and proposes further research possibilities.

2. LITERATURE REVIEW

In recent years, plenty of approaches have been introduced to handle the inherent uncertainties involved in FMEA experts' risk assessment information (Liu *et al.*, 2019a). Among these approaches, fuzzy theory remains most frequently applied. For example, Testik and Unlu (2022) found that fuzzy FMEA is a more suitable way to rank failure modes when handling qualitative, subjective, and incomplete assessments. In addition, IVIFS and cloud model have been applied in FMEA for linguistic representation in current studies. For instance, Ilbahar *et al*. (2022) presented an FMEA framework based on IVIFS to address the hesitancy of experts in assigning risk ratings to the detection factor. Wu *et al*. (2024b) and Li *et al*. (2025) adopted IVIFS to capture the uncertainty and vagueness of expert subjective judgments during the risk evaluation process. Liu *et al*. (2019b) introduced an FMEA approach by combining a cloud model with hierarchical TOPSIS, in which the former quantifies uncertainties in linguistic risk evaluations. Yu *et al*. (2021) developed a modified FMEA approach based on a cloud model and VIKOR to improve the reliability of submarine pipelines. Liu *et al*. (2023b) incorporated cloud model into FMEA to address the fuzziness and randomness of linguistic risk evaluations on failure modes.

Researchers applied various MCDM methods to the failure mode risk ranking process. As one of the classic MCDM methods, TOPSIS is widely used in the improved FMEA methods. Braglia *et al*. (2003) implemented fuzzy TOPSIS to address risk prioritization of failure modes. Gul and Ak (2021) proposed an FMEA framework on the basis of interval-valued spherical fuzzy TOPSIS to address the drawbacks inherent in the conventional RPN method. Liu *et al*. (2019b) employed hierarchical TOPSIS to prioritize the risk of failure modes. Chen *et al*. (2023) applied the behavioral TOPSIS to FMEA to determine the risk priority order of failure modes. Shi *et al*. (2023) presented an innovative FMEA method integrating the best-worst method with TOPSIS. GRA is another popular approach for risk ranking of failure modes in FMEA. Aswin *et al*. (2022) proposed a risk assessment method based on fuzzy sets and GRA, which makes the failure mode risk ranking more realistic and objective. Li *et al*. (2025) presented an FMEA model that integrates the multiple attribute border approximation area comparison (MABAC) method with GRA, in which GRA was used to capture interdependencies among risk factors. Li (2024) proposed a personal information security risk evaluation model integrating fuzzy set, TOPSIS, with GRA to improve the traditional FMEA.

Recently, various consensus models have been employed in FMEA to mitigate the conflicts among expert risk assessments. For instance, Zhang *et al*. (2021) formulated a social network consensus framework minimizing adjustment distance to facilitate the consensus achievement of FMEA team members. Xiao *et al*. (2021) devised a confidence-bound consensus optimization framework for helping the FMEA team reach a consensus. Liu *et al*. (2023a) proposed a consensus-based FMEA based on the minimum adjustment distance consensus model to reach group consensus, which considers cooperative relationships among experts, individual self-confidence levels, and opinion adjustment thresholds. Zhang *et al*. (2023) developed a minimum cost consensus-based FMEA framework, which considers experts' tolerance behaviors and bounded compromise. Chen *et al*. (2023) developed a consensus-reaching process model based on distances among experts, with a feedback mechanism to achieve a satisfactory consensus level within a limited number of iterations. Shi *et al*. (2022) proposed a dynamic consensus model to determine the relative weights of FMEA experts and revise the individual assessment information until reaching an acceptable consensus. Huang *et al*. (2023) carried out a consistency repairing algorithm based on an automatic improving method to address the self-contradictory situation of experts' risk evaluations on failure modes.

The above literature review shows that many efforts have been made to improve the traditional FMEA. Nevertheless, there are still several deficiencies regarding existing FMEA methods. First, FMEA mainly relies on experts' subjective judgments, which involve multiple types of uncertainty, including vagueness, hesitation, and randomness. However, the current approaches seldom consider these types of uncertainty simultaneously. Second, various MCDM methods have been employed to determine the risk ranking of failure modes in FMEA. But these different MCDM techniques vary in their strengths and weaknesses, which can yield different risk rankings of failure modes. Third, although an increasing number of studies have applied the consensus-reaching procedure in FMEA, many of them are based on the minimum cost (or distance) consensus model. In many practical situations, the consensus cost budget is predetermined, and the FMEA team shifts to maximizing consensus coverage within the predetermined budget. To fill the above research gaps, this study aims to construct a hybrid FMEA approach based on the interval-valued intuitionistic fuzzy cloud theory and the TOPSIS-GRA to address multiple types of uncertainties in risk evaluation information and establish a robust risk prioritization of failure modes. Furthermore, the maximum expert consensus model (MECM) under a social network is introduced to maximize FMEA expert consensus within a predefined cost budget. A summary of the aforementioned FMEA studies is shown in Table 1.

Table 1. Summary of FMEA studies in the literature

References	Risk assessment	Consensus reaching	Failure ranking
Testik and Unlu (2022)	Fuzzy set	Not considered	RPN
Ilbahar *et al*. (2022)	IVIFS, prospect theory	Not considered	AHP (Analytic Hierarchy Process)
Wu *et al*. (2024b)	IVIFS	Not considered	TODIM (an acronym in Portuguese of interactive and multi-criteria decision making)
Li *et al*. (2025)	IVIFS	Not considered	MABAC, GRA
Liu *et al*. (2019b)	Cloud model	Not considered	Hierarchical TOPSIS
Yu *et al*. (2021)	Cloud model	Not considered	VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje)
Liu *et al*. (2023b)	Cloud model	Not considered	TOPSIS, DEA (Data Envelopment Analysis)
Braglia *et al*. (2003)	Fuzzy set	Not considered	TOPSIS
Gul and Ak (2021)	Interval-valued spherical fuzzy set	Not considered	TOPSIS
Chen *et al*. (2023)	Relative basic uncertain linguistic information	Consensus-reaching process model based on distances	Behavioral TOPSIS
Shi *et al*. (2023)	Probabilistic linguistic term set	Not considered	TOPSIS, BWM (best-worst method)
Aswin *et al*. (2022)	Fuzzy set	Not considered	GRA
Li (2024)	Fuzzy set	Not considered	TOPSIS, GRA
Zhang *et al*. (2021)	Linguistic distribution assessment	Social network consensus model with minimum adjustment distance	Weighted RPN
Xiao *et al*. (2021)	Linguistic distribution assessment	Minimum adjustment element & distance consensus model	Risk classifications of failure modes
Liu *et al*. (2023a)	Probabilistic linguistic term set	Minimum adjustment distance consensus model	GLDS (gained and lost dominance score), SMAA (stochastic multi-criteria acceptability analysis)
Zhang *et al*. (2023)	Linguistic distribution assessment	Minimum cost consensus model	Weighted RPN
Shi *et al*. (2022)	Hesitant linguistic preference relation	Dynamic consensus model	Least squares method
Huang *et al*. (2023)	Double hierarchy hesitant linguistic preference relation	Automatic improving method	Weighted risk value
This paper	Interval-valued intuitionistic fuzzy cloud theory	Social network consensus model with maximum expert consensus	TOPSIS-GRA hybrid model

3. PRELIMINARIES

3.1 IVIFS theory

Definition 1 (Atanassov & Gargov, 1989; Wang *et al*., 2016)**.** Let $U = \{u_1, u_2, \dots, u_n\}$be a universe of discourse, the IVIFS $\widetilde{A}$ in U is an object that has the following form.

$$\tilde{A} = \{\langle u, \tilde{\mu}_{\tilde{A}}(u), \tilde{v}_{\tilde{A}}(u)\rangle | u \in U\} \tag{1}$$

where $\tilde{\mu}_{\tilde{A}}(u) = \left[\mu^1_{\tilde{A}}(u), \mu^2_{\tilde{A}}(u)\right] \subseteq [0,1]$ and $\tilde{v}_{\tilde{A}}(u) = \left[v^1_{\tilde{A}}(u), v^2_{\tilde{A}}(u)\right] \subseteq [0,1]$ are closed intervals representing the membership and non-membership degrees of element u to $\tilde{A}$, constrained by $0 \le \mu^1_{\tilde{A}}(u) \le \mu^2_{\tilde{A}}(u) \le 1, 0 \le v^1_{\tilde{A}}(u) \le v^2_{\tilde{A}}(u) \le 1, 0 \le \mu^2_{\tilde{A}}(u) + v^2_{\tilde{A}}(u) \le 1$for all $u \in U$.

