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A Fuzzy Decision Support System for Risk Prioritization in Fine Kinney-based Occupational Risk Analysis

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ABSTRACT

Analyzing Occupational Health and Safety (OHS) risks requires prioritizing risk, a vital step in hazard and effect analysis (HEA). Currently, there is no existing approach to determine the priority of risk in HEA-based occupational risk analysis that incorporates interactive risk factors and spherical fuzzy risk information. This paper presents a novel approach to address the constraints by introducing a fresh framework for evaluating job-related hazards using HEA by combining the spherical fuzzy set (SFS), the multi-attributive border approximation area comparison (MABAC) technique, and the Ordered Weighted Averaging (OWA) operator, a more sophisticated approach is achieved within this framework. The SFS is utilized in this framework to depict the more ambiguous and unsure data given by specialists, offering a more efficient approach to handling the fuzzy risk information, encompassing the non-membership degree and hesitation. In addition, an advanced MABAC method is used to prioritize occupational risk. Afterward, we provide a practical instance of utilizing the MABAC technical-oriented risk prioritization approach for evaluating potential occupational dangers in risk analysis.

1. Introduction

In recent years, improvements in technology and industrial manufacturing have resulted in enhanced efficiency in production and more significant economic benefits. Nevertheless, it may lead to new potential risks related to Occupational Health and Safety (OHS). These risks may cause damage or losses to humans and the environment [1]. In such cases, evaluating and prioritizing the potential occupational risks is essential to reducing, eliminating, or controlling them. Similarly, different approaches have been utilized to identify evaluation techniques, including the analysis of fault tree analysis (FTA) fault [2], hazard and effect analysis (HEA) [3], the Fine-Kinney (F-K) model [4,5] and the safety and critical effect analysis (SCEA) [6], etc. The F-K method is a suitable approach for risk assessment among these techniques as it can consider a more significant number of risk parameters. Nevertheless, the current risk prioritization methods encounter various constraints

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when ranking risks using the F-K method under intricate uncertainty. A risk prioritization framework is essential in this scenario to improve the efficiency of the F-K model.

When employing the F-K model for analyzing occupational risk, the evaluation of linguistic uncertainty in occupational risk assessment becomes significant. Nevertheless, numerous ambiguous statements have arisen while evaluating occupational risks. Additionally, the experts' interpretations of uncertain information. Various techniques are utilized in the F-K model to represent uncertain risk data to manage uncertain risk ratings. Among these techniques [7-9], fuzzy sets are widely regarded as the most popular way to process these risk data. However, these approaches are not without their constraints when dealing with complex and unpredictable data in evaluating risks owing to the intricacy and uncertainty of real-world problems. Compared to the methods above, the SFS is a more flexible technique to convey comprehensive occupational risk assessment information [10,11]. Moreover, the SFS has been widely utilized in diverse fields because of its capacity to encompass the precision, constraint, and inaccuracy of uncertain information. As a result, we utilize the SFS for handling the risk data provided by professionals. Moreover, the risk priority calculation (RPC) is another important consideration in the F-K method's risk analysis process. The evaluation of risk priority is commonly acknowledged as a challenge in multi-criteria decision-making (MCDM) [12]. Consequently, various MCDM methods have been integrated into the risk prioritization process for the F-K approach in recent studies [3,13-16]. Out of all these MCDM techniques, the MABAC method, which is mentioned in the reference, offers consistent priority outcomes using a straightforward computation procedure. The MABAC method has been expanded to address priority ranking concerns, including the evaluation of rapeseed varieties [17], the selection of suppliers [18], the issues in a recyclable and sustainable environment [19], the choice of fuel alternatives [20], the management of plastic waste [21]. Hence, utilizing the MABAC technique for developing a sophisticated RPC structure in the F-K model with SF data is beneficial.

As previously mentioned, the F-K model has certain drawbacks in prioritizing risks. First, the current information expression methods cannot fully capture the risk data under the SF environment. Then, the deviation among risk scores from experts is seldom considered, especially under the SF context. However, the risk prioritization problem may not be resolved due to the inclusion of SF risk information and interactive criteria, despite the expansion of MABAC's risk prioritization approach to include risk priority calculation. Furthermore, as far as the author knows, no prior investigation has been carried out on prioritizing risks utilizing a combined SF-MABAC approach that integrates the OWA operator.

In previous studies regarding the F-K framework, developing a method for prioritizing risks is essential, especially when dealing with uncertain circumstances. Hence, many researchers have focused on developing risk prioritization methods by integrating the MCDM techniques with fuzzy sets. A new method for prioritizing occupational risk was suggested by Gul and Celik [22], which involved integrating the F–K technique with a fuzzy rule-based expert system. Krishankumar *et al.,* [23] propose the WASPAS method that incorporates the hesitant fuzzy set to tackle the risk priority issue in F-K. Karasan [24] provided a combined AHP method to prioritize the operational risk in F-K. The TOPSIS with an R-number - is also applied to evaluate occupational risk in the F-K model [25]. The risk prioritization problem was effectively solved by enhancing DEMATEL's integration with ANP [26]. Gul and Ak [27] devised an innovative method of assessing workplace hazards by combining BWM and MAIRCA. Ramavandi *et al.,* [28] introduced the F-AHP and F-VIKOR methods to evaluate and prioritize the risk. According to Wang *et al.,* [29], a new technique known as the mixed gained-lost dominance score method was introduced to evaluate and prioritize the risk in the F-K model. In an investigation conducted by Gul *et al.,* [7], the evaluation of potential hazards at an oil station was constructed using a combined method using Bayesian BWM and Fuzzy VIKOR. Wang *et al.*, [30] use a spherical fuzzy CRADIS approach to analyze and prioritize occupational risk. The conclusion of the integration of MARCOS and Fermatean fuzzy in the F-K model's occupational risk priority is mentioned by Wang *et al.,* [31]. Fang *et al.,* [32] introduced a novel ranking method that combines Fermatean fuzzy sets with the GLDS technique to prioritize risks in F-K.

