Decision Science Letters 13 (2024) 545–564

Contents lists available at GrowingScience

Decision Science Letters

homepage: www.GrowingScience.com/dsl

Enhancing safety and risk management through an integrated spherical fuzzy approach for managing laboratory errors

Shayandokht Sadat Eftekharzadeh[a], Saeid Jafarzadeh Ghoushchi[a] and Farid Momayezi[a]*

[a]*Faculty of Industrial Engineering, Urmia University of Technology, Urmia, Iran*

C H R O N I C L E

Article history:
Received: December 1, 2023
Received in the revised format: April 27, 2024
Accepted: May 26, 2024
Available online: May 26, 2024

Keywords:
Laboratory errors
Risk management
Spherical fuzzy
FMEA
MOORA
COPRAS

A B S T R A C T

Hospital hazards and human errors pose a significant and complex problem, with rising incidents and irreversible consequences. Managing laboratory errors and risks is vital due to the presence of chemicals, electrical equipment, and the involvement of students, professors, and staff. The high value of laboratory equipment further underscores the need for robust risk management strategies. To address these challenges, researchers have explored the Failure Mode and Effects Analysis (FMEA) method for risk identification and assessment in healthcare settings. However, recognizing its limitations, this study aims to prioritize and evaluate laboratory errors using an integrated approach that combines the Best-Worst Method (BWM) and Complex Proportional Assessment with a Fuzzy Spherical Environment (CoCoSo-FSE). By applying the BWM, criteria such as severity, detectability, and occurrence probability are weighted to account for the nature of laboratory errors. The CoCoSo-FSE is then employed to evaluate and prioritize 18 identified laboratory errors, reducing uncertainty and enhancing decision-making. The fuzzy spherical set is used to address uncertainties by providing a flexible framework for decision-makers to define membership functions in specific spherical regions, enhancing the representation of knowledge and decision-making information. The proposed approach is compared with other decision-making methods, namely MOORA and COPRAS, demonstrating reliable ranking results. Sensitivity analysis confirms the stability of the approach's ranking when adjusting the flexibility parameter. This integrated approach offers a reliable and robust decision-making technique for managing laboratory errors, providing valuable insights to enhance laboratory safety and risk management for stakeholders, managers, and policymakers.

1. Introduction

Medical errors are a significant threat to patient safety and pose a major challenge for healthcare systems worldwide. In the United States, medical errors are estimated to be one of the leading causes of death, with some studies suggesting they may be the third most common reason for death (Makary & Daniel, 2016). Medical errors have a significant impact on patient safety and healthcare outcomes, with an estimated 250,000 deaths annually attributed to medical errors in the US (Makary & Daniel, 2016; Ghoushchi, 2019, 2021). While medical errors are not limited to surgical procedures or laboratory errors, they can occur in various healthcare settings and during diagnosis, medication administration, and other aspects of patient care. Efforts to reduce medical errors include enhancing communication, applying standardized protocols, and promoting a safety-conscious culture in healthcare institutions. Patients can also play an active part in their own care by asking questions, providing accurate information about their medical history, and reporting any concerns or adverse events. Similar trends have been observed in other countries, including Canada and England. In Canada, adverse events occurred in approximately 7.5% of hospital admissions, with 36% of these events deemed preventable (Baker et al., 2004). One of the most important errors in medical error is laboratory errors. Laboratory errors are a serious problem in healthcare. They can lead to misdiagnosis, inappropriate treatment, and even death. In fact, a study by the Institute of Medicine estimated that up to 10% of all hospital deaths in the United States are due to medical errors, and a significant proportion of these errors are laboratory

* Corresponding author.
E-mail address: farid.momayezi@uut.ac.ir (F. Momayezi)

doi: 10.5267/dsl.2024.5.006

related (Kohn et al., 2000). There are three main types of laboratory errors: pre-analytical, analytical, and post-analytical. Pre-analytical errors occur before the test is even performed, and they account for most of all laboratory errors. Analytical errors occur during the testing process, and post-analytical errors occur after the test has been performed (Bonini et al., 2002). The most common pre-analytical errors include incorrect patient identification, improper sample collection or handling, inappropriate storage or transportation of samples, and defective or outdated test kits. Analytical errors are less common than pre-analytical errors, but they can still have serious consequences. Some of the most common analytical errors are human error, equipment malfunction, reagent contamination, and calibration errors. Post-analytical errors are the least common type of laboratory error, but they can still be harmful. Some of the most common post-analytical errors are incorrect reporting of results, Failure to follow up on abnormal results, and Misinterpretation of results. Despite the wide range of research design variations and limited available data, most researchers agree that the pre- or post-analytical phases are where laboratory errors are most common, with the analytical section accounting for a small percentage. This highlights the necessity of using suitable technology and a more stringent approach for error detection and categorization in order to lower errors in laboratory medicine and blood transfusion. (Bonini et al., 2002).

The Institute of Medicine (IOM) found that errors in clinical diagnostic laboratories ranged from 0.3% to 9.3%, with a considerable percentage of these happening throughout the pre- and post-analytical stages of testing. While the frequency of errors in clinical diagnostic laboratories may be lower compared to other areas in a hospital context, the sheer volume of laboratory tests utilized in healthcare indicates that this tiny rate could still reflect a large number of errors (Kalra, 2004). Clinical laboratories are crucial in-patient care, but many diagnostic errors often occur. Although there have been improvements in analytical performance, error rates remain high, especially in pre- and post-analytical phases. Recognizing the importance of all testing cycle phases, collaboration among laboratory professionals and care providers is needed to enhance patient safety (Plebani, 2014). The occurrence of laboratory errors poses a risk of adverse events and inadequate care, which can range from 2.7% to 12%. However, in a higher proportion of cases (24.4% to 30%), a laboratory error leads to issues in patient care, specifically unnecessary repetition of laboratory tests and additional inappropriate investigations. Our group's research publications have highlighted instances where errors have led to improper admissions to critical care units, inappropriate transfusions, and adjustments in heparin and digoxin treatments ((Astion, 2003), (ISO/TS, 2008), (Carraro, and Plebani (2007)), and (Carro et al., 2012)). Pradhan et al., (2022) assessed the performance of the extra-analytical phase in a laboratory by calculating preanalytical and postanalytical quality indicators and sigma values. The findings contribute to improving the quality of laboratory medicine. To reduce medical errors, especially laboratory errors, healthcare organizations can implement evidence-based guidelines and protocols, promote a culture of safety, and provide proper training to healthcare professionals. Risk management strategies can also help reduce the incidence of medical errors. Currently, evaluating and analyzing errors is considered an ethical, professional, and legal responsibility. However, there can be discrepancies between expected communication functions and what occurs in practice. Therefore, conducting comprehensive analysis of the risks associated with medical and laboratory errors is important.

Risk can be broadly defined as the possibility of reality deviating from what was expected, which can lead to medical errors resulting from deviations from expected practices (Vincent, 2016). From a risk management perspective, risk is defined as the possibility of an unfavorable deviation from what was expected. Different groups may have varying views on risk management. Some view it as a complementary task of management, while others view it as a new term for preventing damage and reducing its impact. A third group believes that risk management should only deal with preventable and compensable risks within the scope of managers' duties (Ran, 2018). Overall, risk management involves measuring and evaluating risk, and developing strategies to manage risks or errors. Risk management strategies encompass the following: shifting risk to alternative sectors, evading risk altogether, mitigating the adverse consequences of risk, and embracing a portion or entirety of the consequences associated with a specific risk. (Bromiley et al., 2015). One of the conventional methods of risk management is the FMEA method (Bagheri et al., 2016). FMEA, a collaborative and proactive approach, is a systematic tool utilized to proactively identify errors, their underlying causes, and the potential impacts of those errors, with an emphasis on prevention rather than reaction. Control and preventive measures are used in a system to eliminate or reduce the occurrence of potential problems, unlike reactive methods (Yousefi et al., 2018). In the implementation of FMEA, by predicting potential problems and calculating their riskiness, measures are defined and implemented to eliminate or reduce their occurrence. This preventive strategy is a reaction to potential future events. Applying corrective measures in the early phases of the process saves money and time when compared to applying corrective measures after errors occur (Yousefi et al., 2018). Therefore, with the help of this method, risks can be rooted and prevented from occurring so that the final service can be performed with high quality. FMEA is an important method for identifying and preventing risks from occurring in healthcare systems (Bromiley et al., 2015), and it is critical to understand its potential benefits for improving patient safety. Through control and preventive measures, FMEA serves to define and implement measures aimed at eliminating or minimizing the occurrence of potential issues, ultimately leading to the delivery of a final service of exceptional quality. It is crucial to acknowledge that the identification, likelihood, and consequences of these failures are predicated on a series of anticipations since these failures have not yet occurred. Therefore, FMEA is an essential tool for healthcare professionals to address medical errors and improve patient safety. The use of FMEA method for identifying and ranking medical errors is associated with several limitations. One of the major drawbacks is the lack of consideration for the weight of criteria and stochasticity, which leads to results that may not reflect reality (Jahangoshai Rezaee et al., 2017; Yousefi et al., 2018). Additionally, the traditional Risk Priority Number (RPN) index used in FMEA focuses on the risk

