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A Calibrated Linguistic Semantic Based on Group Consensus Decision Making for FMEA of Industrial Internet Platform

Jian Wu, Shanghai Maritime University, China
Jun Chen, Shanghai Maritime University, China
Jin Fang, Shanghai Maritime University, China
Tiantian Gai, Shanghai Maritime University, China
Mingshuo Cao, Shanghai Maritime University, China*

ABSTRACT

Failure mode and effects analysis (FMEA) is a powerful risk management tool and engineering technique for eliminating potential failures. This paper aims to improve FMEA by introducing the calibrated linguistic semantic (CIS) and a consensus reaching process with minimum adjustment cost. CIS can effectively solve the problem that different individuals may have different understandings of the same term, and the consensus reaching process can reduce the potential inconsistency and conflict to make the result of rank more accurate and convincing. A novel criteria weight allocation method based on the performance of alternatives is used to obtain the relative weights of risk factors (RF), which is not only based on the function framework but also can obtain the relative weight of RFs through the evaluation matrix directly. Then, the proposed FMEA framework is applied to the industrial internet platform. Finally, the comparisons between the proposed and other methods are presented to demonstrate the effectiveness and advantages of the new method.

KEYWORDS

CIS, Consensus, FMEA, Group Decision Making, Industrial Internet Platform

INTRODUCTION

In response to the new industrial revolution, General Electric (GE) developed the first industrial Internet platform, Predix, to meet its large-scale industrial analytics (Chen et al., 2018). Subsequently, more and more industry Internet platforms have been produced, such as Bosch IoT Suite, Kaa IoT Platform, and COSMOPlat. However, as industry Internet platform is a new product, most research mainly focuses on opportunities, challenges, factors, etc. (Chen et al. 2018; Sisinni et al. 2018). However, the research on the risk management of the industrial Internet platform is limited. Therefore, in this paper, we will introduce the framework of FMEA to reduce the problems and challenges.

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*Corresponding Author

FMEA, developed by NASA in the 1960s, is a useful risk management tool and engineering technique to manage the quality and reliability of products (Baykasoglu et al., 2020; Liu et al., 2018). FMEA was introduced into the automobile industry in the 1970s (Zhou et al., 2016). After many standardization efforts, such as International Organization for Standardization (ISO) 9000 series, FMEA has become one of the most important risk management and reliability analysis tools (Baykasoglu et al., 2020). Nowadays, it has been widely utilized in industrial systems, designs, and production to identify and solve potential failures (Kutlu et al., 2012). Unlike other reliability management tools that look for solutions after failures occurred, FMEA can previously identify and eliminate known or potential failures in a system and prevent them from happening (Huang et al., 2017; Liu et al., 2018b). Owing to its advantages, FMEA has been widely applied to various fields, such as marine (Bashan et al., 2020; Chang et al., 2021), aircraft (Daneshvar et al., 2020), cold-chain logistics management (Wu et al., 2021), healthcare services (Liu et al., 2018c), new energy resources (Duan et al., 2019; Karatop et al., 2020), and semiconductor manufacturing (Jee et al., 2015; Kerk et al., 2017).

The traditional FMEA mainly includes the following several stages: (1) Identify known or potential Failure Modes (FMs); (2) Confirm the cause and effect of every FM by DMs; (3) Calculating the Risk Priority Numbers (RPNs) of FMs, the product of three RFs: Occurrence (O), Severity (S) and Detection (D); (4) Rank the FMs according to the RPNs by descending order; (5) Take remedial actions for the high-risk FMs (Liu et al., 2018c; Huang et al., 2020; Liu et al., 2015).

Related Work

FMEA has made a huge number of contributions in many fields. However, there are still some drawbacks to the traditional FMEA method.

As a form of multi-attribute decision-making, conventional FMEA requires decision-makers (DMs) to assess FMs about RFs with crisp numbers, while it is rather difficult for DMs to describe their views by accurate values (Huang et al., 2017). DMs are inevitably hesitant or uncertain in the evaluation due to various subjective and objective factors.

To deal with this problem, many risk assessment methods have been reported, mainly including Fuzzy Set theory, Evidential Reasoning theory, and extended approaches based on the 2-tuple linguistics (Liu et al., 2019). The introduction of Fuzzy Set allowed DMs to assess FMs and the relative weights of RFs in linguistic terms to improve accuracy of evaluation (Hadivencheh et al., 2013); the use of Evidential Reasoning theory can increase the effectiveness and flexibility of subjective information processing in FMEA framework (Qin et al., 2020; Wu et al., 2020; Zhou et al., 2016).

Compared with these methods, linguistic assessment method can accommodate DMs' lack of sufficient knowledge and fuzziness of human thinking process (Li et al., 2022). 2-tuple linguistic model and its extended methods are more popular because of their similarity to natural language (Huang et al., 2017). Since the concept of computing with words (CW) was proposed by (La, 1996) and the 2-tuple linguistic representation model was initiated by (Herrera et al., 2000), a huge number of extended methods based on the 2-tuple linguistic model have been greatly developed (Huang et al., 2017; Nie et al., 2018; Zhang et al., 2014). Linguistic distribution assessment allows DMs to evaluate with semantic intervals rather than individual semantics to reflect their opinions more exactly and reduce information loss (Huang et al., 2017; Nie et al., 2018). Probabilistic hesitant fuzzy language was developed to solve the problem that DMs can be hesitant when facing some relatively close options in evaluation (Huang et al., 2019). Double hierarchy hesitant fuzzy linguistic term sets expand linguistic expression scales, allowing DMs to evaluate problems and alternatives with much more intuitive expression (Duan et al., 2019).

However, an issue still needs to be considered: different DMs may have different understanding of the same term and each individual can have own risk attitude or word preference. Thus, an optimization-based Personalized Individual Semantic (PIS) model was designed to achieve linguistic calibration for different DMs (Li et al., 2017). However, the PIS model needs to suppose that the preferences of DMs are as consistent as possible, and it is not suitable for the multi-attribute decision-making when the numbers of alternatives and criteria are larger. On the other hand, CIS proposed by Wu et al. based on 2-tuple linguistic and membership calibration can well solve these problems (Wu et al., 2022). Therefore, we introduce CIS as an evaluation method in this paper.

In addition, the calculation of RPN or the weight allocation of RFs in traditional FMEA is criticized (Almashaqbeh et al., 2019). Conventional FMEA has not considered relative importance among RFs, which can cause RPN distortion problems that a FM may be more serious, though its RPN value is lower than other FMs (Park et al., 2018). For example, let RPN_1 of FM_1 be $54 = 9 \times 3 \times 2$ and RPN_2 of FM_2 be $56 = 4 \times 4 \times 4$. According to the calculated RPN value, the risk of FM_2 is higher than that of FM_1, while it is hard to get the conclusion that FM_2 is more serious after observing the OSD value of each FM. The reason is that three RFs are given the same importance or equally weighted, and the multiplicative calculation used in RPN will amplify the effect of little change of individual RF.