The MABAC technique was initially introduced by Pamučar and Ćirović [33]. The MABAC advancement consistently employs the fusion of the MABAC method and fuzzy set theory to improve the efficiency of information processing and the accuracy of priority results, encompassing the hesitant fuzzy set, the intuitionistic fuzzy set, and other variations. Liu and Zhang [12] presented a new CCSD-PT-MABAC technique in a standard uncertain fuzzy scenario with normal wiggly, hesitant fuzzy conditions. The studies conducted by Verma [34] and Zhao *et al.,* [35] combined an intuitionistic fuzzy set and the MABAC method to create a hybrid approach for assessing and prioritizing risks. Jana *et al.,* [36] improved efficiency by integrating Pythagorean fuzzy numbers with the MABAC method. A novel MABAC method was introduced by Jiang *et al.,* [18] in the context of picture fuzzy sets (PFSs) and picture fuzzy numbers (PFNs). Wang *et al.,* [37] developed a combination of an extended MABAC technique and a Dual probabilistic linguistic term set (DPLTS). Researchers have recently shown interest in the MABAC, a traditional MCDM technique, for addressing alternative ranking concerns in various fields. Considering possible losses and gains, this approach yields consistent outcomes to its simple calculation. Deveci *et al.,* [38] used a novel and expanded MABAC framework to choose the offshore wind location in the USA. Chattopadhyay *et al.,* [39] utilized the MABAC technique with Rough numbers to select the iron and steel industry supplier. A hybrid MABAC method incorporating the Fermatean fuzzy set was developed and used by authors Tan *et al.,* [40] in risk investment assessment.

This research paper uses the F-K technique to introduce a combined strategy for prioritizing hazards in occupational risk assessment. This paper presents key findings:

(i) The extended information fusion method considers the differences in risk assessment information given by various experts while constructing the matrix for group risk assessment. To determine the specialists' significance level, we utilize a weighting technique that relies on a minimal variance measure during the fusion procedure.

(ii) A new approach for prioritizing occupational risk using a proposed MCDM technique, which involves the application of SFS to handle risk assessment information that is independently hesitant, inconsistent, and uncertain.

(iii) To the authors' best understanding, this is the initial occurrence of combining the MABAC method with SFS and the OWA operator. In such a scenario, the F-K model can prioritize risks in occupational risk analysis. Under the SF environment, the suggested approach offers a fresh approach to establish the priority ranking of occupational risks by considering interactive risk factors.

(iv) The new risk prioritization method offers a fresh solution based on the F-K model for occupational risk analysis issues. It ensures a reliable and understandable ranking of risk priorities. To illustrate the rationality and effectiveness of the proposed method, we present a numerical example that demonstrates the application of the risk prioritization framework using the hybrid MABAC approach.

The remaining portion of this document is structured in the following manner. Section 2 has a concise overview of SFS. Section 3 introduces the MABAC approach for F-K based on occupational risk analysis. In Section 4, there is a numerical example that demonstrates occupational risk analysis. The concluding part of this section entails summarizing the findings and outlining the areas for future research.

2. Preliminaries

2.1 Spherical fuzzy set

Kutlu Gündoğdu and Kahraman [41] first introduced the concept of spherical fuzzy sets (SFSs), which are considered as an extension of the intuitionistic fuzzy set (IFS), Pythagorean fuzzy set (PFS), and the neutrosophic set. The comparison of the four fuzzy sets is depicted in Figure 1. The SFSs were implemented to extract the ambiguous risk assessment information from every specialist [42,43]. The specific concepts and operation rules of SFSs are introduced as follows:

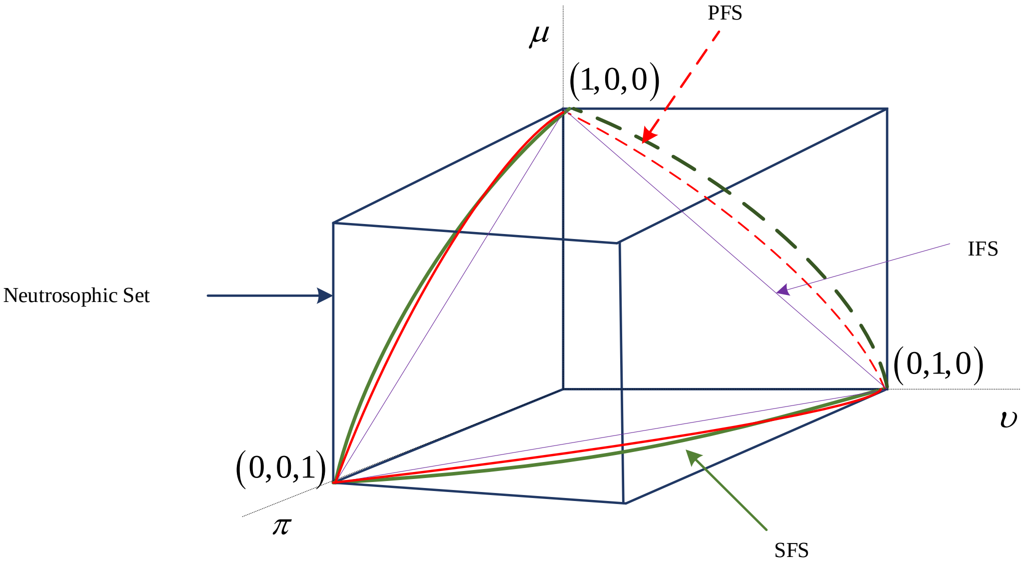

Fig.1. The diagrammatic presentation of four fuzzy sets in a 3D plane (adapted from Mathew *et al.,* [44])