condition with the highest RPN, potentially ignoring other risks that may have a lower RPN but a higher likelihood of deterioration (Jahangoshai Rezaee et al., 2017; Liu et al., 2013). The classic RPN index has additional flaws, including a lack of complete ranking and an assumption of equal relevance for RPN determinants. According to the collaborative structure of the FMEA method and the numerous elements that might influence the RPN score, it is frequently difficult to definitely establish the most severe risks (Ma et al., 2019). To strengthen the reliability of the results and account for the perspectives of different team members, it is required to prioritize risks depending on the uncertainty of the RPN score's criteria (Jafarzadeh et al., 2019). Furthermore, to evaluate this priority, it may be important to consider the principle of reliability alongside the stochastic of the RPN-determining criteria (Ma et al., 2019). One of the restrictions of the classic RPN score is that it does not provide a complete ranking of the risks, and it assumes that all determining factors are equally important (Liu et al., 2013). Furthermore, the traditional score may not accurately reflect the relative priorities of different risks. To overcome these shortcomings, a new index is needed to effectively prioritize risks (Ma et al., 2019). Given the limitations of the traditional RPN index, a new approach is needed to prioritize medical errors. This research proposed a new approach that involves the use of the CoCoSo method, which considers uncertainty and allows for more freedom in expert opinions. In this method, potential errors are detected through the application of FMEA while risk elements are assessed and measured. The desired criteria are subsequently assigned weights using the BWM. Finally, the identified errors are prioritized using the CoCoSo method, which offers a more effective approach compared to the traditional RPN method. The laboratory and testing procedures are potential sources of medical errors that can lead to severe complications and waste of resources. The pre-test stage is identified as the most error-prone stage, and attention to this stage is needed to detect and eliminate potential errors. The suggested methodology is applied to investigate and identify potential medical errors caused by laboratory errors and implement corrective measures.

In this study, the proposed approach provides a more accurate and effective method for prioritizing medical errors. It considers uncertainty and expert opinions while considering the weight of criteria. The approach is demonstrated through its application to laboratory and testing procedures. The proposed approach can help healthcare organizations improve patient care quality and minimize the occurrence of medical errors.

2. Methodology

The patient's health relies on the accurate reporting, analysis, and prevention of medical errors, which can sometimes lead to severe complications. In addition to the many risks that threaten the patient's health, these errors also result in the waste of significant financial resources. One of the areas where the probability of medical errors is relatively high is during laboratory and testing procedures. The process of conducting laboratory tests comprises three distinct stages: pre-test, during the test, and post-test, all of which carry the potential for errors. Given the critical role of laboratory results in patient health, it is imperative to diligently address error sources throughout each of these stages. Extensive studies have consistently highlighted the pre-test stage as the most significant source of error in laboratory testing. Focusing on this stage to identify and eliminate errors can result in reliable laboratory results, which can ultimately enhance patient health. In this section, we present an approach for evaluating laboratory risks utilizing the FMEA, BWM, and CoCoSo methods within a spherical fuzzy framework. The methodology comprises three steps.

1. The initial values of the three criteria factors are established.
2. The spherical fuzzy BWM approach is applied to assess the three criteria.
3. The risks of known laboratories are prioritized based on the significance of the differences among the factors using the spherical fuzzy CoCoSo method.

The three criteria factors serve as crucial considerations in evaluating laboratory risks. The spherical fuzzy BWM method, unlike the conventional BWM approach, incorporates the reliability of each factor in addition to considering fuzzy values. By employing spherical fuzzy sets, the CoCoSo method effectively handles fuzzy problems and better captures uncertainty in real-world scenarios compared to classical and intuitive fuzzy sets.

This strategy is implemented by creating a decision matrix with linguistic parameters. Table 1 serves the purpose of transforming linguistic values into spherical fuzzy numbers. The CoCoSo method is then used in the spherical fuzzy environment. In this procedure, after calculating the decision matrix, which consists of linguistic parameters, the values are then transformed into spherical fuzzy numbers utilizing Table 1. Then, the CoCoSo technique is implemented within the context of a spherical fuzzy environment. Gündoğdu and Kahraman (2019) introduced spherical fuzzy sets as an innovative extension to Pythagorean fuzzy sets, intuitionistic fuzzy sets, and neutrosophic sets. These sets provide experts with the capability to define a membership function within a spherical region, encompassing and expanding upon the characteristics of other components found in fuzzy sets. By employing the flexibility parameter, spherical fuzzy sets enable an independent assignment of membership function parameters over a broader domain, allowing decision makers to express their awareness comprehensively and accurately describe the range of decision-making information. The degrees of membership function in spherical fuzzy sets effectively convey decision makers' awareness and precisely represent the extent of decision-making information. In the context of spherical fuzzy sets, the squared degrees of membership, non-membership, and uncertainty

can be varied between 0 and 1, enabling the independent definition of each parameter within this range (Jafarzadeh et al., 2022). This section introduces the fundamental principles of spherical fuzzy sets and underscores their effectiveness in capturing decision-making awareness.

Definition 1: A fuzzy set H defined in reference X is in the form of Eq. (1).

$$H = \left[\left(x \cdot \left(\mu_H (x) \cdot V_H (x) \cdot \pi_H (x) \right) \right) \middle| x \in X \right] \tag{1}$$

In this relation, $\mu_H : X \to [0,1]. V_H : X \to [0,1]$. $\pi_H : X \to [0,1]$ shows the degrees of membership, non-membership, and uncertainty for each xϵX in H, respectively.

$$0 \le \left(\mu_z (x) \right)^2 + \left(V_z (x) \right)^2 + \left(\pi_z (x) \right)^2 \le 1 \tag{2}$$

Definition 2: Suppose $H_1 = [\mu_{H1} \cdot V_{H1} \cdot \pi_{H1}]$ and $H_2 = [\mu_{H2} \cdot V_{H2} \cdot \pi_{H2}]$ represent two spherical fuzzy numbers, with K being a fixed number greater than zero, the mathematical operations involving these two spherical fuzzy numbers can be carried out using the following equations.

$$H_1 \oplus H_2 = \left[\sqrt{\mu_{H1}^2 + \mu_{H2}^2 - \mu_{H1}^2 \mu_{H2}^2} \cdot V_{H1} V_{H2} \cdot \sqrt{\left(1 - \mu_{H2}^2\right) \pi_{H1} + \left(1 - \mu_{H1}^2\right) \pi_{H2} - \pi_{H1} \pi_{H2}} \right] \tag{3}$$

$$H_1 \otimes H_2 = \left[\mu_{H1} \mu_{H2} \cdot \sqrt{V_{H1}^2 + V_{H2}^2 - V_{H1}^2 V_{H2}^2} \cdot \sqrt{\left(1 - V_{H2}^2\right) \pi_{H1}^2 + (1 - V_{H1}^2) \pi_{H1}^2 - \pi_{H1}^2 \pi_{H1}^2} \right] \tag{4}$$

$$kH = \left[\sqrt{1 - \left(1 - \mu_H^2\right)^k} \cdot V_H^2 \cdot \sqrt{(1 - \mu_H^2)^k - (1 - \mu_H^2 - \pi_H^2)^k} \right] \tag{5}$$

$$H^k = \mu_H^k \cdot \sqrt{1 - (1 - V_H^2)^k} \cdot \sqrt{(1 - V_H^2)^k - (1 - V_H^2 - \pi_H^2)^k} \tag{6}$$