The AHP method was used to obtain the relative weight of RFs to solve the problem (Almashaqbeh et al., 2019). Park et al. proposed a new risk assessment method by using the importance risk priority number (IRPN), which not only overcame the shortcomings of RPN distortion in conventional FMEA, but also could be useful for assessing the structural risks that involve functional influence between risks (Park et al., 2018). Qin et al. developed a new approach combining Interval Type-2 Fuzzy Sets (IT2FSs) with Evidential Reasoning method to allocate relative weight to the RFs (Qin et al., 2020b). In this paper, a weight allocation method based on the performance of alternatives is introduced, in which the relative weight of the RFs can be obtained only according to the evaluation matrix provided by the DMs and function calculating.

Contributions

The main work of our paper can be summarized as follows. First, we introduce CIS to deal with DMs' personal understanding and expression habits. Second, the consensus reach process handles the probable inconsistencies of DMs based on minimum adjustment cost. Third, a novel weight allocation method based on the performance of alternatives is used to obtain the weights of RFs to solve the problem that different OSD values can get the same RPN value. The main advantages of the proposed method are as follows:

1. CIS can improve the accuracy of FMEA evaluation and decision quality by collecting and calibrating the individual semantic expression concisely.
2. The introduction of consensus reach process with minimum adjustment cost can effectively deal with the potential conflict or inconsistency, which promote the implement of decision better.
3. The novel weight allocation method makes the proposed framework of FMEA effectively solve the potential RPN distortion, which makes the final FMEA ranking more convincing.

The rest of this paper is organized as follows. Section 2 introduces the preliminaries of the 2-tuple linguistic, consensus-reaching process, and weight allocation method. Section 3 describes a novel framework of FMEA in detail based on a weight allocation method based on the performance of alternatives and a consensus-reaching process. Section 4 applies the proposed method to a case on Industrial Internet. Section 5 gives comparisons between the proposed and related FMEA methods to discuss their advantages. Finally, Section 6 concludes this paper and points out future directions.

PRELIMINARIES

The concepts of the CIS model, consensus reach process with minimum adjustment cost, and weight allocation method based on alternatives performance are provided below.

Calibrated Linguistic Semantic Model

As mentioned, it is sometimes difficult for a DM to quantify his/her assessment as an exact value by crisp numbers. Thus, many methods have been reported to deal with the uncertainties of evaluation information (Liu et al., 2019). Heterogeneous multi-attribute group decision-making (HMAGDM) with preference deviation is a kind of complex and important problems in many decision situations (Yu et al., 2018). However, it is seldom to consider the effect of evaluation that the word understanding and preference of different DMs. CIS model proposed by Wu et al. can effectively overcome this issue, which is based on 2-tuple linguistic and calibration of membership function (Wu et al. 2022). The CIS model mainly includes three steps: (1) design a linguistic calibration experiment with graphics;(2) linguistic term collection based on the areas of graphics, and (3) the calibration process of linguistic terms; the process of CIS is shown in Figure 1.

First, a linguistic calibration experiment is designed to measure word preference. There are u sets of graphics $G_i\left(i=1,2,\ldots,u\right)$ with g figures $F_j\left(j=1\ldots\ldots,g\right)$, and $f_{ij}\left(i\ldots,2,\ldots,m\ldots=1,2,\ldots,g\right)$ denotes j-th figure in set G_i, with properties.

1. The area of each figure must be random.
2. There are total g figures with area t in the u sets.

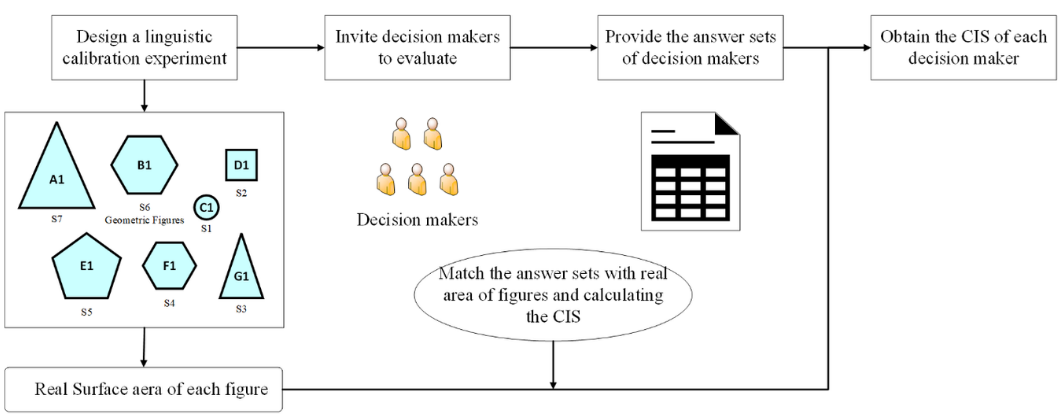
Second, $\ldots\left(k=1,2,\ldots,l\right)$ have to evaluate the graph sets by 2-tuple linguistic term set $S=\ldots$ and provide the answer sets $A^k\left(k=1,2,\ldots,l\right)$. The concept of 2-tuple linguistic model is described in La (1996) and Herrera (2000).

Third, the answer sets of DMs are matched with the real areas of figures, and the CIS of each DM can be obtained.

DMs are required to use 2-tuple linguistic to evaluate the designed graph set and provide answer sets. Herrera and Martinez proposed the 2-tuple linguistic model, and La (1996) provided a detailed process of it. This model is a classical approach to solving assessment uncertainties, and it has been widely used in various fields as a linguistic representation model (Herrera et al., 2000).

Definition 1. Let $A^k=\left(a_{yx}^k\right)_{u\times g}$ be the integrated answer set provided by $DM_k\left(k=1,2,\ldots,l\right)$, where a_{yx}^k is a 2-tuple linguistic term assessment. The CIS of DM_k about each linguistic term s_t can be calculated as follows.

Figure 1.
The CIS process



$$CIS^k\left(s_t\right) = \frac{1}{u}\sum_{y=1}^{u} \Delta^{-1}\left(a_{yx}^k\right),\ \ k = 1, 2, \ldots, l \tag{1}$$

Here, $CIS^k\left(s_t\right) < CIS^k\left(s_{t+1}\right)$. If $CIS^k\left(s_t\right) \geq CIS^k\left(s_{t+1}\right)$, there may exist wrong information provided by DMs or the design of the experiment is wrong or unreasonable, thus, DMs must update their evaluation, or the experiment should be adjusted.

Let $V^k = \left(v_{ij}^k\right)_{m\times n}\left(k = 1, 2, \ldots, l\right)$ be the initial evaluation matrices provided by DM_k. Next, V^k can be transformed into an individual numerical evaluation matrix $E^k = \left(e_{ij}^k\right)_{m\times n}\left(k = 1, 2, .., l\right)$ by the $CIS^k\left(s_t\right), k = 1, 2, \ldots, l$. Then, the collective numerical evaluation matrix E^c can be defined as follows.

Definition 2. Let $E^k = \left(e_{ij}^k\right)_{m\times n}\left(k = 1, 2, .., l\right)$ be the individual numerical evaluation matrices, the collective numerical evaluation matrix $E^c = \left(e_{ij}^c\right)_{m\times n}$ can be calculated.

$$e_{ij}^c = \sum_{k=1}^{k} e_{ij}^k \cdot w^k \tag{2}$$

Where w^k denotes the weight of DM_k.