Definition 1: Let X be a nonempty fixed set, then a SFS $\tilde{S}$ on X can be expressed as follows:

$$\tilde{S} = \left\{ \left\langle x, \left(\mu_{\tilde{S}}(x), \nu_{\tilde{S}}(x), \pi_{\tilde{S}}(x) \right) \right\rangle \middle| x \in X \right\} \tag{1}$$

where $\mu_{\tilde{S}}(x): X \to [0,1], \nu_{\tilde{S}}(x): X \to [0,1]$ and $\pi_{\tilde{S}}(x): X \to [0,1]$ denote the degree of membership, degree of abstinence, and degree of non-membership of x to $\tilde{S}$, respectively, which satisfy every condition $x \in X: 0 \le \mu_{\tilde{S}}^2(x) + \nu_{\tilde{S}}^2(x) + \pi_{\tilde{S}}^2(x) \le 1$. The rejective degree of the element $x \in X$ is given as $R_{\tilde{S}}(x) = \left[1 - \mu_{\tilde{S}}^2(x) - \nu_{\tilde{S}}^2(x) - \pi_{\tilde{S}}^2(x)\right]^{1/2}$.

For simplicity, the triplet $\langle \mu, \nu, \pi \rangle$ is called a spherical fuzzy number (SFN).

Definition 2: Suppose that the sets $\tilde{S}_1 = \left[\mu_{\tilde{S}_1}, \nu_{\tilde{S}_1}, \pi_{\tilde{S}_1}\right]$ and $\tilde{S}_2 = \left[\mu_{\tilde{S}_2}, \nu_{\tilde{S}_2}, \pi_{\tilde{S}_2}\right]$ are two SFNs; then the operation rules between $\tilde{S}_1$ and $\tilde{S}_2$ are expressed as follows [44]:

① Addition of $\tilde{S}_1$ and $\tilde{S}_2$

$$\begin{aligned} \tilde{S}_1 + \tilde{S}_2 = \Big\langle & \left(1 - \left(1 - \mu_{\tilde{S}_1}^2\right)\left(1 - \mu_{\tilde{S}_2}^2\right)\right)^{1/2}, \\ & \left(\left(1 - \mu_{\tilde{S}_1}^2\right)\left(1 - \mu_{\tilde{S}_2}^2\right) - \left(1 - \mu_{\tilde{S}_1}^2 - \nu_{\tilde{S}_1}^2\right)\left(1 - \mu_{\tilde{S}_2}^2 - \nu_{\tilde{S}_2}^2\right)\right)^{1/2}, \\ & \left(\left(1 - \mu_{\tilde{S}_1}^2 - \nu_{\tilde{S}_1}^2\right)\left(1 - \mu_{\tilde{S}_2}^2 - \nu_{\tilde{S}_2}^2\right) - \left(1 - \mu_{\tilde{S}_1}^2 - \nu_{\tilde{S}_1}^2 - \pi_{\tilde{S}_1}^2\right)\left(1 - \mu_{\tilde{S}_2}^2 - \nu_{\tilde{S}_2}^2 - \pi_{\tilde{S}_2}^2\right)\right)^{1/2} \Big\rangle \end{aligned} \tag{2}$$

②Multiplication of $\tilde{S}_1$ and $\tilde{S}_2$

$$\tilde{S}_1 \otimes \tilde{S}_2 = \langle \left(\left(1-\pi_{\tilde{S}_1}^2 - \nu_{\tilde{S}_1}^2\right)\left(1-\pi_{\tilde{S}_2}^2 - \nu_{\tilde{S}_2}^2\right) - \left(1-\pi_{\tilde{S}_1}^2 - \nu_{\tilde{S}_1}^2 - \mu_{\tilde{S}_1}^2\right)\left(1-\pi_{\tilde{S}_2}^2 - \nu_{\tilde{S}_2}^2 - \mu_{\tilde{S}_2}^2\right)\right)^{1/2},$$
$$\left(\left(1-\pi_{\tilde{S}_1}^2\right)\left(1-\pi_{\tilde{S}_2}^2\right) - \left(1-\pi_{\tilde{S}_1}^2 - \nu_{\tilde{S}_1}^2\right)\left(1-\pi_{\tilde{S}_2}^2 - \nu_{\tilde{S}_2}^2\right)\right)^{1/2}, \tag{3}$$
$$\left(1-\left(1-\pi_{\tilde{S}_1}^2\right)\left(1-\pi_{\tilde{S}_2}^2\right)\right)^{1/2}\rangle$$

③Multiplication of a crisp value λ

Let the set $\tilde{S} = \left[\mu_{\tilde{S}}, \nu_{\tilde{S}}, \pi_{\tilde{S}}\right]$ be an SFS; then the multiplication of a crisp value λ with $\tilde{S}$ is defined as.

$$\lambda\tilde{S} = \langle \left(1-\left(1-\mu_{\tilde{S}}^2\right)^{\lambda}\right)^{1/2},$$
$$\left(\left(1-\mu_{\tilde{S}}^2\right)^{\lambda} - \left(1-\mu_{\tilde{S}}^2-\nu_{\tilde{S}}^2\right)^{\lambda}\right)^{1/2}, \tag{4}$$
$$\left(\left(1-\mu_{\tilde{S}}^2-\nu_{\tilde{S}}^2\right)^{\lambda} - \left(1-\mu_{\tilde{S}}^2-\nu_{\tilde{S}}^2-\pi_{\tilde{S}}^2\right)^{\lambda}\right)^{1/2}\rangle$$