The interval-valued hesitation degree of $\widetilde{A}$ can be calculated as (Nguyen, 2016):

$$\tilde{\pi}_{\tilde{A}}(u) = \left[\pi^1_{\tilde{A}}(u), \pi^2_{\tilde{A}}(u)\right] = \left[1 - \mu^2_{\tilde{A}}(u) - \nu^2_{\tilde{A}}(u), 1 - \mu^1_{\tilde{A}}(u) - \nu^1_{\tilde{A}}(u)\right]. \tag{2}$$

Similarly, the pair $\tilde{\alpha} = (\tilde{\mu}_{\tilde{\alpha}}, \tilde{\nu}_{\tilde{\alpha}})$ is called an interval-valued intuitionistic fuzzy number (IVIFN) (Wang *et al.*, 2016), and every IVIFN can be expressed as $\tilde{\alpha} = ([a_1, a_2], [b_1, b_2])$, where $0 \le a_1 \le a_2 \le 1, 0 \le b_1 \le b_2 \le 1$ and $a_2 + b_2 \le 1$.

3.2 Cloud model theory

Definition 2 (Li *et al.*, 2009). Assume a qualitative notion Q is defined over a universe of discourse U. Let a quantitative number z $(z \in U)$ be a random instance of Q. The membership degree $G_Q(z) \in [0,1]$ of z in Q corresponds to a stochastic numerical value with a steady tendency. Then the distribution of the membership function across the domain U is referred to as a cloud.

Definition 3 (Li *et al.*, 2009; Wang *et al.*, 2015). A normal cloud y is characterized by three fundamental parameters: expectation (*Ex*), entropy (*En*), and hyper entropy (*He*). *Ex* represents the expectation value of the linguistic concept; *En* captures its ambiguity; *He* measures the dispersion of cloud droplets, indicating randomness in membership. Clouds can be denoted by $\tilde{y} = (Ex, En, He)$. Furthermore, the cloud $\tilde{y} = \left(\left[\underline{Ex}, \overline{Ex}\right], En, He\right)$ is termed as an interval cloud if its *Ex* is a bounded interval $\left[\underline{Ex}, \overline{Ex}\right]$.

Definition 4 (Huang & Xiao, 2021; Wang *et al.*, 2015)**.** Given an interval linguistic value $\tilde{s} = \left[s_i, s_j\right]$, convert s_i and s_j into clouds $\tilde{y}_i = (Ex_i, En_i, He_i)$ and $\tilde{y}_j = \left(Ex_j, En_j, He_j\right)$, respectively. Afterwards, the interval cloud $\tilde{y} = \left(\left[\underline{Ex}, \overline{Ex}\right], En, He\right)$ is derived by

$$\begin{cases} \underline{Ex} = min\left\{Ex_i, Ex_j\right\}, \\ \overline{Ex} = max\left\{Ex_i, Ex_j\right\}, \\ En = \sqrt{\dfrac{\left(En_i^2 + En_j^2\right)}{2}}, \\ He = \sqrt{\dfrac{\left(He_i^2 + He_j^2\right)}{2}}. \end{cases} \tag{3}$$

Definition 5. Consider any two interval clouds $\tilde{y}_1 = \left(\left[\underline{Ex_1}, \overline{Ex_1}\right], En_1, He_1\right)$ and $\tilde{y}_2 = \left(\left[\underline{Ex_2}, \overline{Ex_2}\right], En_2, He_2\right)$, then

$$\tilde{y}_1 + \tilde{y}_2 = \left(\left[\underline{Ex_1} + \underline{Ex_2}, \overline{Ex_1} + \overline{Ex_2}\right], \sqrt{En_1{}^2 + En_2{}^2}, \sqrt{He_1{}^2 + He_2{}^2}\right), \tag{4}$$

$$\tilde{y}_1 \times \tilde{y}_2 = \left(\left[\underline{Ex_1 Ex_2}, \overline{Ex_1 Ex_2}\right], \sqrt{(En_1 Ex_2)^2 + (En_2 Ex_1)^2}, \sqrt{(He_1 Ex_2)^2 + (He_2 Ex_1)^2}\right), \tag{5}$$

$$w\tilde{y}_1 = \left(\left[w\underline{Ex_1}, w\overline{Ex_1}\right], \sqrt{w}En_1, \sqrt{w}He_1\right), \quad w > 0, \tag{6}$$

$$\tilde{y}_1^w = \left(\left[\underline{Ex_1^w}, \overline{Ex_1^w}\right], \sqrt{w}(Ex_1)^{w-1}En_1, \sqrt{w}(Ex_1)^{w-1}He_1\right), \quad w > 0. \tag{7}$$

Here, $Ex_1 = 0.5 \cdot \left(\underline{Ex_1} + \overline{Ex_1}\right)$, $Ex_2 = 0.5 \cdot \left(\underline{Ex_2} + \overline{Ex_2}\right)$.

Definition 6 (Huang & Xiao, 2021)**.** Given any two interval clouds $\tilde{y}_1 = \left(\left[\underline{Ex_1}, \overline{Ex_1}\right], En_1, He_1\right)$ and $\tilde{y}_2 = \left(\left[\underline{Ex_2}, \overline{Ex_2}\right], En_2, He_2\right)$, they can be converted into corresponding interval number $a = \left[\underline{a}, \overline{a}\right]$ and $b = \left[\underline{b}, \overline{b}\right]$ using the 3*En* rule. For example, $\underline{a} = \underline{Ex_1} - 3En_1$, $\bar{a} = \overline{Ex_1} + 3En_1$. The comparison principle between two clouds is shown as follows:

(1) if $S_{a,b} > 0$, then $\tilde{y}_1 > \tilde{y}_2$;
(2) if $S_{a,b} = 0$ and $En_1 < En_2$, then $\tilde{y}_1 > \tilde{y}_2$;
(3) if $S_{a,b} = 0$, $En_1 = En_2$ and $He_1 < He_2$, then $\tilde{y}_1 > \tilde{y}_2$;
(4) if $S_{a,b} = 0$, $En_1 = En_2$ and $He_1 = He_2$, then $\tilde{y}_1 = \tilde{y}_2$.
Note that $S_{a,b} = \bar{a} + \underline{a} - \bar{b} - \underline{b}$.

Definition 7 (Wang *et al*., 2015). Let $\tilde{y}_1 = \left(\left[\underline{Ex_1}, \overline{Ex_1}\right], En_1, He_1\right)$ and $\tilde{y}_1 = \left(\left[\underline{Ex_1}, \overline{Ex_1}\right], En_1, He_1\right)$ be two arbitrary interval clouds, their distance $d(\tilde{y}_1, \tilde{y}_2)$ is computed by

$$d(\tilde{y}_1, \tilde{y}_2) = \frac{1}{2}\begin{pmatrix} \left|\left(1 - \frac{En_1 + He_1}{Ex_1}\right)\underline{Ex_1} - \left(1 - \frac{En_2 + He_2}{Ex_2}\right)\underline{Ex_2}\right| \\ + \left|\left(1 - \frac{En_1 + He_1}{Ex_1}\right)\overline{Ex_1} - \left(1 - \frac{En_2 + He_2}{Ex_2}\right)\overline{Ex_2}\right| \end{pmatrix}, \tag{8}$$

where $Ex_1 = 0.5 \cdot \left(\underline{Ex_1} + \overline{Ex_1}\right)$, $Ex_2 = 0.5 \cdot \left(\underline{Ex_2} + \overline{Ex_2}\right)$.