Feedback Recommendation with Minimum Adjustment Cost

Identification of Inconsistent Elements

In group decision-making, we usually assign experts from different departments associated weights to solve the impact of educational background, work experience, and preference. However, weight allocation cannot completely deal with potential conflicts, while group consensus methods can effectively improve decision quality (Wang et al.,2022). Therefore, many Consensus Reaching Process (CRP) methods have been reported (Cao et al., 2021; Zhang et al., 2019; Zhang et al., 2014b; Zhang et al. 2022).

The consensus-reaching process with a minimum adjustment cost feedback mechanism was proposed by Wu et al. (2018), based on a consensus model in a social network (Wu et al. 2015), which could let DMs reach the threshold value of group consensus incurring a minimum modification of their opinions or adjustment cost. Once the collective evaluation matrix based on the CIS model is calculated, we can express the consensus degree at three levels for each team member as: (1) elements level; (2) FMs level; (3) decision matrix level.

Definition 3. The consensus degree of a FMEA team member with the group at the three different levels of the relation is defined next:

Level 1. The consensus degree of FM_i for RF_j provided by DM_k is calculated as:

$$CE_{ij}^k = 1 - d\left(v_{ij}^k, v_{ij}^c\right) = 1 - \frac{\left|v_{ij}^k - v_{ij}^c\right|}{g},\ \ k = 1, 2, \ldots, l \tag{3}$$

Level 2. The consensus degree of FM_i provided by DM_k is calculated as:

$$CF_i^k = \frac{1}{n}\sum_{j=1}^{n} CE_{ij}^k, \ \ k = 1,2,\ldots,l \tag{4}$$

Level 3. The consensus degree of DM_k at decision matrix is calculated as:

$$CM^k = \frac{1}{m}\sum_{i=1}^{m} CF_i^k, \ \ k = 1,2,\ldots,l \tag{5}$$

Then, DM_k with consensus degree at decision matrix lower than the threshold value γ are identified:

$$EXPCH = \{k \mid CM^k < \gamma\} \tag{6}$$

For the identified DM_k, their FMs with a consensus degree CF_i^k lower than the threshold γ are identified:

$$ALT = \{(k,i) \mid k \in EXPCH \wedge \ CF_i^k < \gamma\} \tag{7}$$

Finally, the evaluation elements need to be replaced are those with a consensus degree CE_{ij}^k under the threshold γ .

$$APS = \{(k,i,j) \mid (k,i) \in ALT \wedge \ CE_{ij}^k < \gamma\} \tag{8}$$

Recommendation and Adjustment

Generation of recommendation advice with boundary feedback parameter: The feedback mechanism generates advice to the inconsistent team members and for the preference values previously identified in APS containing the new preference values for a higher consensus state.

For all $(k,i,j) \in APS$, the following rule is feedbacked to the corresponding team member: "Change your evaluation elements v_{ij}^k to a value closer to rv_{ij}^k". The rv_{ij}^k can be calculated as follow:

$$rv_{ij}^k = (1-\delta)\cdot v_{ij}^k + \delta \cdot v_{ij}^c \tag{9}$$

Where $\delta \in [0,]$ is a feedback mechanism parameter to control the acceptable degree of recommendation advice.

The original evaluation matrices are divided into two groups: the most inconsistent expectation matrix $V^p \left(p \in \{1,2,\ldots,l\}\right)$ and other expectation matrices $V^o \left(o \in \{1,2,\ldots,l, o \neq p\}\right)$. After the most inconsistent decision maker DM_p adopts the recommendation advice, we obtain that $\{RV^p = \left(rv_{ij}^p\right)_{m\times n} \mid rv_{ij}^p = (1-\delta)\cdot v_{ij}^p + \delta \cdot v_{ij}^c, i,j \in APS; rv_{ij}^p = v_{ij}^p, i,j \notin APS\}$ be the new decision making matrix after adoption, and $RV^o = \left(v_{ij}^o\right)_{m\times n}, o = 1,2,\ldots,l, o \neq p$ be the set of unchanged decision making matrices. Then, the adjustments cost of the most inconsistent matrix V^p can be obtained by the model (10) as follows.

$$Min \sum_{p,i,j\in APS} \delta\left|v_{ij}^p - v_{ij}^c\right|$$

$$s.t.\begin{cases} CM^p\left(RV^p, RV^c\right) \geq \gamma \\ CM^o\left(RV^o, RV^c\right) \geq \gamma, o = 1,2,\ldots,l, o \neq p \\ RV^c = DTWA\left(RV^p, RV^1,\ldots, RV^l\right) \end{cases} \tag{10}$$

By resolving the above model, we can determine the boundary feedback parameter δ_{min}, and then the minimum adjustments cost can be provided to the inconsistent decision maker DM_p. If there is still any inconsistent decision maker, return to step 2. Once all FMEA team members achieve consensus, the final collective expectation matrix is obtained.

Weight Allocation Based on Performance of Alternatives

Let $X = \left\{x_1, x_2,\ldots, x_n\right\}\left(n \geq 2\right)$ and $C = \left\{c_1, c_2,\ldots, c_m\right\}\left(m \geq 2\right)$ denote the sets of finite alternatives and criteria, respectively. $\left\{c_{1j}, c_{2j},\ldots, c_{mj}\right\}$ are the individual performance values of the alternatives X on the set of criteria C. There exists a function $h : \left[0, +\infty\right) \to \left[0,1\right)$ with properties (Wang et al., 1997).

1. $h\left(0\right) = 0$, (boundary condition);
2. $x \leq y \to h\left(x\right) \leq h\left(y\right)$, (non-decreasing).

Definition 4. Function h derives the weight of a criterion c_k based on its variability $h\left(v_k\right) = v_k : w_k$. Since the total sum of the weights is 1, therefore the weight of a criterion w_k can be defined as:

$$w_k = \frac{h\left(v_k\right)}{\sum_{i=1}^{m} h\left(v_i\right)} \tag{11}$$

Definition 5. Let $h\left(x\right) = x$. The standard variability v_k of the weight and the weight w_k of a criterion can be represented as:

$$v_k = \sum_{r=1}^{n}\sum_{s=1}^{n}\left|c_{kr} - c_{ks}\right| \tag{12}$$

$$w_k = \frac{\sum_{r=1}^{n}\sum_{s=1}^{n}\left|c_{kr} - c_{ks}\right|}{\sum_{k=1}^{m}\sum_{r=1}^{n}\sum_{s=1}^{n}\left|c_{kr} - c_{ks}\right|} = \frac{v_k}{\sum_{k=1}^{m} v_k} \tag{13}$$

the Proposed framework of Failure Mode and effect analysis

This section presents the framework of the proposed method utilized in this paper. We introduced the proposed methodology and provided algorithmic steps. The proposed methodology comprises the following process, as shown in Figure 2.