④Exponent($\lambda > 0$) of SFS

Assume that the set $\tilde{S} = \left[\mu_{\tilde{S}}, \nu_{\tilde{S}}, \pi_{\tilde{S}}\right]$ is an SFS, then the exponent ($\lambda > 0$) of the set $\tilde{S}$ is denoted as follows:

$$\tilde{S}^{\lambda} = \langle \left(\left(1-\pi_{\tilde{S}}^2-\nu_{\tilde{S}}^2\right)^{\lambda} - \left(1-\pi_{\tilde{S}}^2-\nu_{\tilde{S}}^2-\mu_{\tilde{S}}^2\right)^{\lambda}\right)^{1/2},$$
$$\left(\left(1-\pi_{\tilde{S}}^2\right)^{\lambda} - \left(1-\pi_{\tilde{S}}^2-\nu_{\tilde{S}}^2\right)^{\lambda}\right)^{1/2}, \tag{5}$$
$$\left(1-\left(1-\pi_{\tilde{S}}^2\right)^{\lambda}\right)^{1/2}\rangle$$

Definition 3: For any SFN $S = \left(\mu_x, \nu_x, \pi_x\right), q \geq 1$, the score and accuracy functions can be defined in the following [45]:

$$F\left(S\right) = \frac{\left(1+\mu_x^2+\nu_x^2+\pi_x^2\right)}{2}, F\left(S\right) \in \left[0,1\right] \tag{6}$$

$$T\left(S\right) = \mu_x^2+\nu_x^2+\pi_x^2, T\left(S\right) \in \left[0,1\right] \tag{7}$$

Next, the rules for comparing SFNs are presented as follows:

1.If $F\left(S_1\right) < F\left(S_2\right)$, then $\left(S_1\right) < \left(S_2\right)$;

2.If $F\left(S_1\right) = F\left(S_2\right)$, then

(1). If $T\left(S_1\right) < T\left(S_2\right)$, then $S_1 < S_2$;

(2). If $T\left(S_1\right) = T\left(S_2\right)$, then $S_1 = S_2$.

Definition 4: Let $b_1 = \langle \mu_1, \nu_1, \pi_1 \rangle$ and $b_2 = \langle \mu_2, \nu_2, \pi_2 \rangle$ represent two SFSs, the distance between them can be defined as follows [46]:

$$d\left(b_1, b_2\right) = \left(\left|\mu_1^2-\mu_2^2\right|^2 + \left|\nu_1^2-\nu_2^2\right|^2 + \left|\pi_1^2-\pi_2^2\right|^2\right)^{\frac{1}{2}} \tag{8}$$

3. A developed MABAC method-based risk prioritization for occupational risk analysis

The current F-K-based occupational risk analysis approach has been used to avoid potential hazards and prevent possible accidents. The F-K model includes three parameters: probability, consequence, and exposure. Algorithmically, the risk index is a product of the values of the three parameters.

Nevertheless, there are shortcomings in treating the importance of uncertain language and risk parameters equally and in selecting precise figures that lack flexibility in quantitatively evaluating risk. Therefore, this article presents an enhanced MABAC technique-driven risk ranking approach to the F-K model, illustrating the interconnected dual relationships and showcasing the fundamental structure of this methodology in Figure 2. This flowchart is composed of three phases. The SFS-based linguistic scale is initially employed to obtain linguistic risk information from each expert and create the individual risk matrix. Additionally, introducing a SFS-OWA operator is demonstrated to merge the fusion risk matrix, thus considering the importance of risk information's placement. The detailed calculation procedures of each phase are listed as follows.