Definition 8 (Wang *et al*., 2015). Let $\tilde{y}_k = \left(\left[\underline{Ex_k}, \overline{Ex_k}\right], En_k, He_k\right)$ $(k = 1,2,\dots,K)$ be a group of interval clouds over domain U, the interval cloud weighted averaging (ICWA) operator is computed by

$$\begin{aligned} \text{ICWA}(\tilde{y}_1, \tilde{y}_2, \dots, \tilde{y}_K) &= \sum_{k=1}^{K} w_k \tilde{y}_k \\ &= \left(\left[\sum_{k=1}^{K} w_k \underline{Ex}_k, \sum_{k=1}^{K} w_k \overline{Ex}_k\right], \sqrt{\sum_{k=1}^{K} w_k (En_k)^2}, \sqrt{\sum_{k=1}^{K} w_k (He_k)^2}\right) \end{aligned} \tag{9}$$

where the weight vector $w = (w_1, w_2, \dots, w_K)^T$ is associated with $\tilde{y}_k (k = 1,2,\dots,K)$, satisfying $0 \le w_k \le 1$ and $\sum_{k=1}^{K} w_k = 1$.

3.3 Integration of IVIFNs and interval clouds

Although IVIFNs capture the fuzziness and hesitation in risk evaluations, they overlook the inherent randomness. The cloud model can effectively capture the stochastic characteristics of evaluation data. Therefore, IVIFN evaluations are converted into cloud representations for comprehensively modeling multiple types of uncertainties (fuzziness, hesitation, and randomness) in risk evaluation data.

Definition 9 (Huang & Xiao, 2021)**.** Let $\tilde{\alpha} = ([a_1, a_2], [b_1, b_2])$ be an IVIFN. The lower approximation $\tilde{\alpha}^L = (Ex^L, En^L, He^L)$ of the $\tilde{\alpha}$ could be computed as: $Ex^L = \frac{a_1 + (1 - b_1)}{2}$, $En^L = \frac{(1 - b_1) - a_1}{6}$, $He^L = \theta_1$, where θ_1 can be designated in advance. Similarly, the upper approximation $\tilde{\alpha}^U = (Ex^U, En^U, He^U)$ of the $\tilde{\alpha}$ could be computed as: $Ex^U = \frac{a_2 + (1 - b_2)}{2}$, $En^U = \frac{(1 - b_2) - a_2}{6}$, $He^U = \theta_2$, where θ_2 can be designated in advance.

Then, based on **Definition 4**, both clouds $\tilde{\alpha}^L$ and $\tilde{\alpha}^U$ can be transformed into an interval cloud, shown by $\tilde{\alpha} = \left(\left[\underline{Ex}, \overline{Ex}\right], En, He\right)$.

4. THE PROPOSED FMEA APPROACH

A new risk assessment approach is presented in this section by using the maximum expert consensus model under social network (SN-MECM) and the TOPSIS-GRA hybrid model for risk prioritization of failure modes in the IVIFC context. Details of the proposed FMEA approach are depicted in Figure 1.

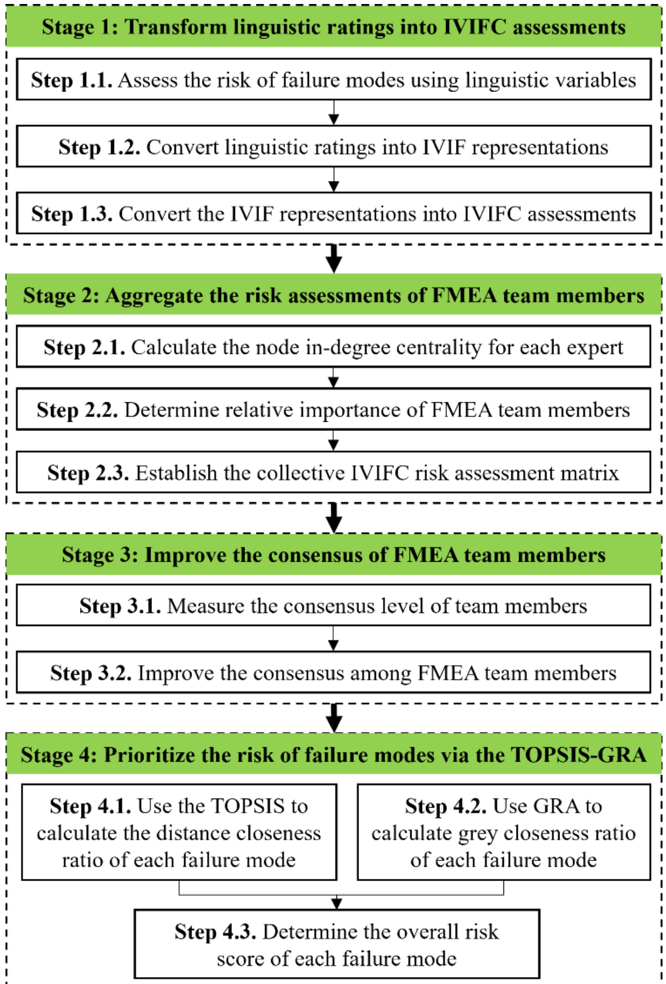

Figure 1. Conceptual diagram of the proposed FMEA

In a risk evaluation scenario, assume the FMEA team consists of l cross-department members TM_k (k=1,2,…,l) for evaluating m failure modes FM_i (i=1,2,…,m) concerning n risk factors RF_j (j=1,2,…,n). The social network among FMEA team members is generated through collecting and analyzing trust relationships among them. The adjacency matrix is then constructed as $A=\left(a_{ij}\right)_{l\times l}$where $a_{ij}\in[0,1]$ denotes the trust degree between each pair of individual experts, varying from total lack of trust to total trust. For example,$a_{ij}=1$denotes that TM_i trusts TM_j totally, while $a_{ij}=0$ indicates a complete absence of trust between TM_i and TM_i. Based on the assumptions above, the proposed FMEA is explained as follows.

Stage 1: Transform linguistic ratings into IVIFC assessments

Step 1.1. Assess the risk of failure modes using linguistic variables

The expert team uses a linguistic term set$S=\{s_0,s_1,\dots,s_g\}$ to assess the risk of failure modes. Assume $\widetilde{S}^k=\left(\tilde{s}_{ij}^k\right)_{m\times n}$is the risk assessment matrix of team member k, and $\tilde{s}_{ij}^k$ denotes the linguistic risk judgement of TM_k on FM_i regarding RF_j.

Step 1.2. Convert linguistic ratings into IVIF representations

According to the predefined linguistic-IVIFN conversion rule, the linguistic risk assessments of failure modes are transformed into IVIFNs. Assume $\tilde{S}_k'=\left(\tilde{s}'^k_{ij}\right)_{m\times n}$ is the IVIF risk assessment matrix of TM_k, where $\tilde{s}'^k_{ij}=\left(\left[a_{ij}^k,b_{ij}^k\right],\left[c_{ij}^k,d_{ij}^k\right]\right)$ represents the IVIFN form of $\tilde{s}_{ij}^k$;a_{ij}^k,c_{ij}^k,b_{ij}^k, and d_{ij}^k denote the boundary values for both membership and non-membership levels of$\tilde{s}'^k_{ij}$, respectively.

Step 1.3. Convert the IVIF representations into IVIFC assessments

According to the conversion method between IVIFNs and IVIFCs described in Section 3.3, each expert's IVIF risk assessment $\tilde{s}'^{k}_{ij}$ can be converted into the corresponding IVIFC, denoted as $\tilde{y}^{k}_{ij} = \left(\left[\underline{Ex^{k}_{ij}}, \overline{Ex^{k}_{ij}}\right], En^{k}_{ij}, He^{k}_{ij}\right)$. As a result, the IVIFC risk assessment matrix from experts $\widetilde{Y}_k = \left(\tilde{y}^{k}_{ij}\right)_{m\times n}$ can be obtained.