Definition 3: Let $H_1 = [\mu_{H1} \cdot V_{H1} \cdot \pi_{H1}]$ and $H_2 = [\mu_{H2} \cdot V_{H2} \cdot \pi_{H2}]$ be two spherical fuzzy numbers. The following rules, satisfying the condition k, k_1, k_2 > 0, are in accordance with Eqs (7-12):

$$H_1 \oplus H_2 = H_2 \oplus H_1 \tag{7}$$

$$H_1 \otimes H_2 = H_2 \otimes H_1 \tag{8}$$

$$k \left(H_1 \oplus H_2 \right) = kH_1 \oplus kH_2 \tag{9}$$

$$k_1 H_1 + k_2 H_1 = (k_1 + k_2) H_1 \tag{10}$$

$$(H_1 \otimes H_2)^k = H_1^k \otimes H_2^k \tag{11}$$

$$H_1^{k1} \otimes H_1^{k2} = H_1^{k1+k2} \tag{12}$$

Definition 4: Let H = [$\mu_H . v_H . \pi_H$] denote a spherical fuzzy number. The performance score and accuracy score of *H* are calculated as follows:

$$Score(H) = (\mu_H - \pi_H)^2 - (V_H - \pi_H)^2 \tag{13}$$

$$Accuracy\ (H) = \mu_H^2 + V_H^2 + \pi_{|H}^2 \tag{14}$$

Note that: H1 < H2 if and only if:

$$I.\ score(H_1) < score(H_2)\ or \tag{15}$$
$$II.\ score(H_1) = score(H_2)\ and\ Accuracy\ (H_1) < Accuracy(H_2)$$

Sometimes, the values obtained through the performance score and accuracy score may not be suitable, and it is possible to obtain a negative or zero quantity. For instance, zero is obtained when the value function of a spherical fuzzy number (0.5, 0.5, 0.5) is calculated. Moreover, there exist situations in which the execution accuracy may be identical and the score function of several spherical fuzzy numbers is equally obtained. As a result, for spherical numbers, a prioritizing function (PF) is utilized, and it is defined by Eq. (16):

$$\mathcal{PF}(z) = \mu_z * (1 - V_z) * (1 - \pi_z) \tag{16}$$

Definition 5: The single-valued spherical arithmetic mean weight (SWAM) is calculated according to the weight vector $w = (w_1, w_2, \ldots, w_n)$, where $w_i \in [0,1]$ and $\sum_{i=1}^{n} w_i = 1$. The SWAM is computed using Eq. (17), as shown below.

$$SWAM_W(H_1 \ldots H_n) = w_1 H_1 + w_2 H_2 + \ldots + w_n H_n = \left\{ \left[1 - \Pi_{i=1}^{n} (1 - \mu_H^2)^{wi} \right]^{\frac{1}{2}} \cdot \Pi_{i=1}^{n} V_H^{wi} \cdot \left[\Pi_{i=1}^{n} (1 - \mu_H^2 - \pi_H^2)^{wi} \right]^{\frac{1}{2}} \right\} \tag{17}$$

Definition 6: The single-valued spherical geometric mean weight (SWGM) is calculated based on the weight vector $w = (w_1, w_2, \ldots, w_n)$, where $w_i \in [0,1]$ and $\sum_{i=1}^{n} w_i = 1$. The SWGM is calculated using Eq. (18) as follows:

$$SWGM_W(H_1 \ldots H_n) = H_1^{w_1} + H_2^{w_2} + \ldots + H_n^{w_n} = \left\{ \Pi_{i=1}^{n} \mu_H^{wi} \cdot \left[1 - \Pi_{i=1}^{n} (1 - V_H^2)^{wi} \right]^{\frac{1}{2}} \cdot \left[\Pi_{i=1}^{n} (1 - V_H^2)^{wi} - \Pi_{i=1}^{n} (1 - V_H^2 - \pi_H^2)^{wi} \right]^{\frac{1}{2}} \right\} \tag{18}$$

2.1. Spherical Best Worst Method (SF-BWM)

The BWM technique, introduced by (Rezaei, 2015), is a recent and efficient multi-criteria decision-making method used for weighting decision factors and criteria. In traditional multi-criteria approaches like hierarchical analysis, experts rank decision indicators and criteria based on pairwise comparisons, from most preferred to least important. However, BWM takes a different approach. It involves determining the best and worst indicators and criteria, and then conducting pairwise comparisons between these two extremes and other indicators. This transforms the problem into a linear programming challenge, aiming to minimize the absolute differences between indicator weights. Furthermore, BWM incorporates a formula to calculate the inconsistency rate, ensuring the validity of the comparisons. Compared to other multi-indicator decision-making methods, BWM offers distinct advantages. It requires fewer comparative data, providing more reliable results and stable comparison. Since its introduction (Jafarzadeh et al., 2022), BWM has gained attention from researchers and has been applied in various fields. However, qualitative judgments made by decision makers in BWM, such as pairwise comparisons on a scale of 1-9, often suffer from ambiguity and flaws in real-world scenarios. To address this challenge, recent studies have extended BWM to fuzzy environments. Research on fuzzy BWM indicates that fuzzy set theory is better suited for handling human judgments compared to classical methods, offering enhanced efficiency (Haseli et al., 2021). Moreover, studies have demonstrated that fuzzy BWM exhibits significantly lower inconsistency levels compared to classical BWM (Jafarzadeh et al., 2019). The procedure of spherical fuzzy BWM can be outlined as follows:

Step 1: The panel of specialists has identified a collection of criteria. During this step, the group of experts identifies and assesses a list of criteria that influence the evaluation of options. These criteria should be pertinent, quantifiable, and significant in the decision-making process.

Step 2: Determination of the most favorable (highly desirable or crucial) and least favorable (less significant) criteria among the other criteria. In this step, the team identifies the most favorable and least favorable criteria from the set of criteria. Expert opinions or the Delphi method can be employed to facilitate this determination.

Step 3: Evaluation of the superiority of the top criterion compared to the remaining criteria, and the other criteria compared to the least favorable criterion. During this phase, the superiority of the leading criterion over the remaining criteria, as well as the superiority of the criteria over the least favorable criterion, are determined utilizing the spherical fuzzy linguistic variables outlined in the provided table. The table showcases nine spherical fuzzy linguistic variables that can be employed to express the preference of one criterion over another.

Table 1
Spherical fuzzy linguistic measures of significance used for pairwise comparisons

Linguistic variables	μ	V	π	CI
Absolutely More Importance (AMI)	0.90	0.10	0.10	8
Very High Importance (VHI)	0.80	0.20	0.20	6
High Importance (HI)	0.70	0.30	0.30	4
Slightly More Importance (SMI)	0.60	0.40	0.40	2
Equally Importance (EI)	0.50	0.50	0.50	0
Slightly Low Importance (SLI)	0.40	0.60	0.40	0
low Importance (LI)	0.30	0.70	0.30	0
Very Low Importance (VLI)	0.20	0.80	0.20	0
Absolutely Low Importance (ALI)	0.10	0.90	0.10	0

Step 4: Determining definitive values. At this stage, the definitive values of all expressed preferences are calculated using Eq. (17). The definitive value of a preference is a real number that represents the degree of preference of one criterion over another.