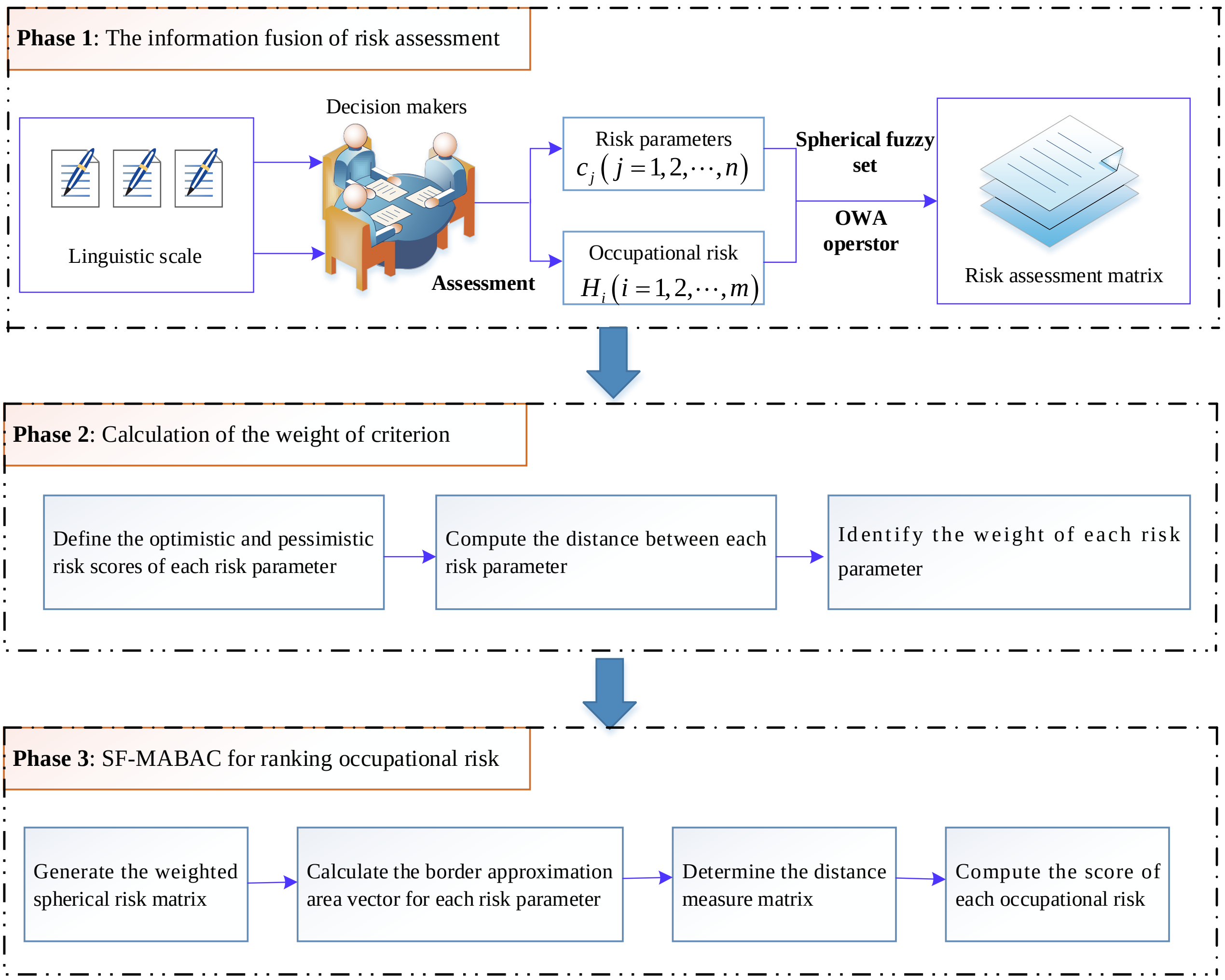

Fig. 2. The flowchart of the developed risk prioritization approach

3.1 The information fusion of risk assessment

As mentioned in Section 1, the MABAC-based occupational risk analysis can be seen as an MCDM problem. We consider the MABAC-based occupational risk analysis as an MCDM problem in such a case. Therefore, we need to dispose of uncertain fuzziness and random linguistic context in occupational risk analysis. So, we suppose that $H_i=\{H_1,H_2,H_3,\ldots,H_m\}$ is a group of occupational risk and $c_j = \{c_1, c_2, c_3, ..., c_n\}$ is the group of risk parameters, and it is the same as the initial linguistic, occupational risk assessment information. Hypothesize that $w = (w_1, w_2, w_3, ..., w_n)^T$ is the weight vector of risk parameters, in which $0 \le w_j \le 1$ and $\sum_{j=1}^{n} w_j = 1$. What's more, we assume that a set of decision-makers $e^\tau (\tau = 1,2,3,...,t)$ are required to use the linguistic terms providing risk assessment information of the ith occupational hazard under jth risk parameters. Then, $\omega = \{\omega^1, \omega^2, \omega^3, ..., \omega^t\}$ is the importance degree of the τth decision-maker, which complies with the following conditions $\omega^\tau \in [0,1]$ and $\sum_{\tau=1}^{t} \omega^\tau = 1$. Ultimately, this approach can transform the data from linguistic risk assessment. There are two sub-steps in this phase shown in the following context.

Step 1. Identify the potential occupational hazards

Understanding the complete range of potential workplace dangers, viewed through the lens of three risk factors called likelihood probability (P), exposure (E), and consequence (C), forms the core of this particular stage. The involvement of a panel of decision-makers $e^\tau (\tau = 1,2,3,...,t)$, comprising diverse specialists with relevant skills, expertise, knowledge, background, and more, is a crucial foundation for this stage.

Step 2. Convert the linguistic terms related to risk assessment information

The method transforms linguistic variables into measurable risk rating scores based on the information $L^\tau = [l_{ij}^\tau]_{m\times n}$ obtained from various decision-makers during the linguistic risk assessment. The final result is presented as $S^\tau = [\tilde{y}_{ij}^\tau]_{m\times n}$.

$$S_{ij}^\tau = \left[\tilde{y}_{ij}^\tau\right]_{m\times n} = \begin{bmatrix} (\mu_{11}^\tau, \nu_{11}^\tau, \pi_{11}^\tau) & \cdots & \cdots & (\mu_{1n}^\tau, \nu_{1n}^\tau, \pi_{1n}^\tau) \\ \vdots & \cdots & \cdots & \vdots \\ \vdots & \cdots & \cdots & \vdots \\ (\mu_{m1}^\tau, \nu_{m1}^\tau, \pi_{m1}^\tau) & \cdots & \cdots & (\mu_{mn}^\tau, \nu_{mn}^\tau, \pi_{mn}^\tau) \end{bmatrix} \tag{9}$$

Step 3. Establish the risk assessment matrix

Based on the literature [47], the weights of experts are $\omega_1 = \omega_2 = \cdots = \omega_t = \frac{1}{t}$.

$$\begin{aligned} \tilde{y}_{ij} &= SF - OWA_{\omega_\tau}\left(\tilde{y}_{ij}^1, \tilde{y}_{ij}^2, \cdots, \tilde{y}_{ij}^\tau\right) \\ &= \left\langle \begin{array}{c} \sqrt{1 - \prod_{\tau=1}^{t}\left(1 - \mu_{\tilde{y}_{ij}^\tau(j)}^2\right)^{\omega_\tau}}, \prod_{\tau=1}^{t}\left(\nu_{\tilde{y}_{ij}^\tau(j)}\right)^{\omega_\tau} \\ \prod_{\tau=1}^{t}\left(\pi_{\tilde{y}_{ij}^\tau(j)}\right)^{\omega_\tau} \end{array} \right\rangle \end{aligned} \tag{10}$$

where $\tilde{y}_{ij}^\tau(j)$ is jth largest value consequently by total order $\tilde{y}_{ij}^\tau(1) \ge \tilde{y}_{ij}^\tau(2) \ge \cdots \ge \tilde{y}_{ij}^\tau(n)$.