Stage 2: Aggregate the risk assessments of FMEA team members

Since individual experts might have different knowledge and experience, each expert could be assigned a specific weighting coefficient, reflecting their differential influence on the collective risk analysis. In this phase, expert weights are calculated by analyzing their social network relationships, followed by the application of the ICWA operator to aggregate the team's risk assessment matrices.

Step 2.1. Calculate the node in-degree centrality for each expert

The node in-degree centrality index for expert TM_k is calculated based on the adjacency matrix A:

$$\varphi_k = \frac{1}{l-1}\sum_{i=1,i\neq k}^{l} a_{ik}, \quad k = 1,\ldots,l. \tag{10}$$

This centrality index reflects an individual's received trust, i.e., an elevated value represents an enhanced influence among peers.

Step 2.2. Determine relative importance of FMEA team members

According to the centrality index related to each expert, the relative weight λ_k of TM_k is computed via

$$\lambda_k = \frac{\varphi_k}{\sum_{k=1}^{l}\varphi_k}, \quad k = 1,\ldots,l. \tag{11}$$

Here $\sum_{k=1}^{l}\lambda_k = 1$, $0 \le \lambda_k \le 1$.

Step 2.3. Establish the collective IVIFC risk assessment matrix

The ICWA operator is utilized to aggregate individual risk evaluation matrices, which produces a collective IVIFC risk assessment matrix $\tilde{Y} = \left(\tilde{y}_{ij}\right)_{m\times n}$. Specifically, the collective IVIFC risk value $\tilde{y}_{ij} = \left(\left[\underline{Ex_{ij}}, \overline{Ex_{ij}}\right], En_{ij}, He_{ij}\right)$is obtained through

$$\begin{aligned}\tilde{y}_{ij} &= \text{ICWA}\left(\tilde{y}^{1}_{ij}, \tilde{y}^{2}_{ij}, \ldots, \tilde{y}^{l}_{ij}\right) = \sum_{k=1}^{l}\lambda_k \tilde{y}^{k}_{ij}\\ &\left(\left[\sum_{i=1}^{n}\lambda_k \underline{Ex_{ij}}, \sum_{i=1}^{n}\lambda_k \overline{Ex_{ij}}\right], \sqrt{\sum_{k=1}^{l}\lambda_k\left(En^{k}_{ij}\right)^2}, \sqrt{\sum_{k=1}^{l}\lambda_k\left(He^{k}_{ij}\right)^2}\right).\end{aligned} \tag{12}$$

Stage 3: Improve the consensus of FMEA team members

During this stage, the maximum expert consensus model under social network (Ma *et al.*, 2024) is implemented to facilitate the convergence of experts' risk evaluations.

Step 3.1. Measure the consensus level of team members

For TM_k, the consensus level CL_k is calculated as

$$CL_k = CL\{\tilde{Y}_k, \tilde{Y}\} = 1 - \frac{1}{m\times n}\sum_{i=1}^{m}\sum_{j=1}^{n} d\left(\tilde{y}^{k}_{ij}, \tilde{y}_{ij}\right). \tag{13}$$

The team member TM_k achieves a satisfactory consensus if consensus level $CL_k \ge \beta$, where $0 \le \beta \le 1$ is a predefined target consensus parameter.

Step 3.2. Improve the consensus among FMEA team members

According to SN-MECM, the optimal collective risk assessment matrix $\widetilde{Y}^{*} = \left(\tilde{y}^{*}_{ij}\right)_{m\times n}$ is obtained. The SN-MECM problem is formulated as:

$$max \sum_{k=1}^{l} x_k \tag{14}$$

$$\text{s.t.}\begin{cases}\sum_{k=1}^{l} c_k d\left(\tilde{y}_{ij}^{k}, \tilde{y}_{ij}^{k*}\right) \le C \\ \tilde{y}_{ij}^{*} = \text{ICWA}\left(\tilde{y}_{ij}^{1*}, \tilde{y}_{ij}^{2*}, \dots, \tilde{y}_{ij}^{l*}\right) \\ CL\{\tilde{Y}_k^{*}, \tilde{Y}^{*}\} = 1 - \frac{1}{m\times n}\sum_{i=1}^{m}\sum_{j=1}^{n} d\left(\tilde{y}_{ij}^{k*}, \tilde{y}_{ij}^{*}\right) \\ x_k = \begin{cases}1, \text{if } CL\{\tilde{Y}_k^{*}, \tilde{Y}^{*}\} \ge \beta \\ 0, \text{else}\end{cases}, k = 1, \dots, l \\ i = 1, \dots, m \\ j = 1, \dots, n\end{cases}$$

The objective is to maximize the number of experts that can fit within the consensus. $\widetilde{Y}_k = \left(\tilde{y}_{ij}^{k}\right)_{m\times n}$ is the original opinion of TM$_k$;$\tilde{Y}_k^{*} = \left(\tilde{y}_{ij}^{k*}\right)_{m\times n}$ is the adjusted opinion of TM$_k$, and c_k denotes the unit modification cost for TM$_k$, constrained by the consensus cost budget C;$\tilde{y}_{ij}^{*}$is the consensus opinion yielded by synthesizing individual opinions based on the ICWA.

x_k is 0-1 variable representing whether TM$_k$ reaches satisfactory consensus. $x_k = 1$ indicates the agreement of TM$_k$ to $\tilde{y}_{ij}^{*}$. Or, the moderator initiates persuasion protocols to guide TM$_k$ toward consensus. The soft consensus inequality $CL\{\tilde{Y}_k^{*}, \tilde{Y}^{*}\} \ge \beta$ is to facilitate the convergence of $\widetilde{y}_{ij}^{k}$ towards $\widetilde{y}_{ij}^{*}$.

Stage 4: Prioritize the risk of failure modes via the TOPSIS-GRA

This study constructs a TOPSIS-GRA hybrid model to establish a robust risk prioritization of failure modes in the IVIFC environment.

Step 4.1. Use the TOPSIS to calculate the distance closeness ratio of each failure mode

Construct the weighted IVIFC assessment matrix: The weighted IVIFC risk assessment matrix $\hat{\tilde{Y}}^{*} = \left(\hat{\tilde{y}}_{ij}^{*}\right)_{m\times n}$ is constructed based on the optimal collective risk assessment matrix $\widetilde{Y}^{*} = \left(\tilde{y}_{ij}^{*}\right)_{m\times n}$and the risk factor weight w_j, i.e.,

$$\hat{\tilde{y}}_{ij}^{*} = \tilde{y}_{ij}^{*} w_j,\ i = 1, \dots, m,\ j = 1, \dots, n. \tag{15}$$

Define the ideal alternatives: The cloud-based positive ideal alternative (CPIA)y^{+} and the negative ideal alternative (CNIA)$y^{-}$are defined as the highest rating $\hat{\tilde{y}}_j^{+} = \max_i\left(\hat{\tilde{y}}_{ij}^{*}\right)$and the lowest rating $\hat{\tilde{y}}_j^{-} = \min_i\left(\hat{\tilde{y}}_{ij}^{*}\right)$, respectively. That is,

$$\begin{aligned} y^{+} &= \{\hat{\tilde{y}}_1^{+}, \hat{\tilde{y}}_2^{+}, \dots, \hat{\tilde{y}}_n^{+}\}, \\ y^{-} &= \{\hat{\tilde{y}}_1^{-}, \hat{\tilde{y}}_2^{-}, \dots, \hat{\tilde{y}}_n^{-}\}. \end{aligned} \tag{16}$$

Compute the distance for each FM: The distances from failure mode FM$_i$ to the CPIA or the CNIA are calculated via

$$\begin{aligned} d_i^{+} &= \textstyle\sum_{j=1}^{n} d\left(\hat{\tilde{y}}_{ij}^{*}, \hat{\tilde{y}}_j^{+}\right), \quad i = 1, \dots, m, \\ d_i^{-} &= \textstyle\sum_{j=1}^{n} d\left(\hat{\tilde{y}}_{ij}^{*}, \hat{\tilde{y}}_j^{-}\right), \quad i = 1, \dots, m. \end{aligned} \tag{17}$$

Compute the distance closeness ratio of each failure mode: The distance closeness ratio D_i of FM$_i$ is calculated by

$$D_i = \frac{d_i^{-}}{d_i^{+} + d_i^{-}}, i = 1, \dots, m, \tag{18}$$

where $D_i \in [0,1]$. The greater the distance closeness ratio D_i, the higher the risk of FM$_i$.