Collecting the Evaluation and Calibrated Linguistic Semantic Process

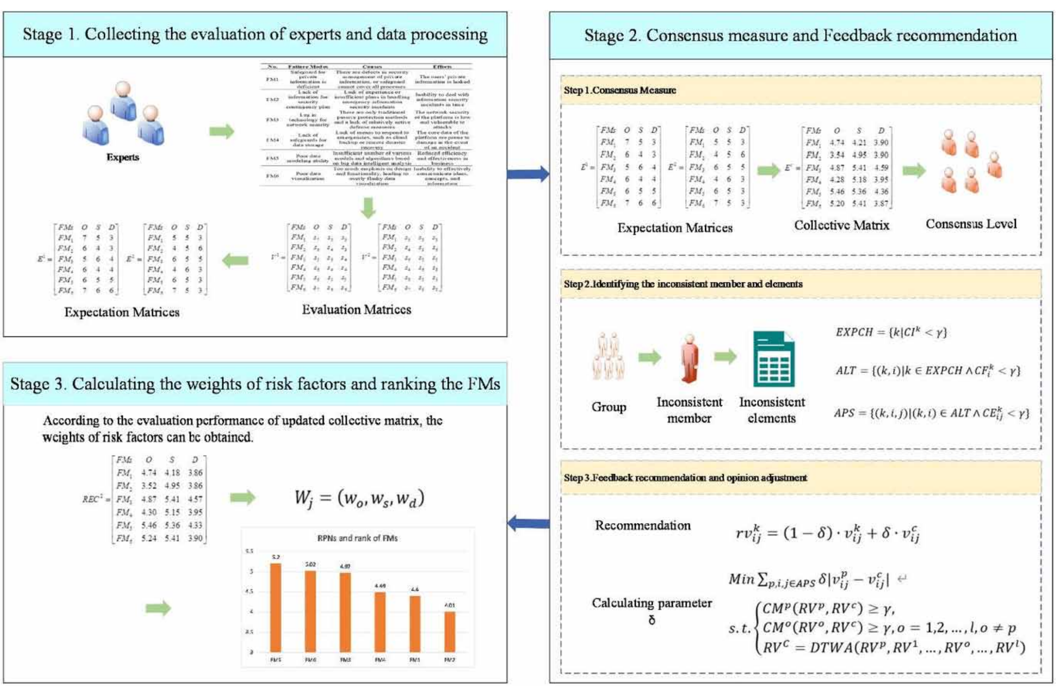
There are m failure modes $FM_i \left(i = 1,2,\ldots,m\right)$ with n risk factors $RF_j \left(j = 1,2,\ldots,n\right)$ as the objects of evaluation and l decision makers $DM_k \left(k = 1,2,\ldots,l\right)$ are invited to be FMEA team members to participant. Each DM is required to provide individual evaluation matrix $V^k = \left(v_{ij}^k\right)_{m\times n} \left(k = 1,2,\ldots,l\right)$ by using 2-tuple linguistic terms set $S = \left\{s_1, s_2, \ldots, s_g\right\}$ according to listed FMs with RFs.

Then, the $CIS^k\left(s_t\right)\left(k = 1,2,\ldots,l; t = 1,2,\ldots,g\right)$ of each DM can be obtained by semantic test performed on all DMs according to Eq. (3). After that, numerical individual evaluation matrices $E^k = \left(e_{ij}^k\right)_{m\times n} \left(k = 1,2,\ldots,l\right)$ are obtained. Let $EW = \left(ew_1, ew_2, \ldots, ew_l\right)^T$ be the relative weight of FMEA team members, with $ew_k \geq 0, \sum_{k=1}^{l} ew_k = 1$. Next, numerical individual evaluation matrix $E^c = \left(e_{ij}^c\right)_{m\times n}$ can be calculated through Eq. (4).

Consensus Measure and Feedback Recommendation

Once the collective evaluation matrix is calculated, the consensus degree at three levels for DMs can be calculated. First, the consensus degree on the decision matrix level and preset consensus threshold

Figure 2.
The proposed FMEA framework



γ are used to judge whether DMs reach consensus. The final collective expectation matrix is obtained if all DMs have reached consensus. Otherwise, the inconsistent members will be identified, and we will activate the feedback mechanism to produce recommendations for them to achieve a higher consensus level.

Step 1. Consensus measure

Let $E^k = \left(e_{ij}^k\right)_{m\times n} \left(k = 1,2,\ldots,l\right)$ and $E^c = \left(e_{ij}^c\right)_{m\times n}$ be the individual and collective numerical evaluation matrices as mentioned above, respectively. Then, $CE_{ij}^k, CF_i^k, CM^k \left(k = 1,2,\ldots,l\right)$ are calculated by Eq. (3) to Eq. (5).

Step 2. Identifying inconsistent DMs and elements

According to the preset consensus threshold γ and $CM^k \left(k = 1,2,\ldots,l\right)$, the inconsistent DM_k can be identified. Next, elements in evaluation matrix need to be adjusted APS are selected by Eq. (6) to Eq. (8).

Step 3. Feedback recommendation and opinion adjustment

First, feedback recommendations re_{ij}^k with minimum feedback parameter δ are provided for DM_k who needs to modify his/her opinion, according to Eq. (11). Second, by calculating the Model (10), the parameter δ can be obtained. Third, check whether all consensus levels of DMs have exceeded the threshold. If all DMs have reached a consensus, the updated collective numerical matrix $RE^c = \left(re_{ij}^c\right)_{m\times n}$ is obtained and then go to stage 3, otherwise return to step 1.

Calculating the Weights of Risk Factors and Ranking Failure Modes

Based on the performance variability of FMs in final collective expectation matrix RE^c, the relative weights $W^{rf} = \left(w_1^{rf}, w_2^{rf}, \ldots, w_n^{rf}\right)^T$ of RFs are calculated as follows.

$$var_j = \sum_{r=1}^{m} \sum_{s=1, s\neq r}^{m} \left|re_{rj}^c - re_{sj}^c\right| \tag{14}$$

$$w_j^{rf} = \frac{var_j}{\sum_{j=1}^{n} var_j},\ j = 1,2,\ldots,n \tag{15}$$

The detail process in shown in Algorithm 1.

```
Algorithm 1: Weight Allocation based on performance of FMs
Input: Adjusted Collective Evaluation Matrix RV^c
Output: Weight Vector W^rf of RFs
(m,n) ← the size of RV^c
Var ← Zeros(1,n)
W^rf ← Zeros(1,n)
Sum ← 0
for j ← 1 to n do
      for r ← 1 to m do
            for s ← 1 to m do
                  Var[j] ← Var[j] + abs(V[r,j] − V[s,j])
            end for
      end for
end for
```

```
for j ← 1 to n do
        Sum ← Sum + Var[j]
end for
for j ← 1 to n do
        W^rf[j] ← Var[j] / Sum
end for
```

According to the final collective evaluation matrix RE^c and the relative weights of RFs $W^{rf} = \left(w_1^{rf}, w_2^{rf}, \ldots, w_n^{rf}\right)^T$, the RPN values of $FM_i \left(i = 1, 2, \ldots, m\right)$ can be calculated by Eq. (16) and then the rank of FMs are sorted in descending order based on the RPNs.

$$RPN_i = \prod_{j=1}^{n} re_{ij}^{c} \cdot w_j^{rf},\ i = 1, 2, \ldots, m \tag{16}$$

APPLICATION TO THE INDUSTRIAL INTERNET PLATFORM

Rapid development of information and communication technology has not only radically changed the landscape of many industries, but also reshaped the research agendas in economics and management (Li et al., 2021). Since General Electric established the first industrial Internet platform Predix (Menon et al., 2019), more and more industrial Internet platforms, such as Bosch IoT Suite, Kaa IoT Platform, and COSMOPlat, have been developed to deal with the new round of industrial revolution (Sisinni et al., 2018). The construction and application of Industrial Internet Platform have attracted more and more attention, while the study on the risk management of industry Internet platforms is still limited.