3.2 Calculation of the weight of criterion

Step 1. Define the optimistic and pessimistic risk scores of each risk parameter.

$$K = \begin{cases} K^+ = (k_1^+, k_2^+, \cdots, k_n^+) \\ K^- = (k_1^-, k_2^-, \cdots, k_n^-) \end{cases} \tag{11}$$

in which, the elements k_j^+ and k_j^- can be denoted as follows:

$$k_j^+ = \begin{cases} \max\limits_i \tilde{y}_{ij}, if\ j \le g \\ \min\limits_i \tilde{y}_{ij}, if\ j > g \end{cases} \quad (12)$$

$$k_j^- = \begin{cases} \min\limits_i \tilde{y}_{ij}, if\ j \le g \\ \max\limits_i \tilde{y}_{ij}, if\ j > g \end{cases} \quad (13)$$

where g indicates the numbers of benefit criteria, $j = g+1, g+2, \dots, n$ are the criteria to be cost criteria.

Step 2. Compute the distance between each risk parameter and the optimistic and pessimistic risk scores.

By definition of distance between the parameters in the spherical fuzzy set, the distance between each risk parameter and the optimistic and pessimistic risk scores can be computed as follows:

$$d_j^+ = \sum_{i=1}^{m} d\left(\tilde{y}_{ij}, k_j^+\right) \quad (14)$$

$$d_j^- = \sum_{i=1}^{m} d\left(\tilde{y}_{ij}, k_j^-\right) \quad (15)$$

Step 3. Identify the weight of each risk parameter.

The larger the risk parameter's dispersion value, the more important the risk parameter will be. The dispersion value of each risk parameter $c_j\ (j = 1, 2, \dots, n)$ can be denoted as follows:

$$w_j' = \frac{d_j^+}{\left(d_j^+ + d_j^-\right)} \quad (16)$$

Then, Eq.(16) needs to carry out the normalization process.

$$w_j = \frac{w_j'}{\sum\limits_{j=1}^{n} w_j'} \quad (17)$$

3.3 SF-MABAC for ranking occupational risk

Step 1. Generate the weighted spherical risk matrix

$$R = \left[r_{ij}\right]_{m\times n} \quad (18)$$

in which, $r_{ij} = w_j \tilde{y}_{ij}$ and in this formula, w_j is the weight of the risk parameters c_j and r_{ij} is also the spherical fuzzy set.

Step 2. Calculated the border approximation area vector $\left(r_j\right)_{1\times n}$ for each risk parameter, and the element r_j is computed as follows:

$$r_j = \left(\bigotimes_{i=1}^{m} r_{ij}\right)^{\frac{1}{m}} \quad (19)$$

Step 3. Determine the distance measure matrix

$$D_{ij} = \begin{cases} d\left(r_{ij}, r_j\right), r_{ij} > r_j \\ 0, r_{ij} = r_j \\ -d\left(r_{ij}, r_j\right), r_{ij} < r_j \end{cases} \quad (20)$$

where $d\left(r_{ij}, r_j\right)$ represents the distance between r_{ij} and r_j, which can be calculated using Eq. (8).

Step 4. Compute the score of each occupational risk

$$RS_i = \sum_{j=1}^{n} d_j \tag{21}$$

in which, d_j represents the jth largest value.

4. A numerical example

The spherical fuzzy MABAC method is demonstrated in this section using the subway operation risk analysis as a case.

4.1 Case background

Reports in previous times have shown that the proportion of life safety accidents caused by the failure of the subway door system is relatively high. The subway door mechanism is crucial for ensuring traffic safety and the smooth functioning of the subway. In addition, the door system's components are in a relatively frequent operation state in the process of subway operation, which is easy to break down and leads to the risk of subway operation. Therefore, it is significant to study the hazards of subway door systems and adopt measures to prevent failure accidents. To improve the precision of the assessment findings and reduce the possible dangers associated with metro traffic operation, a T-spherical fuzzy MABAC approach is introduced as a valuable tool for managing risks.

4.2 The application of the approach

Based on previous relevant research [48], we select ten optional hazards, shown in Table 1.

Table 1
The main hazards of subway door electrical control system

Hazard	Hazard name	P	C	E	Priority
H_1	Cut out relay function failure	6	4	2	48
H_2	The error detection of an emergency unlocks	4	3	7	84
H_3	The door removal switch sends an incorrect isolation signal	2	6	7	84
H_4	Electronic door power supply failure	7	4	3	84
H_5	The closing travel switch can't send a signal	9	2	10	180
H_6	The electronic door function fails	10	3	6	180
H_7	The Travel switch sends an error signal	3	3	2	18
H_8	Position sensor function failure	2	9	1	18
H_9	Electronic door software system failure	3	4	1	12
H_{10}	The Maintenance relay function failure	2	3	2	12

Then, the SF-MABAC approach is presented to assess and give risk priority to the primary hazard of the subway door in the electrical control system. Firstly, three experts $e^{\tau}\left(\tau=1,2,3\right)$ with excellent relevant professional knowledge are invited. Next, we utilize the language scale presented in Table 2 to evaluate these ten hazards $H_i\left(i=1,2,\ldots,10\right)$ from three risk parameters: P, C, and E. The experts' risk assessment language variables are given in Table 3. Finally, the SF-MABAC approach is utilized to evaluate the risk of the hazards shown in Table 4.

Table 2
The language scale for risk evaluation

Language scale	SFN
VL	(0.85, 0.15, 0.10)
L	(0.75, 0.25, 0.20)
M	(0.55, 0.50, 0.25)
H	(0.25, 0.75, 0.20)
VH	(0.15, 0.85, 0.10)

Table 3
The risk assessment language variables given by the experts

Hazard risk	e^1			e^2			e^3		
	P	C	E	P	C	E	P	C	E
H_1	M	M	VH	M	M	M	L	H	VH
H_2	M	H	M	M	VH	VH	H	H	VH
H_3	M	M	H	H	H	VH	M	H	VH
H_4	M	H	VH	M	VH	VH	H	M	VH
H_5	L	VH	VL	L	VH	VL	L	M	VL
H_6	L	VH	VL	L	H	VL	L	VH	VL
H_7	M	VL	M	H	VL	M	M	VL	VH
H_8	L	L	M	M	M	VH	M	VH	VH
H_9	M	VL	VH	M	VL	M	H	M	M
H_{10}	M	VL	VH	M	VL	M	M	VL	M

Based on the above information, how the spherical fuzzy MABAC method applied to this case can be shown as follows.