Step 5: Determining the suitable response of scales and compatibility index. Eq. (19) represents a nonlinear programming model using the components acquired from the vectors(A_B) and (A_W) .

$$\min \varepsilon \tag{19}$$

$$s.t.$$

$$\left|\frac{W_B}{W_j} - a_{Bj}\right| \le \varepsilon$$

$$\left|\frac{W_j}{W_w} - a_{jw}\right| \le \varepsilon$$

$$\sum_{j=1}^{n} w_j = 1$$

$$W_j \ge 0 \ \ for\ all\ j$$

Eq. (20) and Eq. (21) are utilized for calculating the compatibility index of spherical fuzzy numbers as outlined in Table 1.

$$CI = \sqrt{\left|100 * ((\mu - \pi)^2 - (v - \pi)^2)\right|} \tag{20}$$

$$\frac{1}{CI} = \frac{1}{\sqrt{\left|100 * ((\mu - \pi)^2 - (v - \pi)^2)\right|}} \tag{21}$$

Spherical fuzzy linguistic variables that indicate a more positive preference $(AMI, VHI, HI, SMI, and\ EI)$ are represented by Eq. (20), whereas those that imply a more negative preference $(EI, SLI, LI, VLI, and\ ALI)$ are represented by Eq. (21). The following table shows the correspondence between the spherical fuzzy linguistic variables and the equations that are used to represent them:

The compatibility rate (CR) is determined by utilizing the compatibility index provided in Table 1. Eq. (22) is employed to calculate the CR value. It is considered acceptable if the CR is less than 0.1.

$$CR = \frac{\varepsilon}{CI} \tag{22}$$

2.2. Spherical Fuzzy Cocoso method

Yazdani et al. (2019) created the CoCoSo procedure, a unified model that incorporates the weighted multiplication model (WPM) and the common weighted summation approach (SAW). This approach, which is a more recent development in the field of multi-criteria decision-making, offers a practical way to order or choose among several possibilities. CoCoSo, which stands for combined compromise solution, seeks to address the criticism often directed at decision-making approaches, namely the discrepancy between the best options and ranking outcomes for the same issue. By employing the CoCoSo method, decision-making becomes more reliable and stable.

In this method, options are prioritized using three distinct functions. A linear-exponential function is used to investigate the combination of triple relations, thereby identifying the ultimate precedence of possibilities. CoCoSo has proven to be an effective approach in various research fields. For instance, Zolfani et al. (2019) proposed a hybrid MCDM model based on BWM and the fuzzy CoCoSo method for sustainable supplier selection problems. In another study, a hierarchical fuzzy spherical hybrid process, combining AHP and CoCoSo, was employed to determine the distribution location of perishable agricultural products (Kieu et al., 2021). Furthermore, CoCoSo has been effectively used to solve uncertain decision issues in fuzzy contexts. Cui et al. (2021) suggested a new technique for combining SWARA and Pythagorean fuzzy CoCoSo in order to grade production sector organizations. In this research, we extend the classical CoCoSo method to spherical fuzzy CoCoSo, which provides more reliable results when dealing with ambiguity and uncertainty in real-world situations. After identifying the relevant options and criteria, the proposed spherical fuzzy CoCoSo follows the steps outlined below:

Step 1: Formation of the Decision Matrix

Creating the decision matrix is the initial stage in multi-criteria decision-making techniques. The matrix is constructed based on the following relationship. Let $D=\{d_1,d_2,...,d_m\}$ denote a set of options, and $C=\{c_1,c_2,...,c_n\}$ represent the considered criteria. The weights are represented $w=\left(w_1,w_2,...,w_n\right)$, where each weight w_j satisfies the condition $w_i\in[0,1]$. In this relationship, x represents the evaluation of option m based on criterion n by expert k. It is captured in the matrix $S=\left(S_{ij}\right)_{m*n}$, which is established using verbal expressions.

$$S=\left(C_j\left(d_i\right)\right)_{m*n}=\begin{bmatrix} S_{11} & \cdots & S_{1n} \\ \vdots & & \vdots \\ S_{m1} & \cdots & S_{mn} \end{bmatrix} \tag{23}$$

Step 2: Conversion of linguistic variables into Spherical Fuzzy Numbers

During this step, the linguistic variables provided by the experts in the first step are transformed into spherical fuzzy numbers using Table 3-1. Subsequently, based on these spherical fuzzy integers, the decision matrix is constructed.

$$S=\left(C_j\left(d_i\right)\right)_{m*n}=\begin{bmatrix} \{\mu_{11}\cdot v_{11}\cdot\pi_{11}\} & \cdots & \{\mu_{1n}\cdot v_{1n}\cdot\pi_{1n}\} \\ \vdots & & \vdots \\ \{\mu_{m1}\cdot v_{m1}\cdot\pi_{m1}\} & \cdots & \{\mu_{mn}\cdot v_{mn}\cdot\pi_{mn}\} \end{bmatrix} \tag{24}$$

Step 3: Formation of the Accumulated Matrix

During this step, the opinions of the experts are aggregated while accounting for their individual weights. Eqs. (17-18) show how the aggregated matrix is created using the SWAM or SWGM operations.

Step 4: Calculation of Definitive Values

In this step, Eq. (16) is used to calculate the definite values of each spherical fuzzy number. This calculation allows us to derive the definitive values for all elements, resulting in the formation of the matrix $S^*=\left(S^*_{ij}\right)_{m*n}$.

Step 5: Normalization of the Decision Matrix

Normalization is an essential step in nearly all multicriteria decision-making techniques. The decision matrix is normalized in this step using the relationships listed below. Eq. (25) is applied to positive criteria, while Eq. (26) is used for negative criteria. In these equations, $s^*{}_j^+$ denotes the maximum value of each column, and $s^*{}_j^-$ represents the minimum value.

$$\mathcal{S} \diagdown S_{ij} = \begin{cases} \dfrac{s^*{}_{ij} - s^*{}_j}{r_j^+ - r_j^-}, if \quad j \epsilon B. \end{cases} \tag{25}$$

$$\mathcal{S} \diagdown S_{ij} = \begin{cases} \dfrac{s_j^{*+} - s^*{}_{ij}}{s^{*+} + s_j^{*}-} \cdot \quad if \quad j \epsilon C. \end{cases} \tag{26}$$

$$where \quad s^*\bar{j} = \min_i s_{ij} \quad and \quad s^{*+}_j = \max_i s^*{}_{ij} \tag{27}$$

Step 6: Calculation of Weighted Sum and Weighted Multiplication Values

The weighted multiplication (P) and weighted sum (S) values for each choice are determined in this stage using the following relationships. W, which is an input to the COCOSO method, is the weight of the criteria in the given equation. The Simple Weighted Sum (SAW) approach yields the values of S_i, whereas the Weighted Aggregated Sum Product Assessment (WASPAS) method yields the values of P_i.

$$P_i = \sum_{j=1}^{n} \left(S_{ij}\right)^{wj} \tag{28}$$

$$S_i = \sum_{j=1}^{n} w_j * S_{ij} \tag{29}$$

Step 7: Determining the Final Evaluation Score of Options Based on Three Strategies

In this step, the points for each option are obtained using three strategies, as described by the following three relationships. The arithmetic means of the scores from the Weighted Sum Model (WSM) and the Weighted Product Model (WPM) is determined by the first relationship. The relative scores of WSM and WPM in reference to the optimal option are ascertained by the second relationship. An accommodation between the WSM and WPM models can be seen in the third relationship. The decision maker determines the parameter λ in this relationship, and it provides a great deal of flexibility, especially when set to 0.5.

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m}\left(P_i + S_i\right)} \tag{30}$$

$$k_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i} \tag{31}$$

$$k_{ic} = \frac{\lambda S_i + (1-\lambda) P_i}{\lambda \max_i S_i + (1-\lambda) \max_i P_i} \cdot 0 \le \boldsymbol{\lambda} \le \mathbf{1} \tag{32}$$

Step 8: Determining the Final Score and Ranking of Options

The following relationship is used to compute the ultimate score in this stage. The geometric mean and the arithmetic mean of the three techniques from the previous stage are added together in this equation. The supremacy of that particular choice is indicated if its k_i score is higher than that of the other options. The options may be ranked in accordance with the final scores that were determined.

$$k_i = \sqrt[3]{k_{ia} k_{ib} k_{ic}} + \frac{k_{ia} + k_{ib} + k_{ic}}{3} \tag{33}$$

3. Proposed approach

This section introduces the integrated BWM-CoCoSo approach in the realm of spherical fuzzy for laboratory risk assessment and ranking, employing precise measurement of spherical fuzzy uncertainty. The proposed approach consists of three stages. In the initial stage, risks are identified, and the factors influencing the Risk Priority Number (RPN) are quantified using the FMEA method. The FMEA team assigns values to severity factors, probability of occurrence, and detection for each identified risk based on linguistic variables, as outlined in Table 1. The criteria obtained from experts are

initially measured using the Spherical Fuzzy Best-Worst Method (SFBWM). In this method, experts determine the importance of criteria, categorizing the remaining criteria as best or worst using Table 2. A mathematical linear model is then formulated and solved to obtain the criteria weights.