Table 1.
FMEA table of top six FMs on industrial internet platform

No.	Failure Modes	Causes	Effects
FM_1	Protection for individual privacy is insufficient	There are defects in security management of private information, or safeguard cannot cover all processes	The risk of privacy leakage has increased dramatically
FM_2	Lack of contingency plan for security accident	Lack of experience or insufficient plans in handling emergency information security incidents	Inability to deal with information security incidents in time
FM_3	Network protection technology is backward	There are only passive protection and active defense measures is limited	The network security of the platform is low and vulnerable to attacks
FM_4	The technology of safeguards for data storage is limited	Lack of emergency preparedness, such as cloud backup or remote disaster recovery	Data storage is difficult to recover in the event of accidental damage
FM_5	Backward technology of data modeling	Digital models and algorithms based on big data intelligent analysis are not enough	Reduced efficiency and effectiveness in business
FM_6	Poor data visualization	Too much emphasis on design and functionality leads to overly flashy data visualization	Inability to effectively communicate ideas, concepts, and information

This paper uses relevant data from our previous studies, and the top six FMs with the highest RPN are selected from 15 FMs as a case study. The data are provided in Table 1, and a complete data table can obtained from Wu et al. (2022).

Collecting Evaluation and Calibrated Linguistic Semantic Process

Five DMs are invited to provide their risk evaluation matrices $\left\{V^1, V^2, \ldots, V^5\right\}$ of $FM_i\left(i = 1, 2, \ldots, 6\right)$ regarding three RF_j, including Occurrence (O), Severity (S), and Detection (D), using linguistic terms set $S = \{$ s_1 = 'extremely little'; s_2 = 'very little'; s_3 = 'little'; s_4 = 'moderate'; s_5 = 'large'; s_6 = 'very large'; s_7 = 'extremely large'$\}$, as follows.

$$V^1 = \begin{bmatrix} FMs & O & S & D \\ FM_1 & s_7 & s_5 & s_3 \\ FM_2 & s_6 & s_4 & s_3 \\ FM_3 & s_5 & s_6 & s_4 \\ FM_4 & s_6 & s_4 & s_4 \\ FM_5 & s_6 & s_5 & s_5 \\ FM_6 & s_7 & s_6 & s_6 \end{bmatrix} V^2 = \begin{bmatrix} FMs & O & S & D \\ FM_1 & s_5 & s_5 & s_3 \\ FM_2 & s_4 & s_5 & s_6 \\ FM_3 & s_6 & s_5 & s_5 \\ FM_4 & s_4 & s_6 & s_3 \\ FM_5 & s_6 & s_5 & s_3 \\ FM_6 & s_7 & s_5 & s_3 \end{bmatrix} V^3 = \begin{bmatrix} FMs & O & S & D \\ FM_1 & s_4 & s_6 & s_6 \\ FM_2 & s_5 & s_6 & s_6 \\ FM_3 & s_6 & s_6 & s_6 \\ FM_4 & s_3 & s_7 & s_4 \\ FM_5 & s_6 & s_6 & s_6 \\ FM_6 & s_3 & s_6 & s_2 \end{bmatrix}$$

$$V^4 = \begin{bmatrix} FMs & O & S & D \\ FM_1 & s_3 & s_5 & s_4 \\ FM_2 & s_3 & s_4 & s_4 \\ FM_3 & s_3 & s_4 & s_3 \\ FM_4 & s_3 & s_3 & s_4 \\ FM_5 & s_4 & s_4 & s_4 \\ FM_6 & s_3 & s_3 & s_3 \end{bmatrix} V^5 = \begin{bmatrix} FMs & O & S & D \\ FM_1 & s_4 & s_6 & s_4 \\ FM_2 & s_4 & s_6 & s_4 \\ FM_3 & s_4 & s_6 & s_5 \\ FM_4 & s_5 & s_6 & s_5 \\ FM_5 & s_5 & s_7 & s_4 \\ FM_6 & s_5 & s_7 & s_5 \end{bmatrix}$$

The test answers of DMs are integrated as $\left\{A^1, A^2, A^3, A^4, A^5\right\}$ and CIS of each DM can be calculated by Eq. (3), as shown in Table 2.

Table 2.
The CIS numerical scales for different DMs

$CIS^k\left(s_t\right)$	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$	$t = 7$
$k = 1$	1.2	2	3.2	4.4	5.2	5.4	6.6
$k = 2$	1.6	2.6	3.4	4	4.4	5.2	5.6
$k = 3$	1	2	3.2	4	5	5.8	7
$k = 4$	1	2	3	4.2	5.2	6	6.6
$k = 5$	1.2	2.4	3.4	4.4	5.4	6.2	7

$$A^1 = \begin{bmatrix} s_2 & s_3 & s_4 & s_4 & s_4 & s_6 & s_6 \\ s_1 & s_2 & s_3 & s_4 & s_5 & s_6 & s_5 \\ s_2 & s_3 & s_4 & s_4 & s_5 & s_4 & s_6 \\ s_1 & s_2 & s_2 & s_4 & s_4 & s_5 & s_6 \\ s_2 & s_3 & s_4 & s_4 & s_4 & s_5 & s_5 \end{bmatrix} A^2 = \begin{bmatrix} s_1 & s_2 & s_3 & s_4 & s_6 & s_6 & s_6 \\ s_1 & s_2 & s_3 & s_4 & s_6 & s_6 & s_7 \\ s_1 & s_2 & s_3 & s_5 & s_5 & s_4 & s_7 \\ s_1 & s_2 & s_2 & s_4 & s_4 & s_5 & s_7 \\ s_1 & s_1 & s_3 & s_5 & s_5 & s_5 & s_7 \end{bmatrix}$$

$$A^3 = \begin{bmatrix} s_1 & s_2 & s_3 & s_3 & s_5 & s_6 & s_7 \\ s_1 & s_2 & s_4 & s_4 & s_5 & s_6 & s_7 \\ s_1 & s_2 & s_3 & s_5 & s_6 & s_6 & s_7 \\ s_1 & s_2 & s_3 & s_4 & s_4 & s_5 & s_7 \\ s_1 & s_2 & s_3 & s_4 & s_5 & s_5 & s_7 \end{bmatrix} A^4 = \begin{bmatrix} s_1 & s_2 & s_3 & s_4 & s_5 & s_6 & s_6 \\ s_1 & s_2 & s_4 & s_5 & s_6 & s_6 & s_7 \\ s_1 & s_2 & s_3 & s_4 & s_5 & s_7 & s_7 \\ s_1 & s_2 & s_3 & s_4 & s_4 & s_5 & s_6 \\ s_1 & s_2 & s_3 & s_4 & s_4 & s_6 & s_7 \end{bmatrix}$$

$$A^5 = \begin{bmatrix} s_1 & s_2 & s_4 & s_5 & s_6 & s_7 & s_7 \\ s_1 & s_2 & s_4 & s_4 & s_5 & s_6 & s_7 \\ s_1 & s_3 & s_3 & s_4 & s_5 & s_6 & s_7 \\ s_1 & s_2 & s_3 & s_5 & s_5 & s_6 & s_7 \\ s_2 & s_3 & s_4 & s_4 & s_6 & s_6 & s_7 \end{bmatrix}$$