The first step is transforming each specialist's linguistic risk assessment information into a risk assessment matrix based on SFN. Tables 4 to 6 display the risk evaluation matrixes for every specialist.

Table 4
The fuzzy risk assessment matrix from the expert e^1

Hazard risk	P	C	E
H_1	(0.55,0.50,0.25)	(0.55,0.50,0.25)	(0.15,0.85,0.10)
H_2	(0.55,0.50,0.25)	(0.25,0.75,0.20)	(0.55,0.50,0.25)
H_3	(0.55,0.50,0.25)	(0.55,0.50,0.25)	(0.25,0.75,0.20)
H_4	(0.55,0.50,0.25)	(0.25,0.75,0.20)	(0.15,0.85,0.10)
H_5	(0.75,0.25,0.20)	(0.15,0.85,0.10)	(0.85,0.15,0.10)
H_6	(0.75,0.25,0.20)	(0.15,0.85,0.10)	(0.85,0.15,0.10)
H_7	(0.55,0.50,0.25)	(0.85,0.15,0.10)	(0.55,0.50,0.25)
H_8	(0.75,0.25,0.20)	(0.75,0.25,0.20)	(0.55,0.50,0.25)
H_9	(0.55,0.50,0.25)	(0.85,0.15,0.10)	(0.15,0.85,0.10)
H_{10}	(0.55,0.50,0.25)	(0.85,0.15,0.10)	(0.15,0.85,0.10)

Journal of Soft Computing and Decision Analytics
Volume 3, Issue 1 (2025) 1-17

Table 5
The fuzzy risk assessment matrix from the expert e^2

Hazard risk	P	C	E
H_1	(0.55,0.50,0.25)	(0.55,0.50,0.25)	(0.55,0.50,0.25)
H_2	(0.55,0.50,0.25)	(0.15,0.85,0.10)	(0.15,0.85,0.10)
H_3	(0.25,0.75,0.20)	(0.25,0.75,0.20)	(0.15,0.85,0.10)
H_4	(0.55,0.50,0.25)	(0.15,0.85,0.10)	(0.15,0.85,0.10)
H_5	(0.75,0.25,0.20)	(0.15,0.85,0.10)	(0.85,0.15,0.10)
H_6	(0.75,0.25,0.20)	(0.25,0.75,0.20)	(0.85,0.15,0.10)
H_7	(0.25,0.75,0.20)	(0.85,0.15,0.10)	(0.55,0.50,0.25)
H_8	(0.55,0.50,0.25)	(0.55,0.50,0.25)	(0.15,0.85,0.10)
H_9	(0.55,0.50,0.25)	(0.85,0.15,0.10)	(0.55,0.50,0.25)
H_{10}	(0.55,0.50,0.25)	(0.85,0.15,0.10)	(0.55,0.50,0.25)

Table 6
The fuzzy risk assessment matrix from the expert e^3

Hazard risk	P	C	E
H_1	(0.75,0.25,0.20)	(0.25,0.75,0.20)	(0.15,0.85,0.10)
H_2	(0.25,0.75,0.20)	(0.25,0.75,0.20)	(0.15,0.85,0.10)
H_3	(0.55,0.50,0.25)	(0.25,0.75,0.20)	(0.15,0.85,0.10)
H_4	(0.25,0.75,0.20)	(0.55,0.50,0.25)	(0.15,0.85,0.10)
H_5	(0.75,0.25,0.20)	(0.55,0.50,0.25)	(0.85,0.15,0.10)
H_6	(0.75,0.25,0.20)	(0.15,0.85,0.10)	(0.85,0.15,0.10)
H_7	(0.55,0.50,0.25)	(0.85,0.15,0.10)	(0.15,0.85,0.10)
H_8	(0.55,0.50,0.25)	(0.15,0.85,0.10)	(0.15,0.85,0.10)
H_9	(0.25,0.75,0.20)	(0.55,0.50,0.25)	(0.55,0.50,0.25)
H_{10}	(0.55,0.50,0.25)	(0.85,0.15,0.10)	(0.55,0.50,0.25)

Next, the risk information matrixes provided by the experts will be combined using the OWA operator. We use Eq. (10) to integrate the risk assessment information provided in Table 7.

Table 7
Information integration matrix

Hazard risk	P	C	E
H_1	(0.660,0.361,0.200)	(0.850,0.150,0.100)	(0.267,0.477,0.100)
H_2	(0.660,0.361,0.200)	(0.850,0.150,0.100)	(0.267,0.477,0.100)
H_3	(0.750,0.250,0.200)	(0.477,0.267,0.100)	(0.150,0.850,0.100)
H_4	(0.584,0.454,0.215)	(0.150,0.850,0.100)	(0.150,0.850,0.100)
H_5	(0.480,0.572,0.232)	(0.178,0.815,0.126)	(0.267,0.477,0.100)
H_6	(0.480,0.572,0.232)	(0.304,0.542,0.159)	(0.267,0.477,0.100)
H_7	(0.550,0.500,0.250)	(0.250,0.750,0.200)	(0.317,0.457,0.126)
H_8	(0.550,0.500,0.250)	(0.325,0.655,0.215)	(0.412,0.399,0.136)
H_9	(0.550,0.500,0.250)	(0.550,0.500,0.250)	(0.550,0.500,0.250)
H_{10}	(0.550,0.500,0.250)	(0.598,0.200,0.134)	(0.489,0.612,0.211)

Moreover, to acquire the weighted spherical risk matrix, we must first calculate each risk parameter's weight vector. To obtain the optimistic and pessimistic risk scores of each risk parameter, the score function numbers of each hazard under the risk factors are calculated using Eq.(6), and shown in Table 8.