Step 4.2. Use GRA to calculate grey closeness ratio of each failure mode

Compute the grey relational coefficient: Using GRA, the grey relational coefficient between assessment sequences and reference sequences for each failure mode is expressed by

$$G_{ij}^{+} = \frac{\min_i \min_j d\left(\tilde{y}_{ij}^{*}, \tilde{y}_j^{+}\right) + \zeta \max_i \max_j d\left(\tilde{y}_{ij}^{*}, \tilde{y}_j^{+}\right)}{d\left(\tilde{y}_{ij}^{*}, \tilde{y}_j^{+}\right) + \zeta \max_i \max_j d\left(\tilde{y}_{ij}^{*}, \tilde{y}_j^{+}\right)}, \quad (i = 1, \dots, m; j = 1, \dots, n). \tag{19}$$

$$G_{ij}^{-} = \frac{\min_i \min_j d\left(\tilde{y}_{ij}^{*}, \tilde{y}_j^{-}\right) + \zeta \max_i \max_j d\left(\tilde{y}_{ij}^{*}, \tilde{y}_j^{-}\right)}{d\left(\tilde{y}_{ij}^{*}, \tilde{y}_j^{-}\right) + \zeta \max_i \max_j d\left(\tilde{y}_{ij}^{*}, \tilde{y}_j^{-}\right)}, \quad (i = 1, \dots, m; j = 1, \dots, n). \tag{20}$$

Note that $\zeta \in [0,1]$ is an adjustment factor that controls the influence of the average difference between two assessment sequences on the grey relational coefficient. It helps to improve the ability to distinguish between different failure modes, whereas the adjustment factor's impact is minimal on the final risk ranking of failure modes. Usually, $\zeta = 0.5$.$d(\tilde{y}_{ij}^*, \tilde{y}_j^+)$ represents the distance from FM$_i$' assessment sequence in the collective matrix $\tilde{Y}^* = (\tilde{y}_{ij}^*)_{m\times n}$ to the positive ideal reference sequence $\tilde{y}_j^+$, while $d(\tilde{y}_{ij}^*, \tilde{y}_j^-)$ indicates the distance from FM$_i$' assessment sequence to the negative ideal reference sequence $\tilde{y}_j^-$. In addition, $\tilde{y}_j^+ = \max_i(\tilde{y}_{ij}^*)$ and $\tilde{y}_j^- = \min_i(\tilde{y}_{ij}^*)$, respectively.

Compute the grey relational grades of failure modes: FM$_i$' grey relational grades are computed by

$$G_i^+ = \frac{1}{n}\sum_{j=1}^{n} w_j G_{ij}^+, \quad i = 1,\ldots,m. \tag{21}$$

$$G_i^- = \frac{1}{n}\sum_{j=1}^{n} w_j G_{ij}^-, \quad i = 1,\ldots,m. \tag{22}$$

Here w_j is the weight vector of risk factors.

Compute the grey closeness ratios of failure modes: The grey closeness ratio G_i for FM$_i$ is calculated by

$$G_i = \frac{G_i^-}{G_i^+ + G_i^-}, \quad i = 1,\ldots,m. \tag{23}$$

Step 4.3. Determine the overall risk score of each failure mode

The overall risk score of each failure mode can be obtained via

$$O_i = \gamma D_i + (1-\gamma)G_i, \quad i = 1,\ldots,m, \tag{24}$$

where $\gamma \in [0,1]$ is the compromise coefficient depending on decision-makers.

According to the descending order of $O_i (i = 1,\ldots,m)$, the risk levels of m failure modes can be prioritized. The failure mode with the largest O_i value is the most critical one.

5. AN ILLUSTRATIVE EXAMPLE

In this section, an empirical case is used to illustrate the developed FMEA model, and its effectiveness is further verified through simulation and comparative analysis.

5.1 Problem description

The case study analyzes risk events in robotic rehabilitation procedures at a rehabilitation hospital (Liu *et al.*, 2023b). The rehabilitation robots empower patients physically and psychologically in their recovery journey. In robot-aided rehabilitation procedures, potential accidents might mitigate rehabilitation effectiveness or injure patients. A risk analysis of robot-aided rehabilitation procedures in the hospital has been implemented by Liu *et al.* (2023b). To demonstrate the proposed FMEA, ten failure modes listed in Table 2 are selected for risk analysis.

Table 2. Failure modes of the robot-aided rehabilitation process

Failure modes	Causes	Symbol
Excessive cost	Prohibitively expensive	FM$_1$
Noise	Inadequate sound insulation	FM$_2$
Inadequate knowledge training	Lax knowledge training assessment	FM$_3$
Inadequate operation training	Lax operation training	FM$_4$
Unclear workflow	Unskilled operator	FM$_5$
Lack emergency response procedure	Absence of safety awareness	FM$_6$
Inter-rehabilitation therapist communication barriers exist	Absence of communication	FM$_7$
Rehabilitation therapist-patient-family communication barriers exist	Absence of communication	FM$_8$

Failure modes	**Causes**	**Symbol**
Rehabilitation therapist-product engineer communication barriers exist	Absence of communication	FM_9
Individual differences	Poor physical condition	FM_{10}

An FMEA team comprising four experts TM_k (k=1, 2,…, 4), is established to assess the risk of failure modes. The team's social network structure is depicted in Figure 2, with the accompanying adjacency matrix displayed below:

$$A = \begin{pmatrix} 0 & 0.5 & 0.75 & 0.45 \\ 0.6 & 0 & 0.8 & 0.6 \\ 0.45 & 0.6 & 0 & 0.45 \\ 0.45 & 0.55 & 0.75 & 0 \end{pmatrix}.$$

The social network graph uses a graph to depict the social network among FMEA team members, where connecting lines between any two members indicate a direct relationship between them. The notation $TM_1 \rightarrow TM_2$ indicates that TM_1 directly trusts TM_2, in which the trust degree is quantified in the accompanying adjacency matrix.

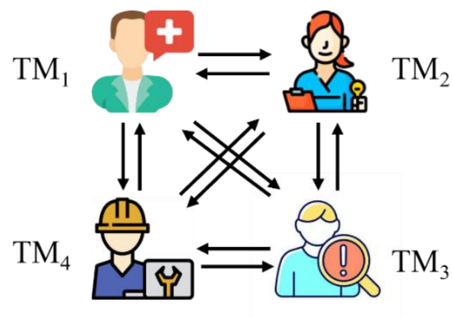

Figure 2. Social network graph of the FMEA experts

5.2 Implementation of the model

In the following, the developed model is implemented to assess and analyze the risk of the considered failure modes. Detailed steps are described below.

Step 1.1. FMEA team members assess the risk of failure modes regarding S, O, and D using a seven-point linguistic term set

$$S = \begin{Bmatrix} s_0 = Extremely\ Low\ (EL), s_1 = Slightly\ Low\ (SL) s_2 = Below\ Average\ (BA),\ s_3 = Average\ (A), \\ s_4 = Above\ Average\ (AA), s_5 = Slightly\ High\ (SH), s_6 = Extremely\ High\ (EH) \end{Bmatrix}.$$

The risk evaluation information from the four team members is obtained and listed in Table 3.