Moving on to the second stage, the initial decision matrix is constructed based on experts' opinions utilizing spherical fuzzy linguistic variables. These values are transformed into spherical fuzzy numbers using Table 2. Laboratory risks are prioritized using the CoCoSo method. Unlike conventional methods like BWM and CoCoSo, SFBWM and SFCoCoSo incorporate expert opinions expressed through spherical fuzzy sets. These sets encompass the degree of membership, degree of non-membership, and degree of uncertainty, which are independently determined. This approach enables experts to express their opinions without modification or distortion. Furthermore, it offers experts greater flexibility in their judgments and reduces decision uncertainty. Fig. 1 illustrates the implementation process of the proposed approach.

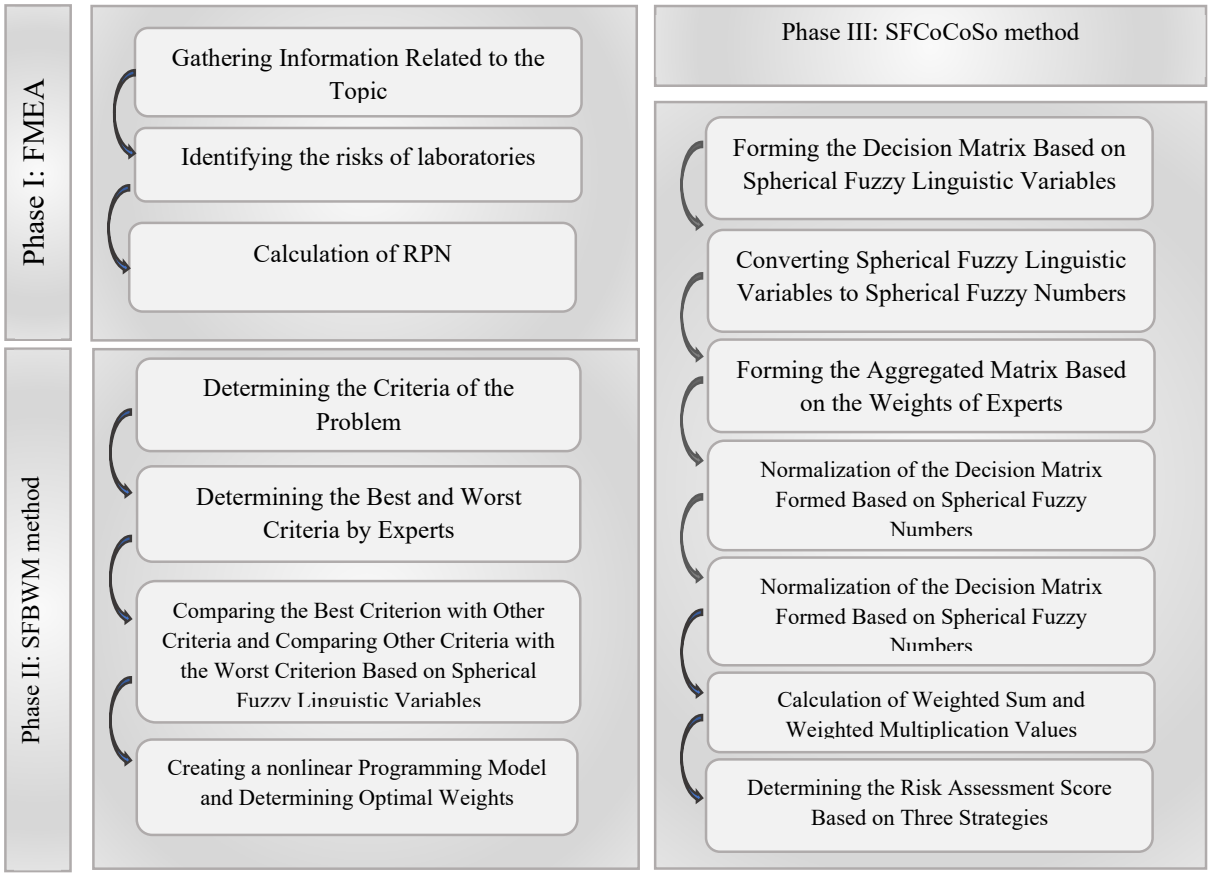

Fig. 1. The Implementation Process of the Proposed Approach

The research's statistical population consists of considerations for identifying and reducing misdiagnosis in hospital laboratories. The informant community comprises laboratory and university experts. To gather information, the opinions of experts in the field of reducing misdiagnosis in hospital laboratories were utilized. Consequently, three categories of people are considered to answer related questions. These categories are as follows:

1. University professors: This group includes individuals who possess both theoretical and practical familiarity with misdiagnosis in hospital laboratories.
2. Managers, supervisors, and experts in the field of therapy.
3. Consultants, lecturers, and experts in the field of medical services.

Table 2 presents the identified risks, their explanations, as well as their causes and effects.

Table 2
Identified Risks

The Main Category of Risks	Symbol of Risks	Risks	Causes	Affection
Risks associated with pathology specimens that have been appropriately labeled and requested by the surgery department	FM1	The surgical department mislabels both the pathology specimen and the request	The surgical team failed to label the specimen and complete the request form in the operating room.	1. The results will be associated with the wrong patient. 2. The results are sent for the wrong patient. 3. Incorrect results are reported
	FM2	The surgical department may label the specimen correctly, but the corresponding request form may have an incorrect label, which may lead to misidentification of the specimen	Both the specimen and the request form have not been labeled/completed in the surgical department.	Results may be sent to the wrong patient
	FM3	The surgical department may mislabel the specimen and/or the corresponding request form.	The surgical department fails to label the specimen and/or the corresponding request form and does not send it to the laboratory for analysis	Correctly assigning the specimen to the patient may not be possible
	FM4	The surgical staff is unable to label either the specimen or the request form	The specimen and the request form have not been labeled/completed in the surgical department	Incorrect results may be reported.
Sample pathology personnel risks, request, and affiliation files	FM5	The specimen is not properly secured in the protective packaging.	The packaging may be unavailable due to distractions or rush.	Delays in results due to breakage
	FM6	The specimen is mistakenly attributed to the wrong patient.	Laboratory personnel do not verify patient identifiers during the accessioning process.	The file is assigned to the wrong patient.
Risks associated with additional labels generated by the LIS for the sample and application request	FM7	An incorrect accession label is attached to the specimen, and pathology staff requests it for analysis.	Before attaching the accession label to the specimen and request form, pathology personnel do not verify two identifiers.	Incorrect results are reported to the patient.
The risks associated with mislabeling tissue cassettes with the case accession number	FM8	An incorrect accession number is printed on the label tape	Pathology staff do not confirm the accession number printed on the cassette label tape against the specimen and the requested access number.	The results are incorrectly reported for the patient.
Risks of handling specimens, cassettes, and tissue cutting for pathologist description	FM9	The specimen, request, and label tape do not match correctly.	Pathology staff do not verify all three components for matching names and/or accession numbers.	The results are reported incorrectly for the patient.
Pathologist Tissue Risks	FM10	The pathologist enters an incorrect name and/or accession number during the registration process.	1. The pathologist does not read the name and/or attachment correctly. 2. The pathologist presents the patient specimen with disorganized request forms.	The results are reported incorrectly for the patient.
Pathologist risks in tissue sections	FM11	The tissue is placed on an incorrect cassette with an inaccurate attachment number.	The pathologist cannot confirm the accession number on the specimen and tissue cassette to ensure their consistency.	The results are reported incorrectly for the patient.
	FM12	The access number is either unreadable or removed by solvents.	1. There is imprecise writing on the cassette label tape. 2. The wrong marker is used to write on the cassette label tape.	There is uncertainty about identifying the tissue.
Risks of tissue processor device	FM13	The tissue cassettes open, and the contents of the tissue spill into the container	1. The cassette surface for reuse is old. 2. The wrong cover is used for the type of cassette. 3. The tissue cassette tape is not properly closed.	The tissue samples are mixed together.
Risks of tissue sectioning from embedded paraffin blocks by a technician	FM14	The tissue is transferred to slides with accession numbers that are incorrect.	1. The technician is unable to verify the accession number on the tissue cassette label tape with the number written on the slide. 2. The technician labels multiple cases in advance and mixes the slides together.	The results are reported incorrectly for the patient.
	FM15	An incorrect accession number is written on the slide.	The technician fails to verify the accession number on the created slide.	The results are reported incorrectly for the patient.
Risks of placing labeled slides in slide trays	FM16	The incorrect requests match with the slide trays.	The technician's failure to perform proper verification resulted in sending the incorrect requests with the slide trays to the pathologist.	The results are reported incorrectly for the patient.
Risks of microscopic examination and diagnosis	FM17	The pathologist reads the slides in the order of the slide tray but identifies some tissues with incorrect names and/or accession numbers.	The pathologist dictates the wrong name and/or accession number.	The results are reported incorrectly for the patient.
Risks of dictation transcription	FM18	Incorrect transcription and diagnosis are recorded for the patient.	The staff is unable to read the patient's name and/or number accurately.	The results are reported incorrectly for the patient.