Table 8
The score function numbers

Hazard	P	C	E
H_1	0.803	0.878	0.654
H_2	0.803	0.878	0.654
H_3	0.833	0.654	0.878
H_4	0.797	0.878	0.878
H_5	0.806	0.856	0.654
H_6	0.806	0.706	0.654
H_7	0.808	0.833	0.663
H_8	0.808	0.791	0.674
H_9	0.808	0.808	0.808
H_{10}	0.808	0.808	0.808

Thus, the optimistic and pessimistic risk scores of each risk parameter are $K^+ = \left[(0.750,0.250,0.200),(0.850,0.150,0.100),(0.150,0.850,0.100)\right]$ and $K^- = \left[(0.660,0.361,0.200),(0.477,0.267,0.100),(0.267,0.477,0.100)\right]$; then it is applied to compute the distance between each risk parameter and the optimistic and pessimistic risk scores; the results are just as follows: $d_j^+ = \sum_{i=1}^{10} d\left|\tilde{y}_{ij} - k_j^+\right| = \left[2.687,5.671,4.195\right]$, $d_j^- = \sum_{i=1}^{10} d\left|\tilde{y}_{ij} - k_j^-\right| = \left[1.560,3.863,1.626\right]$.

The dispersion value of risk parameter P can be calculated as follows: $w_1' = \frac{d_1^+}{\left(d_1^+ + d_1^-\right)} = \frac{2.687}{2.687+1.560} = 0.633$, as well, $w_2' = 0.595$ and $w_3' = 0.721$. And then, after normalization processing, $w_1 = \frac{w_1'}{\sum_{j=1}^{3} w_j'} = 0.325$. In the same way, the dispersion value of risk parameters C and E are calculated, and the result is $w_2 = 0.305$, and $w_3 = 0.370$.

Finally, the weighted spherical risk matrix $R = \left[r_{ij}\right]_{10\times3}$ can be denoted as Table 9.

Table 9
The weighted spherical risk matrix

Hazard	P	C	E
H_1	(0.412,0.260,0.154)	(0.569,0.131,0.089)	(0.165,0.310,0.068)
H_2	(0.412,0.260,0.154)	(0.569,0.131,0.089)	(0.165,0.310,0.068)
H_3	(0.485,0.193,0.162)	(0.275,0.164,0.063)	(0.092,0.623,0.094)
H_4	(0.356,0.317,0.163)	(0.083,0.578,0.089)	(0.092,0.623,0.094)
H_5	(0.285,0.389,0.178)	(0.099,0.543,0.106)	(0.165,0.310,0.068)
H_6	(0.285,0.389,0.178)	(0.171,0.331,0.105)	(0.165,0.310,0.068)
H_7	(0.332,0.346,0.192)	(0.140,0.489,0.158)	(0.196,0.299,0.086)

Hazard	P	C	E
H_8	(0.332,0.346,0.192)	(0.183,0.418,0.158)	(0.258,0.266,0.094)
H_9	(0.332,0.346,0.192)	(0.323,0.337,0.187)	(0.353,0.364,0.201)
H_{10}	(0.332,0.346,0.192)	(0.323,0.337,0.187)	(0.353,0.364,0.201)

Based on this matrix, the distance measure is derived using Eqs.(19) and (20). Finally, the final risk ranking result is exhibited in Table 10.

Table 10
The final ranking result by the OWA operator

Hazard	RS_i	Ranking
H_1	0.0558	3
H_2	0.0558	3
H_3	0.2068	2
H_4	0.3935	1
H_5	-0.0048	5
H_6	-0.3043	9
H_7	-0.0405	8
H_8	-0.3120	10
H_9	-0.0339	6
H_{10}	-0.0339	6

The values of the final risk priority ranking of the ten hazards for the subsystem in subway door components, as shown in Table 10, it is determined by the values of RS_i, and H_4 has the highest risk level, while H_8 has the lowest risk level.

5. Conclusions

This article introduces a unique and comprehensive method to prioritize risks in the F-K model using the spherical fuzzy set. This method consists of three phases. The first step involves creating the matrix containing the information for assessing the risk associated with fuzzy numbers. Next, the experts' weight is incorporated to obtain the integrated risk assessment information matrix. Ultimately, the risk parameters' weight is computed, determining the risk priority ranking. This paper uses the subway operation risk analysis to showcase this method framework's practical application and significance. Moreover, the results show that this information integration method and the MABAC method can encourage relevant professionals to identify potential hazards and reasonably rank risks.

The benefits of utilizing this framework for the F-K model include: (i) incorporating the SFS-OWA operator to merge risk assessment information from experts, representing the importance of risk assessment information location. (ii) The F-K model integrates the SFS-MABAC approach to tackle the problem of ranking risk, considering the interplay between risk scores and parameters throughout the risk assessment procedure.

Its limitations include: (i) F-K's risk parameters are restricted and may not accurately depict risks in complex situations. (ii) Only one approach is used to determine the skills of individuals. Their personality characteristics may be disregarded, resulting in an incomplete assessment of the information they provide. We are concentrating on the following suggestions to mitigate these effects: (i) Integrating extra elements into the F-K model by examining practical implementation scenarios. (ii) Other fuzzy techniques, such as the Q-rung orthopair and Fermatean fuzzy sets, cannot effectively convey intricate and ambiguous information. (iii) This framework can potentially evaluate risks in various other domains.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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