Table 3. Linguistic risk assessments of the FMEA team

Failure modes	**TM₁**			**TM₂**			**TM₃**			**TM₄**		
	S	**O**	**D**	**S**	**O**	**D**	**S**	**O**	**D**	**S**	**O**	**D**
FM_1	SH	SL	SL	EH	SL	SL	EH	A	A	SH	SL	SL
FM_2	SH	SL	SL	AA	SH	BA	SH	A	A	A	SL	SL
FM_3	BA	AA	SH	SL	A	AA	A	SH	AA	A	BA	SH
FM_4	SL	EH	AA	SL	AA	A	A	SH	A	BA	A	BA
FM_5	A	A	A	SL	A	BA	SL	SH	A	BA	AA	A
FM_6	AA	AA	A	EL	EH	A	A	A	AA	EL	SH	AA
FM_7	A	BA	AA	A	A	A	AA	EH	A	SH	AA	BA
FM_8	A	AA	AA	AA	EH	BA	A	EH	BA	AA	AA	A
FM_9	SH	AA	SH	EH	SH	AA	SH	AA	SH	A	SH	AA
FM_{10}	AA	A	SL	SH	SL	BA	SH	SL	A	A	AA	SL

Step 1.2. Through Table 4, the linguistic risk assessments of failure modes are converted into IVIFNs to construct the IVIF risk assessment matrix $\tilde{S}_k^{'} = \left(\tilde{s}'^{k}_{ij}\right)_{10\times 3}$ $(k = 1,2,3,4)$.

Table 4. Linguistic terms and IVIFN equivalents

Linguistic terms	IVIFNs
Extremely Low (EL)	([0.0, 0.1], [0.8, 0.9])
Slightly Low (SL)	([0.2, 0.2], [0.7, 0.7])
Below Average (BA)	([0.3, 0.4], [0.5, 0.6])
Average (A)	([0.5, 0.5], [0.4, 0.5])
Above Average (AA)	([0.6, 0.7], [0.2, 0.3])
Slightly High (SH)	([0.8, 0.8], [0.1, 0.1])
Extremely High (EH)	([0.9, 1.0], [0.0, 0.0])

Step 1.3. The value θ_1 of $\tilde{\alpha}^L$ and θ_2 of $\tilde{\alpha}^U$ are set as $\theta_1 = \theta_2 = 0.003$. Then, the IVIFN assessments of experts are transformed into IVIFC evaluations to obtain the IVIFC risk assessment matrix $\tilde{Y}_k = \left(\tilde{y}_{ij}^k\right)_{10\times 3}$ $(k = 1,2,3,4)$. Table 5 shows the IVIFC risk assessment matrix $\tilde{Y}_1 = \left(\tilde{y}_{ij}^1\right)_{10\times 3}$ provided by TM_1.

Table 5. IVIFC risk assessment matrix for TM_1

Failure modes	**S**	**O**	**D**
FM_1	([0.85,0.85], 0.017, 0.003)	([0.25,0.25], 0.017, 0.003)	([0.25,0.25], 0.017, 0.003)
FM_2	([0.85,0.85], 0.017, 0.003)	([0.25,0.25], 0.017, 0.003)	([0.25,0.25], 0.017, 0.003)
FM_3	([0.4,0.4], 0.024, 0.003)	([0.7,0.7], 0.024, 0.003)	([0.85,0.85], 0.017, 0.003)
FM_4	([0.25,0.25], 0.017, 0.003)	([0.95,1], 0.012, 0.003)	([0.7,0.7], 0.024, 0.003)
FM_5	([0.5,0.55], 0.012, 0.003)	([0.5,0.55], 0.012, 0.003)	([0.5,0.55], 0.012, 0.003)
FM_6	([0.7,0.7], 0.024, 0.003)	([0.7,0.7], 0.024, 0.003)	([0.5,0.55], 0.012, 0.003)
FM_7	([0.5,0.55], 0.012, 0.003)	([0.4,0.4], 0.024, 0.003)	([0.7,0.7], 0.024, 0.003)
FM_8	([0.5,0.55], 0.012, 0.003)	([0.7,0.7], 0.024, 0.003)	([0.7,0.7], 0.024, 0.003)
FM_9	([0.85,0.85], 0.017, 0.003)	([0.7,0.7], 0.024, 0.003)	([0.85,0.85], 0.017, 0.003)
FM_{10}	([0.7,0.7], 0.024, 0.003)	([0.5,0.55], 0.012, 0.003)	([0.25,0.25], 0.017, 0.003)

Step 2.1. The node in-degree centrality indices of experts are derived via Equation (10), as $\varphi_1 = 0.5$, $\varphi_2 = 0.55$, $\varphi_3 = 0.77$, $\varphi_4 = 0.5$.

Step 2.2. Through Equation (11), experts' weights are yielded as: $\lambda_1 = 0.22$, $\lambda_2 = 0.24$, $\lambda_3 = 0.33$, $\lambda_4 = 0.22$, respectively.

Step 2.3. Via Equation (12), the collective IVIFC risk assessment matrix $\widetilde{Y} = \left(\tilde{y}_{ij}\right)_{10\times 3}$ is constructed as showed in Table 6.

Table 6. Collective risk assessment matrix $\widetilde{Y}$

Failure modes	**S**	**O**	**D**
FM_1	([0.916,0.944], 0.014, 0.003)	([0.335,0.352], 0.016, 0.003)	([0.335,0.352], 0.016, 0.003)
FM_2	([0.746,0.757], 0.018, 0.003)	([0.479,0.496], 0.016, 0.003)	([0.371,0.388], 0.018, 0.003)
FM_3	([0.423,0.451], 0.017, 0.003)	([0.643,0.655], 0.02, 0.003)	([0.773,0.773], 0.021, 0.003)
FM_4	([0.368,0.385], 0.018, 0.003)	([0.768,0.79], 0.017, 0.003)	([0.527,0.556], 0.018, 0.003)
FM_5	([0.341,0.352], 0.018, 0.003)	([0.665,0.688], 0.017, 0.003)	([0.481,0.52], 0.016, 0.003)
FM_6	([0.365,0.382], 0.021, 0.003)	([0.734,0.763], 0.017, 0.003)	([0.615,0.638], 0.02, 0.003)
FM_7	([0.648,0.671], 0.018, 0.003)	([0.676,0.704], 0.018, 0.003)	([0.527,0.556], 0.018, 0.003)
FM_8	([0.597,0.625], 0.019, 0.003)	([0.85,0.878], 0.018, 0.003)	([0.492,0.503], 0.022, 0.003)
FM_9	([0.806,0.829], 0.015, 0.003)	([0.776,0.776], 0.021, 0.003)	([0.79,0.79], 0.021, 0.003)
FM_{10}	([0.749,0.76], 0.018, 0.003)	([0.407,0.418], 0.018, 0.003)	([0.371,0.388], 0.018, 0.003)

Step 3.1. By using Equation (13), the individual consensus levels of team members are obtained: CL_1=0.876, CL_2=0.886, CL_3=0.891, CL_4=0.868. The minimum consensus level is set as $\beta = 0.880$ in this study. Since $CL_1 \leq \beta$ and $CL_4 \leq \beta$, **Step 3.2** is conducted to assist FMEA team members in achieving an acceptable consensus. Additionally, assume cost vector (c_1, c_2, c_3, c_4) = (1, 1, 1, 1) and consensus cost budget C = 3.

Step 3.2. Based on the mathematical programming model (14), the individual cloud risk assessment matrices $\tilde{Y}_k^* = \left(\tilde{y}_{ij}^{k*}\right)_{10\times3}(k = 1,2,3,4)$ are adjusted such that the consensus includes as many experts as possible. As a result, the optimal collective cloud risk assessment matrix $\tilde{Y}^* = \left(\tilde{y}_{ij}^*\right)_{10\times3}$ is obtained (see Table 7). Here, all members' consensus level satisfies:$CL_k \geq \beta(k = 1,2,3,4)$.