3.3. The Results Obtained from Prioritizing Research Risks

This section presents the outcomes of the proposed approach in evaluating laboratory risks based on the chosen criteria. The SFBWM method is employed to determine the most important and least important criteria, as specified in the proposed approach, based on expert evaluations. According to the provided explanations, the experts have identified intensity (C1) as the best criterion, while the likelihood of occurrence (C2) is regarded as the worst criterion. Tables 3 display the pairwise comparisons of the best criterion against the other criteria, as well as the comparisons of the other criteria against the worst criterion, utilizing fuzzy linguistic variables.

Table 3
Pairwise Comparison of the Best Criterion and Worst Criterion against Other Criteria Based on Spherical Fuzzy Linguistic Variables by Experts

No. of Expert	Criteria Best criterion	Severity (C_1)	Occurrence (C_2)	Detection (C_3)	Criteria Worst criterion	Severity (C_1)	Occurrence (C_2)	Detection (C_3)
Exp 1	Severity (C_1)	EI	SMI	HI	Occurrence (C_2)	SMI	EI	EI
Exp2	Severity (C_1)	EI	HI	EI	Occurrence (C_2)	EI	EI	HI
Exp3	Severity (C_1)	EI	HI	EI	Occurrence (C_2)	HI	EI	SMI

The spherical fuzzy vectors representing the best criterion to other criteria and other criteria to the worst criterion, based on Tables 3, are shown as follows:

$$\left(\mathcal{A}_{\mathbb{B}}\right)^{P}=((0.6,0.4,0.4),(0.7,0.3,0.3)) \quad \text{Expert I}$$

$$\left(\mathcal{A}_{\mathbb{W}}\right)^{P}=((0.6,0.4,0.4),(0.5,0.5,0.5))$$

$$\left(\mathcal{A}_{\mathbb{B}}\right)^{P}=((0.7,0.3,0.3),(0.5,0.5,0.5)) \quad \text{Expert II}$$

$$\left(\mathcal{A}_{\mathbb{W}}\right)^{P}=((0.5,0.5,0.5),(0.7,0.3,0.3))$$

$$\left(\mathcal{A}_{\mathbb{B}}\right)^{P}=((0.5,0.5,0.5),(0.6,0.4,0.4)) \quad \text{Expert III}$$

$$\left(\mathcal{A}_{\mathbb{W}}\right)^{P}=((0.7,0.3,0.3),(0.6,0.4,0.4))$$

Following that, the transformation of the spherical fuzzy linguistic variables expressed by the experts, employing Table 1, involves converting them into spherical fuzzy numbers. This transformation allows for a more precise representation and analysis of the expert opinions. Subsequently, the crisp values of the spherical fuzzy numbers are determined using the corresponding equations, enabling a clear and quantifiable understanding of the data. To further refine the decision-making process, a nonlinear programming model is formulated. This model incorporates various constraints and objectives to optimize the criteria weights and enhance the accuracy of the assessment. By solving this nonlinear model, sophisticated computational algorithms and techniques are employed to calculate the final weights of the criteria. These final weights, presented in Table 4, provide valuable insights into the relative importance and contribution of each criterion in the laboratory risk assessment. The weights serve as a quantitative measure that decision-makers can utilize to prioritize and allocate resources effectively. This information enables informed decision-making, as it highlights the criteria that have the most significant influence on the overall risk evaluation.

Table 4
Final Weights of Criteria

Weights	Criteria
0.49	Severity (C_1)
0.25	Occurrence (C_2)
0.25	Detection (C_3)

Next, the SF-CoCoSo method is utilized to rank the risks. Following the first step of this approach, the decision matrix is constructed by experts using spherical fuzzy linguistic variables. Hence, the rows of this matrix signify the identified risks, while the columns represent the evaluation criteria (Table 5).

Table 5
Decision Matrix Based on Spherical Fuzzy Linguistic Variables

FMs	Severity			Occurrences			Detection		
	DM1	DM2	DM3	DM1	DM2	DM3	DM1	DM2	DM3
FM1	HI	HI	HI	VHI	VHI	VHI	HI	HI	HI
FM2	SMI	HI	HI	HI	SMI	HI	HI	HI	VHI
FM3	HI	SMI	HI	SMI	HI	HI	VHI	SMI	VHI
FM4	HI	SMI	SMI	SMI	HI	VHI	VHI	HI	HI
FM5	SMI	HI	SMI	HI	HI	VHI	HI	VHI	HI
FM6	HI	SMI	SMI	HI	HI	VHI	VHI	HI	HI
FM7	HI	VHI	HI	HI	HI	HI	HI	HI	VHI
FM8	HI	HI	HI	VHI	SMI	HI	HI	VHI	HI
FM9	HI	HI	HI	SMI	HI	HI	HI	HI	VHI
FM10	HI	HI	HI	HI	VHI	SMI	HI	HI	HI
FM11	HI	SMI	HI	SMI	SMI	HI	HI	VHI	VHI
FM12	HI	HI	HI	SMI	HI	SMI	HI	VHI	HI
FM13	HI	HI	HI	HI	HI	HI	HI	SMI	VHI
FM14	HI	HI	HI	HI	HI	SMI	HI	VHI	HI
FM15	HI	VHI	VHI	SMI	HI	HI	SMI	VHI	VHI
FM16	HI	VHI	HI	HI	SMI	SMI	HI	HI	VHI
FM17	VHI	VHI	AMI	AMI	HI	VHI	VHI	VHI	VHI
FM18	HI	HI	HI	HI	HI	HI	HI	HI	HI

The spherical fuzzy linguistic variables are transformed into spherical fuzzy numbers (Table 6), as shown in Table 1. Next, as shown in Table 7, the aggregation matrix is created utilizing Eq. (17) and the expert weights assigned, following Step (3) of the procedure. Three experts' knowledge and experience have been invaluable to this research in ensuring the validity and reliability of the findings. The decision-makers have been assigned weights and relevance of 0.3, 0.4, and 0.3, respectively, based on their respective backgrounds and experiences.