Then, according to the Initial evaluation matrices of DMs $\left\{V^1, V^2, V^3, V^4, V^5\right\}$ and CIS of each DM, the calibrated evaluation matrices of DMs $\left\{E^1, E^2, E^3, E^4, E^5\right\}$ can be obtained.

$$E^1 = \begin{bmatrix} 6.6 & 5.2 & 3.2 \\ 5.4 & 4.4 & 3.2 \\ 5.2 & 5.4 & 4.4 \\ 5.4 & 4.4 & 4.4 \\ 5.4 & 5.2 & 5.2 \\ 6.6 & 5.4 & 5.4 \end{bmatrix} E^2 = \begin{bmatrix} 4.4 & 4.4 & 3.4 \\ 4 & 4.4 & 5.2 \\ 5.2 & 4.4 & 4.4 \\ 4 & 5.2 & 3.4 \\ 5.2 & 4.4 & 3.4 \\ 5.6 & 4.4 & 3.4 \end{bmatrix} E^3 = \begin{bmatrix} 4.0 & 5.8 & 5.8 \\ 5.0 & 5.8 & 5.8 \\ 5.8 & 5.8 & 5.8 \\ 3.2 & 7 & 4 \\ 5.8 & 5.8 & 5.8 \\ 3.2 & 5.8 & 2.0 \end{bmatrix}$$

$$E^4 = \begin{bmatrix} 3.0 & 5.2 & 4.2 \\ 3.0 & 4.2 & 4.2 \\ 3.0 & 4.2 & 3 \\ 3.0 & 3 & 4.2 \\ 4.2 & 4.2 & 4.2 \\ 3.0 & 3.0 & 3.0 \end{bmatrix} E^5 = \begin{bmatrix} 4.4 & 6.2 & 4.4 \\ 4.4 & 6.2 & 4.4 \\ 4.4 & 6.2 & 5.4 \\ 5.4 & 6.2 & 5.4 \\ 5.4 & 7 & 4.4 \\ 5.4 & 7 & 5.4 \end{bmatrix}$$

Consensus Measure and Feedback Recommendation

The weights of the five DMs are assigned as $W = \left(w_1, w_2, w_3, w_4, w_5\right)^T = \left(0.23, 0.23, 0.18, 0.18, 0.18\right)^T$ based on their positions and work experience. Then, the collective calibrated evaluation matrix E^c

can be aggregated by individually calibrated evaluation matrices $\left\{E^1, E^2, E^3, E^4, E^5\right\}$, according to Eq. (4), as follows.

$$E^c = \begin{bmatrix} 4.58 & 5.30 & 4.11 \\ 4.39 & 4.94 & 4.52 \\ 4.77 & 5.17 & 4.58 \\ 4.25 & 5.12 & 4.24 \\ 5.41 & 5.27 & 4.57 \\ 4.89 & 5.10 & 3.90 \end{bmatrix}$$

Subsequently, the three levels of consensus indexes of DMs are obtained, as follows. The consensus indexes on element-level of DMs are:

$$CE^1 = \begin{bmatrix} 0.66 & 0.98 & 0.85 \\ 0.83 & 0.91 & 0.78 \\ 0.93 & 0.96 & 0.97 \\ 0.81 & 0.88 & 0.97 \\ 0.97 & 0.99 & 0.90 \\ 0.71 & 0.95 & 0.75 \end{bmatrix} CE^2 = \begin{bmatrix} 0.97 & 0.85 & 0.88 \\ 0.93 & 0.91 & 0.89 \\ 0.93 & 0.87 & 0.97 \\ 0.96 & 0.99 & 0.86 \\ 0.99 & 0.86 & 0.81 \\ 0.88 & 0.88 & 0.92 \end{bmatrix} CE^3 = \begin{bmatrix} 0.90 & 0.92 & 0.72 \\ 0.90 & 0.86 & 0.79 \\ 0.83 & 0.90 & 0.80 \\ 0.83 & 0.69 & 0.96 \\ 0.90 & 0.91 & 0.80 \\ 0.72 & 0.88 & 0.68 \end{bmatrix}$$

$$CE^4 = \begin{bmatrix} 0.74 & 0.98 & 0.99 \\ 0.77 & 0.88 & 0.95 \\ 0.71 & 0.84 & 0.74 \\ 0.79 & 0.65 & 0.99 \\ 0.83 & 0.82 & 0.94 \\ 0.68 & 0.65 & 0.85 \end{bmatrix} CE^5 = \begin{bmatrix} 0.97 & 0.85 & 0.95 \\ 0.99 & 0.79 & 0.98 \\ 0.84 & 0.83 & 0.86 \\ 0.81 & 0.82 & 0.84 \\ 0.97 & 0.71 & 0.97 \\ 0.92 & 0.68 & 0.75 \end{bmatrix}$$

Then, the consensus indexes on FMs level of DMs are:

$$CF = \begin{bmatrix} FMs & k=1 & k=2 & k=3 & k=4 & k=5 \\ FM_1 & 0.83 & 0.90 & 0.85 & 0.90 & 0.92 \\ FM_2 & 0.84 & 0.91 & 0.85 & 0.86 & 0.92 \\ FM_3 & 0.95 & 0.92 & 0.84 & 0.76 & 0.88 \\ FM_4 & 0.89 & 0.94 & 0.82 & 0.81 & 0.81 \\ FM_5 & 0.95 & 0.89 & 0.87 & 0.86 & 0.88 \\ FM_6 & 0.80 & 0.89 & 0.76 & 0.73 & 0.78 \end{bmatrix}$$

The consensus indexes on the decision matrix level of DMs are:

$$\left(CM_1, CM_2, CM_3, CM_4, CM_5,\right) = \left(0.878, 0.908, 0.831, 0.821, 0.867\right).$$

Based on the identification rules and given consensus threshold $\gamma = 0.85$, DM_3 and DM_4 are inconsistent. The CI of DM_4 is lower, so DM_4 is firstly chosen and the set of inconsistent elements is such that:

$$APS = \left\{ \left(4,1,1\right), \left(4,2,1\right), \left(4,3,1\right), \left(4,3,2\right), \left(4,3,3\right), \left(4,4,1\right), \left(4,4,2\right), \left(4,5,1\right), \left(4,5,2\right), \left(4,6,1\right), \left(4,6,2\right) \right\}$$