Table 7. Optimal collective cloud risk assessment matrix $\tilde{Y}^*$

Failure modes	**S**	**O**	**D**
FM_1	([0.916,0.944], 0.014, 0.003)	([0.335,0.352], 0.016, 0.003)	([0.335,0.352], 0.016, 0.003)
FM_2	([0.746,0.757], 0.018, 0.003)	([0.479,0.496], 0.016, 0.003)	([0.371,0.388], 0.018, 0.003)
FM_3	([0.423,0.451], 0.017, 0.003)	([0.665,0.688], 0.017, 0.003)	([0.773,0.773], 0.021, 0.003)
FM_4	([0.368,0.385], 0.018, 0.003)	([0.768,0.79], 0.017, 0.003)	([0.527,0.556], 0.018, 0.003)
FM_5	([0.341,0.352], 0.018, 0.003)	([0.665,0.688], 0.017, 0.003)	([0.481,0.52], 0.016, 0.003)
FM_6	([0.321,0.349], 0.019, 0.003)	([0.734,0.763], 0.017, 0.003)	([0.615,0.638], 0.02, 0.003)
FM_7	([0.648,0.671], 0.018, 0.003)	([0.698,0.737], 0.016, 0.003)	([0.527,0.556], 0.018, 0.003)
FM_8	([0.597,0.625], 0.019, 0.003)	([0.85,0.878], 0.018, 0.003)	([0.492,0.503], 0.022, 0.003)
FM_9	([0.85,0.862], 0.018, 0.003)	([0.776,0.776], 0.021, 0.003)	([0.79,0.79], 0.021, 0.003)
FM_{10}	([0.749,0.76], 0.018, 0.003)	([0.363,0.385], 0.015, 0.003)	([0.371,0.388], 0.018, 0.003)

Step 4.1. Via Equation (15), the weighted IVIFC risk assessment matrix $\hat{\tilde{Y}}^* = \left(\hat{\tilde{y}}_{ij}^*\right)_{10\times3}$ is obtained and presented in Table 8. Thus, the CPIA$y^+$and the CNIA$y^-$are defined as:

$$y^+ = \{([0.412,0.425], 0.01,0.002), ([0.297,0.307], 0.011,0.002), ([0.158,0.158], 0.009,0.001)\},$$

$$y^- = \{([0.144,0.157], 0.012,0.002), ([0.117,0.123], 0.009,0.002), ([0.067,0.07], 0.007,0.001)\}.$$

By using Equations (17) and (18), the distance closeness ratios $D_i(i = 1,2,\ldots,10)$ of failure modes are calculated, as shown in Figure 3.

Table 8. Weighted IVIFC risk assessment matrix

Failure modes	**S**	**O**	**D**
FM_1	([0.412,0.425], 0.01, 0.002)	([0.117,0.123], 0.009, 0.002)	([0.067,0.07], 0.007, 0.001)
FM_2	([0.335,0.34], 0.012, 0.002)	([0.168,0.173], 0.009, 0.002)	([0.074,0.078], 0.008, 0.001)
FM_3	([0.19,0.203], 0.011, 0.002)	([0.233,0.241], 0.01, 0.002)	([0.155,0.155], 0.01, 0.001)
FM_4	([0.166,0.173], 0.012, 0.002)	([0.269,0.276], 0.01, 0.002)	([0.105,0.111], 0.008, 0.001)
FM_5	([0.153,0.158], 0.012, 0.002)	([0.233,0.241], 0.01, 0.002)	([0.096,0.104], 0.007, 0.001)
FM_6	([0.144,0.157], 0.012, 0.002)	([0.257,0.267], 0.01, 0.002)	([0.123,0.128], 0.009, 0.001)
FM_7	([0.292,0.302], 0.012, 0.002)	([0.244,0.258], 0.009, 0.002)	([0.105,0.111], 0.008, 0.001)
FM_8	([0.269,0.281], 0.012, 0.002)	([0.297,0.307], 0.011, 0.002)	([0.098,0.101], 0.01, 0.001)
FM_9	([0.382,0.388], 0.012, 0.002)	([0.272,0.272], 0.013, 0.002)	([0.158,0.158], 0.009, 0.001)
FM_{10}	([0.337,0.342], 0.012, 0.002)	([0.127,0.135], 0.009, 0.002)	([0.074,0.078], 0.008, 0.001)

Step 4.2. Through Equations (21) and (22) the grey relational grades ($G_i^+$and$G_i^-(i = 1,2,\ldots,10)$) of failure modes are obtained. Then, the grey closeness ratios$G_i(i = 1,2,\ldots,10)$of failure modes are determined by Equation (23). The results are shown in Figure 3.

Step 4.3. The overall risk scores of failure modes $O_i = 1,\ldots,10$ are calculated through the Equation (24), as shown in Figure 3. The risk levels of ten failure modes are prioritized based on their overall risk scores $O_i = 1,\ldots,10$. Specifically, $FM_9 \succ FM_8 \succ FM_7 \succ \ldots \succ FM_6 \succ FM_5$ and FM_9 (rehabilitation therapist-product engineer communication barriers exist) is the most critical failure in the robot-aided rehabilitation process, which should be treated preferentially.

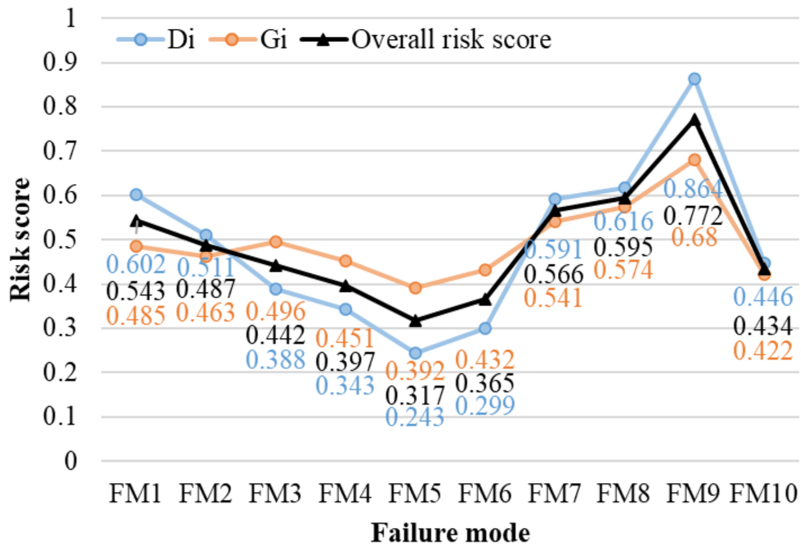

Figure 3. Risk scores and prioritization results of failure modes

5.3 Sensitivity analysis

To examine the influence of consensus threshold β on the FMEA results, a sensitivity analysis of different consensus threshold values (i.e., β=0.87, β=0.88, and β=0.89) are conducted in this section. Moreover, under each β case, γ ranges from 0 to 1 to examine the interaction between the consensus threshold and the compromise coefficient. We select the three most important failure modes under each combination of consensus threshold and compromise coefficient, as shown in Table 9. As consensus threshold β grows, the risk prioritization result of failure modes is more robust to the compromise coefficient. For example, when β=0.87, the compromise coefficient requires careful calibration since it directly influences the risk ranking of failure modes. In contrast, when β=0.89, the top three failure modes maintain identical rankings under different compromise coefficient values. Thus, higher degrees of expert consensus lead to more stable risk rankings of failure modes that are less sensitive to model parameters.