Table 6
Formed Decision Matrix Based on Spherical Fuzzy Numbers

FMs	**Severity**								
	DM1			DM2			DM3		
	μ	v	π	μ	v	π	μ	v	π
FM1	0.7	0.3	0.3	0.7	0.3	0.3	0.7	0.3	0.3
FM2	0.6	0.4	0.4	0.7	0.3	0.3	0.7	0.3	0.3
FM3	0.7	0.3	0.3	0.6	0.4	0.4	0.7	0.3	0.3
FM4	0.7	0.3	0.3	0.6	0.4	0.4	0.6	0.4	0.4
FM5	0.6	0.4	0.4	0.7	0.3	0.3	0.6	0.4	0.4
FM6	0.7	0.3	0.3	0.6	0.4	0.4	0.6	0.4	0.4
FM7	0.7	0.3	0.3	0.8	0.2	0.2	0.7	0.3	0.3
FM8	0.7	0.3	0.3	0.7	0.3	0.3	0.7	0.3	0.3
FM9	0.7	0.3	0.3	0.7	0.3	0.3	0.7	0.3	0.3
FM10	0.7	0.3	0.3	0.7	0.3	0.3	0.7	0.3	0.3
FM11	0.7	0.3	0.3	0.6	0.4	0.4	0.7	0.3	0.3
FM12	0.7	0.3	0.3	0.7	0.3	0.3	0.7	0.3	0.3
FM13	0.7	0.3	0.3	0.7	0.3	0.3	0.7	0.3	0.3
FM14	0.7	0.3	0.3	0.7	0.3	0.3	0.7	0.3	0.3
FM15	0.7	0.3	0.3	0.8	0.2	0.2	0.8	0.2	0.2
FM16	0.7	0.3	0.3	0.8	0.2	0.2	0.7	0.3	0.3
FM17	0.8	0.2	0.2	0.8	0.2	0.2	0.9	0.1	0.1
FM18	0.7	0.3	0.3	0.7	0.3	0.3	0.7	0.3	0.3

Table 6
Formed Decision Matrix Based on Spherical Fuzzy Numbers (Continued)

FMs	Occurrence								
	DM1			DM2			DM3		
	μ	v	π	μ	v	π	μ	v	π
FM1	0.8	0.2	0.2	0.8	0.2	0.2	0.8	0.2	0.2
FM2	0.7	0.3	0.3	0.6	0.4	0.4	0.7	0.3	0.3
FM3	0.6	0.4	0.4	0.7	0.3	0.3	0.7	0.3	0.3
FM4	0.6	0.4	0.4	0.7	0.3	0.3	0.8	0.2	0.2
FM5	0.7	0.3	0.3	0.7	0.3	0.3	0.8	0.2	0.2
FM6	0.7	0.3	0.3	0.7	0.3	0.3	0.8	0.2	0.2
FM7	0.7	0.3	0.3	0.7	0.3	0.3	0.7	0.3	0.3
FM8	0.8	0.2	0.2	0.6	0.4	0.4	0.7	0.3	0.3
FM9	0.6	0.4	0.4	0.7	0.3	0.3	0.7	0.3	0.3
FM10	0.7	0.3	0.3	0.8	0.2	0.2	0.6	0.4	0.4
FM11	0.6	0.4	0.4	0.6	0.4	0.4	0.7	0.3	0.3
FM12	0.6	0.4	0.4	0.7	0.3	0.3	0.6	0.4	0.4
FM13	0.7	0.3	0.3	0.7	0.3	0.3	0.7	0.3	0.3
FM14	0.7	0.3	0.3	0.7	0.3	0.3	0.6	0.4	0.4
FM15	0.6	0.4	0.4	0.7	0.3	0.3	0.7	0.3	0.3
FM16	0.7	0.3	0.3	0.6	0.4	0.4	0.6	0.4	0.4
FM17	0.9	0.1	0.1	0.7	0.3	0.3	0.8	0.2	0.2
FM18	0.7	0.3	0.3	0.7	0.3	0.3	0.7	0.3	0.3
FMs	**Detection**								
	DM1			DM2			DM3		
	μ	v	π	μ	v	π	μ	v	π
FM1	0.7	0.3	0.3	0.7	0.3	0.3	0.7	0.3	0.3
FM2	0.7	0.3	0.3	0.7	0.3	0.3	0.8	0.2	0.2
FM3	0.8	0.2	0.2	0.6	0.4	0.4	0.8	0.2	0.2
FM4	0.8	0.2	0.2	0.7	0.3	0.3	0.7	0.3	0.3
FM5	0.7	0.3	0.3	0.8	0.2	0.2	0.7	0.3	0.3
FM6	0.8	0.2	0.2	0.7	0.3	0.3	0.7	0.3	0.3
FM7	0.7	0.3	0.3	0.7	0.3	0.3	0.8	0.2	0.2
FM8	0.7	0.3	0.3	0.8	0.2	0.2	0.7	0.3	0.3
FM9	0.7	0.3	0.3	0.7	0.3	0.3	0.8	0.2	0.2
FM10	0.7	0.3	0.3	0.7	0.3	0.3	0.7	0.3	0.3
FM11	0.7	0.3	0.3	0.8	0.2	0.2	0.8	0.2	0.2
FM12	0.7	0.3	0.3	0.8	0.2	0.2	0.7	0.3	0.3
FM13	0.7	0.3	0.3	0.6	0.4	0.4	0.8	0.2	0.2
FM14	0.7	0.3	0.3	0.8	0.2	0.2	0.7	0.3	0.3
FM15	0.6	0.4	0.4	0.8	0.2	0.2	0.8	0.2	0.2
FM16	0.7	0.3	0.3	0.7	0.3	0.3	0.8	0.2	0.2
FM17	0.8	0.2	0.2	0.8	0.2	0.2	0.8	0.2	0.2
FM18	0.7	0.3	0.3	0.7	0.3	0.3	0.7	0.3	0.3

Table 7
Aggregated Matrix Based on Expert Weights

FMs	Severity			Occurrence			Detection		
	μ	v	π	μ	v	π	μ	v	π
FM1	0.70	0.30	0.30	0.80	0.20	0.20	0.70	0.30	0.30
FM2	0.67	0.33	0.33	0.66	0.34	0.34	0.74	0.27	0.27
FM3	0.66	0.34	0.34	0.67	0.33	0.33	0.74	0.26	0.28
FM4	0.63	0.37	0.37	0.71	0.29	0.30	0.74	0.27	0.27
FM5	0.64	0.36	0.36	0.74	0.27	0.27	0.75	0.26	0.26
FM6	0.63	0.37	0.37	0.74	0.27	0.27	0.74	0.27	0.27
FM7	0.75	0.26	0.26	0.70	0.30	0.30	0.74	0.27	0.27
FM8	0.70	0.30	0.30	0.70	0.30	0.31	0.75	0.26	0.26
FM9	0.70	0.30	0.30	0.67	0.33	0.33	0.74	0.27	0.27
FM10	0.70	0.30	0.30	0.72	0.28	0.29	0.70	0.30	0.30
FM11	0.66	0.34	0.34	0.63	0.37	0.37	0.77	0.23	0.23
FM12	0.70	0.30	0.30	0.64	0.36	0.36	0.75	0.26	0.26
FM13	0.70	0.30	0.30	0.70	0.30	0.30	0.70	0.30	0.31
FM14	0.70	0.30	0.30	0.67	0.33	0.33	0.75	0.26	0.26
FM15	0.77	0.23	0.23	0.67	0.33	0.33	0.76	0.26	0.26
FM16	0.75	0.26	0.26	0.63	0.37	0.37	0.74	0.27	0.27
FM17	0.84	0.16	0.17	0.81	0.19	0.20	0.80	0.20	0.20
FM18	0.70	0.30	0.30	0.70	0.30	0.30	0.70	0.30	0.30

In the following stage, Eq. (16) is used to determine the crisp values of the spherical fuzzy numbers (Table 8). Table 9 shows how the normalized matrix is generated. After normalizing the decision matrix, the weighted sums and weighted product values are calculated using the weights acquired from the SFBWM approach.