According to Model (12), the minimum adjustment cost feedback parameter for DM_4 is solved as $\delta_4 = 0.23$. Then, RE^4 the adjusted expectation matrix of DM_4 and first updated collective numerical risk evaluation matrix REC^1 can be obtained as follows:

$$RE^4 = \begin{bmatrix} 3.36 & 5.20 & 4.20 \\ 3.32 & 4.20 & 4.20 \\ 3.41 & 4.42 & 3.36 \\ 3.29 & 3.49 & 4.20 \\ 4.43 & 4.45 & 4.20 \\ 3.43 & 3.48 & 3.00 \end{bmatrix} REC^1 = \begin{bmatrix} 4.65 & 5.30 & 4.11 \\ 4.45 & 4.94 & 4.52 \\ 4.84 & 5.21 & 4.65 \\ 4.30 & 5.21 & 4.24 \\ 5.25 & 5.31 & 4.57 \\ 4.97 & 5.18 & 3.90 \end{bmatrix}$$

Then, the consensus level of DM_3 have to be recalculated after the collective expectation matrix has been adjusted, to determine whether DM_3 needs feedback recommendation. According to calculating, the new consensus level of DM_3 $CM_3^{'} = 0.834$ is lower than the preset threshold. Therefore, DM_3 also must accept feedback recommendations, and the set of inconsistent elements is such that:

$$APS = \left\{ \left(3,1,3\right), \left(3,2,3\right), \left(3,3,1\right), \left(3,3,3\right), \left(3,4,1\right), \left(3,4,2\right), \left(3,5,3\right), \left(3,6,1\right), \left(3,6,3\right) \right\}$$

According to Model (12), the minimum adjustment cost feedback parameter for DM_3 is solved as $\delta_3 = 0.1$. Then, RE^3 the adjusted expectation matrix of DM_3 and second, updated collective numerical risk evaluation matrix REC^2 can be obtained as follows:

$$RE^3 = \begin{bmatrix} 4.00 & 5.80 & 5.51 \\ 5.00 & 5.80 & 5.58 \\ 5.64 & 5.80 & 5.60 \\ 3.36 & 6.70 & 4.00 \\ 5.80 & 5.80 & 5.59 \\ 3.50 & 5.80 & 2.32 \end{bmatrix} REC^2 = \begin{bmatrix} 4.65 & 5.30 & 4.06 \\ 4.45 & 4.94 & 4.49 \\ 4.81 & 5.21 & 4.61 \\ 4.33 & 5.16 & 4.24 \\ 5.25 & 5.31 & 4.53 \\ 5.03 & 5.18 & 3.95 \end{bmatrix}$$

After the feedback mechanism, the new CMs of DMs are calculated as

$$CM^{''} = \left(CM_1^{''}, CM_2^{''}, CM_3^{''}, CM_4^{''}, CM_5^{''}\right) = \left(0.883, 0.906, 0.851, 0.850, 0.871\right).$$

Since the CM of each DM in FMEA team has reached the consensus threshold, the final stage is activated to rank FMs.

Calculating the Weights of Risk Factors and Ranking Failure Modes

Once the updated collective expectation matrix REC^2 is obtained, the relative weight w_j of RFs can be calculated through algorithm 1.

$$w_j = \left(w_S, w_S, w_D\right) = \left(0.47, 0.17, 0.36\right)$$

Through REC^2 and the relative weight of RFs w_j, the RPN values of FMs are calculated by Eq. (16), shown in Table 3, and the FMs are sorted in descending as:

$$FM_5 > FM_3 > FM_6 > FM_1 > FM_2 > FM_4 .$$

This article postulates that the prior weightage assigned to DMs is contingent upon their role and expertise; however, an exhaustive elucidation of these methods surpasses the this paper's limits. Furthermore, in the managerial practice of the proposed methodology, more interesting techniques can be introduced to extend the entire FMEA framework.

COMPARISONS AND DISCUSSIONS

A comparative study of consensus level between the proposed method and traditional Failure Modes and Effects Analysis (FMEA) without Criticality Index System (CIS) is visualized in Figure 3. We find that the individual understanding and preference of evaluation terms will affect the eventual result and consensus measure that consensus levels can be increased or decreased. Using CIS can reduce the distortion caused by factors including the DMs' psychological scale, word preference, and decision-making attitudes.

Second, to demonstrate the effect of the proposed method of FMEA, a comparison analysis is performed between different weight methods of RFs.

The conventional FMEA method has not considered the relative weight of RFs, so the relative weight of RFs is $W^c = \left(w_S, w_S, w_D\right) = \left(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\right)$. According to the updated collective expectation matrix REC^2 and relative weight W^c of RFs, the RPNs of FMs based on conventional FMEA can be calculated, as shown in Table 4. The rank of FMs is: $FM_5 > FM_3 > FM_6 > FM_1 > FM_2 > FM_4$.

The entropy method is one of the most popular methods to obtain weight. Therefore, the entropy method is also adopted in this paper to obtain the weight of RFs for comparison. The relative weight of RFs obtained by the Entropy method (Yalcin et al., 2021) is $W^E = \left(w_S, w_S, w_D\right) = \left(0.35, 0.33, 0.32\right)$. According to W^E and REC^2, the RPNs of FMs based on the Entropy method can be calculated, as shown in Table 4. The rank of FMs is: $FM_5 > FM_3 > FM_6 > FM_1 > FM_2 > FM_4$.