Table 9. Risk ranking of the most important three failure modes with different β values

β		**0.87**	**0.88**	**0.89**
γ	0	FM_9>FM_8>FM_7	FM_9>FM_8>FM_7	FM_9>FM_8>FM_7
	0.1	FM_9>FM_8>FM_7	FM_9>FM_8>FM_7	FM_9>FM_8>FM_7
	0.2	FM_9>FM_8>FM_7	FM_9>FM_8>FM_7	FM_9>FM_8>FM_7
	0.3	FM_9>FM_8>FM_7	FM_9>FM_8>FM_7	FM_9>FM_8>FM_7
	0.4	FM_9>FM_8>FM_7	FM_9>FM_8>FM_7	FM_9>FM_8>FM_7
	0.5	FM_9>FM_8>FM_7	FM_9>FM_8>FM_7	FM_9>FM_8>FM_7
	0.6	FM_9>FM_8>FM_1	FM_9>FM_8>FM_7	FM_9>FM_8>FM_7
	0.7	FM_9>FM_8>FM_1	FM_9>FM_8>FM_7	FM_9>FM_8>FM_7
	0.8	FM_9>FM_8>FM_1	FM_9>FM_8>FM_7	FM_9>FM_8>FM_7
	0.9	FM_9>FM_8>FM_1	FM_9>FM_8>FM_1	FM_9>FM_8>FM_7
	1	FM_9>FM_8>FM_1	FM_9>FM_8>FM_1	FM_9>FM_8>FM_7
# consensus experts		4	4	4
Total consensus cost		0.163	0.763	2.015

Table 9 also shows that the total consensus cost that the moderator needs to adjust individual opinions will increase as a higher consensus among the experts is expected. For instance, when β=0.87, the total consensus cost is 0.163 to reach the maximum expert consensus (i.e., 4 experts). Contrarily, the total consensus cost becomes 2.015 when β is increased to 0.89. This implies that decision-makers need to balance between the consensus cost budget and the consensus threshold so as to obtain a reliable risk priority of failure modes.

5.4 Simulation analysis

To further validate the efficacy of the consensus-reaching process, this section performs a simulation analysis using the previous case. The initial linguistic risk assessment matrices of FMEA team members are randomly generated during the simulation. Specifically, under the constraint that the randomly generated linguistic risk evaluation matrices are slightly different from those in the baseline case, the linguistic risk assessment matrices of FMEA team members are simulated 1000 times randomly. A boxplot for the overall risk scores of failure modes under the 1000 rounds is drawn in Figure 4.

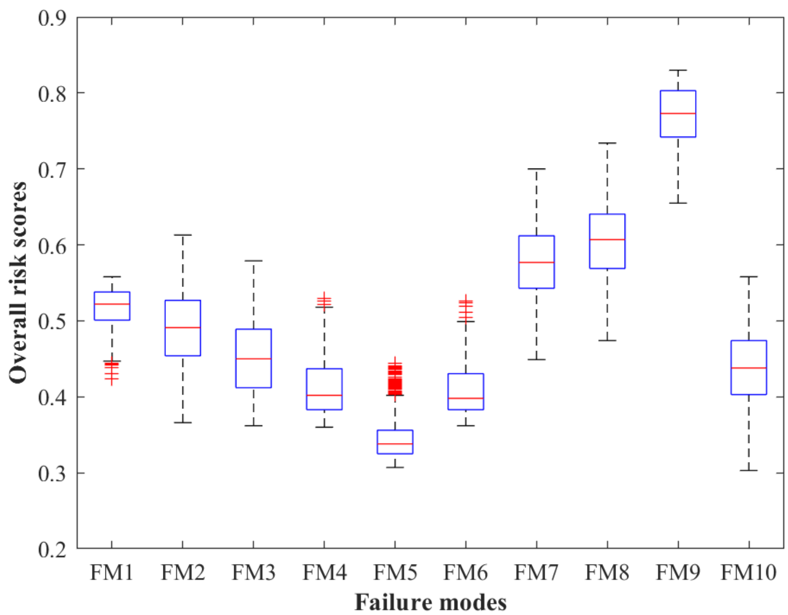

Figure 4. Overall risk scores of failure modes under random simulation

Through the median overall risk scores, the risk of failure modes are prioritized: $\mathrm{FM}_9 \succ \mathrm{FM}_8 \succ \mathrm{FM}_7 \succ \ldots \succ \mathrm{FM}_6 \succ \mathrm{FM}_5$. The risk ranking result obtained is identical to the initial risk prioritization result generated in Section 5.2. Additionally, although there are some fluctuations in the failure mode overall risk scores in different simulation runs, FM_9, FM_8, and FM_7 remain high-risk in almost all the random rounds. These findings demonstrate the robustness of the proposed FMEA approach in the risk prioritization of failure modes.

5.5 Comparisons and discussion

In this section, the proposed approach is compared with some current FMEA methods to demonstrate its advantages and capabilities. These methods include the classical RPN, the cloud-PROMETHEE FMEA (Liu *et al*., 2017), and the cloud-DEA FMEA (Liu *et al*., 2023b). Table 10 displays the risk ranking results of failure modes obtained by the listed FMEA methods. It can be observed that FM_9, FM_8, and FM_7 are identified as the most critical failure modes by the classical RPN and the cloud-PROMETHEE FMEA. This confirms the rationality and practicality of the proposed FMEA approach.

Nevertheless, the ranking results have some differences between the proposed approach and the compared FMEA methods. First, the most apparent difference is FM_1, which ranks tenth in the traditional RPN but ranks fourth in the proposed FMEA. This difference can be explained by the limitations of the RPN method. For example, the traditional RPN assumes that risk factors are equally important, but this is not reasonable in practice. Second, FM_3, FM_4, FM_6, and FM_{10} have slightly inconsistent risk orders according to the proposed FMEA and the cloud-PROMETHEE FMEA methods. This is because the qualitative linguistic risk assessments of expert cannot be well handled by the cloud-PROMETHEE FMEA, and the inter-expert social network is not considered in the cloud-PROMETHEE implementation. Third, the observed inconsistency between the proposed FMEA and the cloud-DEA FMEA primarily stems from the following reason: The cloud-DEA method does not consider consensus-building in FMEA, while empirical evidence demonstrates significant inter-expert variations in risk assessments originating from heterogeneous expert profiles.

Table 10. Comparison of different methods

Failure modes	Traditional RPN	Cloud-PROMETHEE	Cloud-DEA	Proposed model
FM_1	10	4	2	4
FM_2	7	5	5	5
FM_3	4	7	9	6
FM_4	6	9	7	8
FM_5	8	10	10	10
FM_6	5	8	8	9
FM_7	3	3	4	3
FM_8	2	2	3	2
FM_9	1	1	1	1
FM_{10}	9	6	6	7

Compared with the conventional RPN and other improved FMEA methods, the new FMEA approach has the following strengths: (1) Various uncertainties in qualitative assessment information of robot-aided rehabilitation processes, such as hesitation, fuzziness, and randomness, can be adequately described by integrating IVIFNs and clouds. (2) Individual weights in the FMEA team are calculated utilizing their social relationships, facilitating the aggregation of individual assessments and mitigating opinion divergence. (3) Implementing social network consensus analysis in FMEA is helpful in dealing with inconsistent risk assessments among risk experts and in improving the quality of the FMEA. (4) A hybrid risk ranking approach is constructed through integrating TOPSIS and GRA in the IVIFC environment. It can help hospital managers derive reliable risk orders of failure modes.

6. CONCLUSIONS

This research presents a new FMEA approach by integrating the maximum expert consensus model under a social network with the TOPSIS-GRA hybrid model under the IVIFC context. The IVIFC is adopted to describe experts' linguistic risk assessments, which combines the strengths of IVIFS in manipulating vagueness and hesitation, and the cloud model in quantifying the randomness of assessment information. The SN-MECM model considers experts' social relationships, is used to improve the FMEA team's consensus. The hybrid method of TOPSIS and GRA is presented to determine the risk priority of failure modes. Finally, the proposed FMEA is illustrated through a real-world application concerning robot-aided rehabilitation processes, and further verified through simulation and comparative analysis. The results show that the new FMEA approach being proposed can resolve major deficiencies of the traditional RPN method and offer a reliable and robust solution for complex FMEA applications.

There are some limitations and challenges in this research, which indicate directions for future research. First, we assume social trust to be predefined and static during the consensus-reaching process in FMEA. Investigating dynamic trust modification presents a promising avenue for improving FMEA consensus in subsequent studies. Second, there might be some interactions between failure modes in practice, and this is not considered in the current study. In future research, it is interesting to analyze the interactions among failure modes. Third, the proposed FMEA is challenged by the dynamic and evolving nature of failure modes. Future research could explore dynamic risk modeling techniques to enhance adaptability. Finally, the challenge of the proposed FMEA is that its computational complexity might increase when applied to complex FMEA problems. Future work could create a user-friendly decision-support platform for enhancing the practical applicability of the proposed model approach.

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