Table 3.
The RPNs of FMs

FMs	FM_1	FM_2	FM_3	FM_4	FM_5	FM_6
RPN	4.40	4.01	4.97	4.49	5.20	5.02

Figure 3.
Consensus levels of DMs in different risk assessment methods

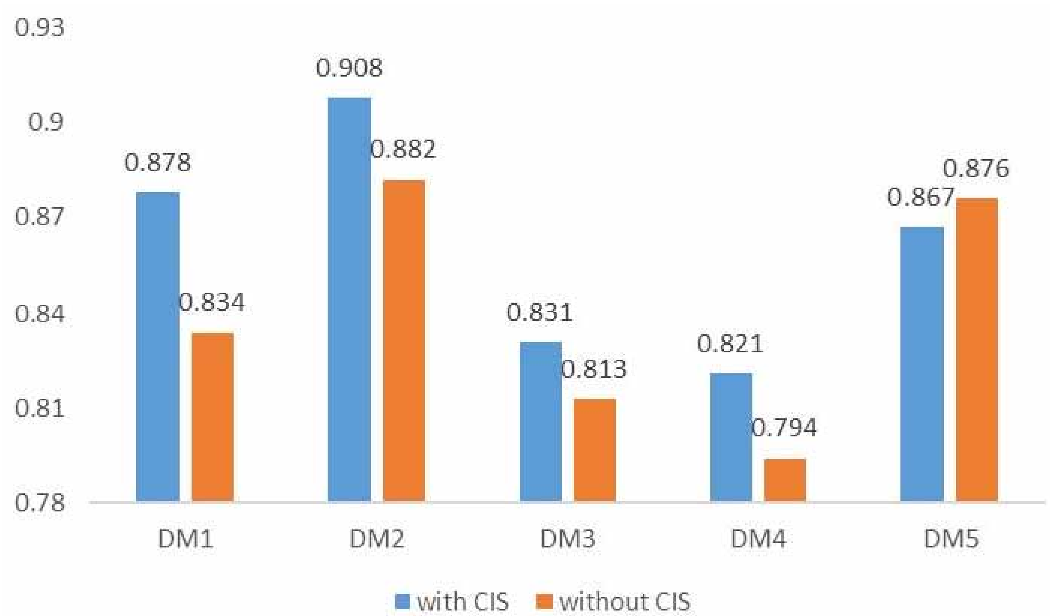
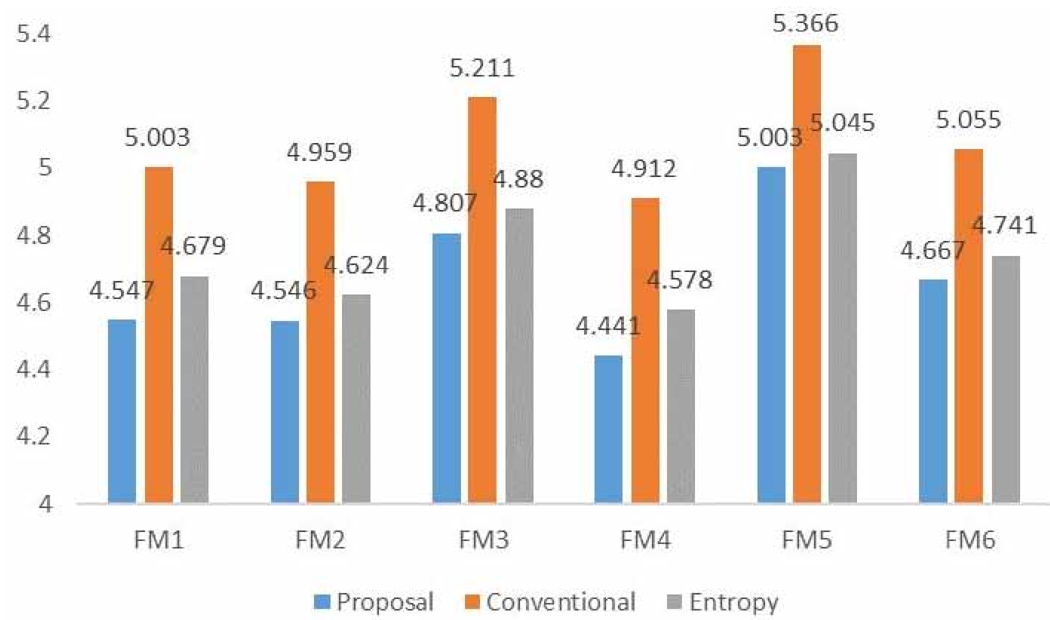


Table 4.
The RPNs of FMs based on different weight allocation methods

Rank	Proposed Method	RPNs	Conventional Method	RPNs	Entropy Method	RPNs
No.1	FM_5	5.003	FM_5	5.366	FM_5	5.045
No.2	FM_3	4.807	FM_3	5.211	FM_3	4.880
No.3	FM_6	4.667	FM_6	5.055	FM_6	4.741
No.4	FM_1	4.547	FM_1	5.003	FM_1	4.679
No.5	FM_2	4.546	FM_2	4.959	FM_2	4.624
No.6	FM_4	4.441	FM_4	4.912	FM_4	4.578

The technique of RF weight allocation method will affect the final rank of FMs by comparing the RPNs and ranking results of FMs, whose differences can be attributed to the weights of RFs obtained by the performances of collective evaluation. Based on Table 4 and Figure 4, we can find a similar result between the proposal method and other methods in the ranking of FMs with RPNs, demonstrating that our approach is feasible and effective.

Figure 4.
Consensus levels of DMs based on different weight allocation methods



CONCLUSIONS AND FUTURE WORK

This paper proposes a novel FMEA framework with a weight allocation method based on the performance of alternatives and a consensus-reaching process. Through comparative analysis, the CIS model can improve the evaluation bias caused by decision-makers' subjectivity, and the weight allocation method based on the performance of alternatives is effective. Its major contributions are as follows.

An improved FMEA approach must consider issues such as effectiveness, difficulty, and practicality. The proposed method does so as follows. First, using CIS can improve the ability to deal with uncertain information and solve the problem that different DMs have different understandings of the same term. Second, in our paper, the consensus-reaching process can effectively solve the potential conflict or inconsistency across different apartments with a minimum adjustment cost feedback mechanism. Third, the proposed method uses a novel weight allocation method based on alternatives' performances to assign weights to RFs to solve the problem that different OSD values may get the same result. Fourth, applying FMEA in the Industrial Internet fills the risk management problem research gap to a certain extent.

Although this paper optimizes the weight allocation of RFs, it does not consider the weight problem among decision-makers. Different departments, positions, work experiences, and other factors will affect the actual work of decision-making issues, so it is necessary to consider the weight of decision-makers in the FMEA framework in the future. Besides, considering that there may be much more decision-makers taking part in FMEA work, the frameworks of large-scale group decision-making and consensus in social network group decision-making can be introduced into FMEA problems to extend application scenarios (Ji et al., 2023; Wu et al., 2022b; Zhou et al., 2023). Additionally, RFs of FMEA extend beyond OSD, and can be tailored according to the decision-making environment and specific attributes of the object. Consequently, further investigations into the Industrial Internet Platform could yield an expanded range of RFs, more accurately reflecting the distinctive properties of the Industrial Internet. Finally, the consensus-based FMEA framework can be extended and applied to other sectors, such as the shipping industry, new vehicles (Wang et al., 2023), and other fields.

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Jian Wu is an AE of Computers & Industrial Engineering, Applied Intelligence, IEEE Senior Member. He proposed the Social network Group decision making (SN-GDM), has 100+papers published in leading journals such as IEEE TFS, IEEE CYB, IEEE SMC. Prof. Jian Wu has 19 journal papers classed as highly cited (HCP). He was an academic research visitor in CCI, at De Montfort University.

Jun Chen received the B.S. degree in Management Science from Shanghai Maritime University in 2020. He is currently an academic master's in management science and engineering at Shanghai Maritime University. His current research interests include failure mode and effect analysis, computing with words, consensus process. He has published an international journal paper in Mathematics.

Jin Fang got her Bachelor of Engineering degree from University of Science and Technology of China in 2010, and PhD degree from The Hong Kong University of Science and Technology in 2015, major in Industrial Engineering and Logistics Management. She joined the Shanghai Maritime University in 2018 and is currently a lecturer of School of Economics & Management. Her research interests include machine learning, stochastic modeling, and optimization.

Mingshuo Cao received his B.E. degree in Business from Shanghai Maritime University in 2018. He is a Ph.D. candidate in Management Science of Shanghai Maritime University since 2018. From Nov. 2021, he is a visiting PhD student in the Institute of Artificial Intelligence (IAI) at De Montfort University (DMU), funded by China Scholarship Council and Top-notch innovative program of Shanghai Maritime University. His research interests include group decision making, consensus and group behavior.