Table 8
Decision Matrix Based on Crisp Numbers

FMs	Crisp values		
	Severity	Occurrence	Detection
FM1	0.343	0.512	0.343
FM2	0.304	0.291	0.395
FM3	0.291	0.304	0.393
FM4	0.253	0.355	0.395
FM5	0.266	0.395	0.412
FM6	0.253	0.395	0.395
FM7	0.412	0.343	0.395
FM8	0.343	0.343	0.412
FM9	0.343	0.304	0.395
FM10	0.343	0.373	0.343
FM11	0.291	0.253	0.462
FM12	0.343	0.266	0.412
FM13	0.343	0.343	0.343
FM14	0.343	0.304	0.412
FM15	0.462	0.304	0.423
FM16	0.412	0.253	0.395
FM17	0.585	0.523	0.512
FM18	0.343	0.343	0.343
MAX	0.343	0.512	0.343
MIN	0.304	0.291	0.395

Table 9
Normalized Decision Matrix

FMs	Severity	Occurrence	Detection
FM1	0.271	0.960	0.997
FM2	0.153	0.141	0.692
FM3	0.115	0.189	0.699
FM4	0.000	0.380	0.692
FM5	0.038	0.525	0.591
FM6	0.000	0.525	0.692
FM7	0.479	0.333	0.692
FM8	0.271	0.332	0.591
FM9	0.271	0.189	0.692
FM10	0.271	0.443	0.997
FM11	0.115	0.000	0.292
FM12	0.271	0.047	0.591
FM13	0.271	0.333	1.000
FM14	0.271	0.189	0.591
FM15	0.631	0.189	0.524
FM16	0.479	0.000	0.692
FM17	1.000	1.000	0.000
FM18	0.271	0.333	0.997

Finally, Eqs. (30-32) are then used to calculate k_{ia}, k_{ib}, and k_{ic}. For balance, it is assumed that the value of $\boldsymbol{\lambda}$ in these equations is 0.5. Eq. (33) yields an ultimate value for each risk based on these three values. The ranking is then determined based on the final scores. Table 10 makes it clear that, out of all risks, FM17 has the highest priority with a score of 3.770. Additionally, FM1 and FM7 are placed second and third, respectively, with scores of 3.540 and 3.216. FM11, with a score of 1.243, ranks last in terms of priority. Consequently, based on this prioritization, experts can implement corrective actions for the risks accordingly.

Table 10
Results of CoCoSo Method

FMs	S_i	p_i	K_{ia}	K_{ib}	K_{ic}	K_i	Rank
FM1	0.603	2.517	0.072	7.079	0.961	3.540	2
FM2	0.275	1.939	0.051	3.955	0.880	2.278	14
FM3	0.269	1.934	0.051	3.905	0.875	2.256	15
FM4	0.257	1.708	0.045	3.602	0.781	2.074	17
FM5	0.286	1.939	0.051	4.046	0.884	2.316	12
FM6	0.292	1.772	0.048	3.938	0.820	2.228	16
FM7	0.481	2.381	0.066	5.988	1.137	3.216	3
FM8	0.354	2.176	0.058	4.801	1.005	2.684	8
FM9	0.344	2.113	0.057	4.662	0.976	2.611	9
FM10	0.479	2.349	0.065	5.943	1.123	3.190	4
FM11	0.126	1.091	0.028	2.000	0.483	1.243	18
FM12	0.286	1.888	0.050	3.995	0.864	2.281	13
FM13	0.453	2.296	0.063	5.691	1.092	3.075	6
FM14	0.320	2.079	0.055	4.440	0.953	2.512	10
FM15	0.480	2.324	0.065	5.934	1.114	3.180	5
FM16	0.401	1.612	0.046	4.650	0.800	2.477	11
FM17	0.730	2.000	0.063	7.613	1.085	3.770	1
FM18	0.452	2.295	0.063	5.685	1.092	3.072	7

3.4. Sensitivity Analysis and Discussion of Results

This section encompasses a sensitivity analysis conducted to evaluate the reliability of the results generated by the presented methods. The CoCoSo method yields the parameter **λ**, which is used in this methodology to determine the final ranking. To evaluate the impact of varying the **λ** parameter on the ranking results, various scenarios were examined and analyzed, as depicted in Fig. 2. The findings of the analysis reveal that altering the **λ** parameter does not significantly influence the ranking outcomes. The ranking remains consistent across all scenarios, with FM17 consistently identified as the top priority. It is noteworthy that the **λ** parameter has minimal impact on the ranking results. Nonetheless, experts are advised to consider the specific characteristics of the data and the subject matter when making decisions regarding the appropriate value for **λ**. This sensitivity analysis provides valuable insights into the stability and robustness of the ranking results obtained through the proposed approach. It demonstrates that the ranking is not heavily influenced by variations in the **λ** parameter, reinforcing the reliability of the assessment. Decision-makers can have confidence in the consistency of the rankings and rely on the obtained results to prioritize and address the identified risks effectively. The comparison of the results suggests that the proposed model is robust. Therefore, it is acceptable to consider the preliminary rankings as the final rating. It is acceptable to consider the preliminary rankings as the final rating. Experts may, however, use their judgment to assess the value of **λ** in light of the topic matter and data characteristics.

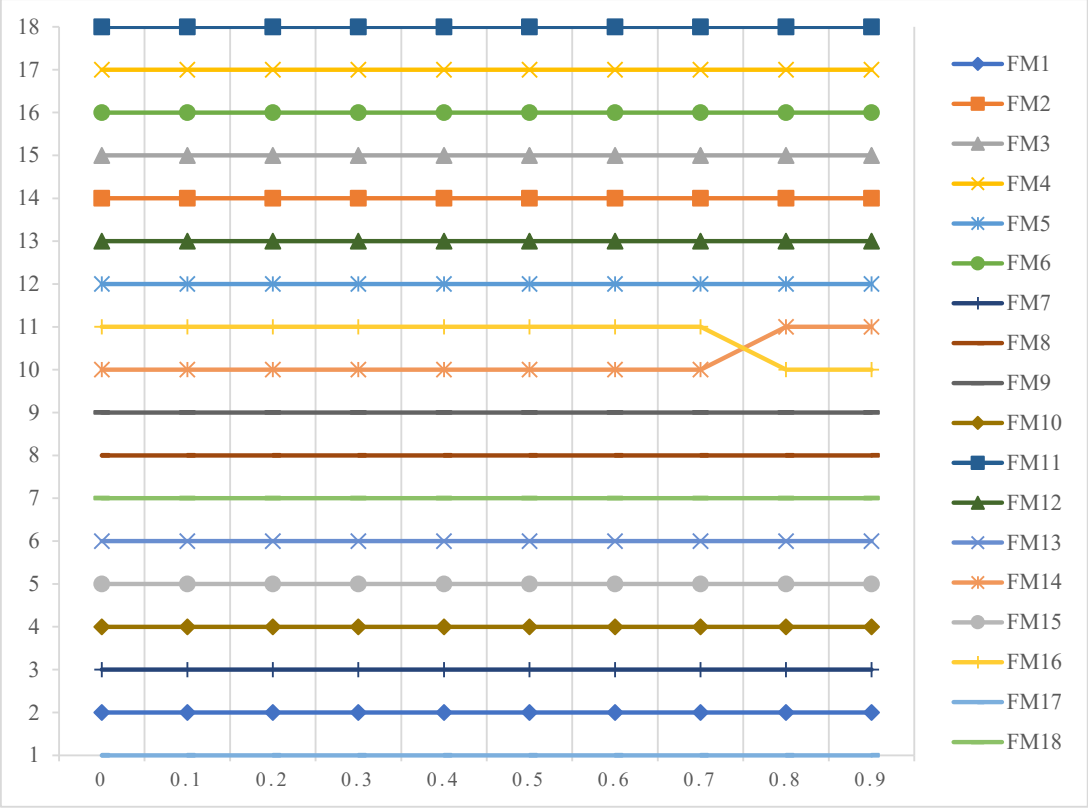

Fig. 2. Comparison of Ranking Results with **λ** Variation

Moreover, in this section, a comparison has been conducted between the CoCoSo method and other decision-making procedures in the spherical fuzzy environment to validate the effectiveness of the presented approach. When applying the FMEA method, it was found that FM2 and FM3 risks, with a Risk Priority Number (RPN) of 325.926, are jointly ranked 14th. Similarly, FM10, FM13, and FM18 have obtained equal scores and are placed in the 6th position. An overall examination of the results reveals that the FMEA method does not provide a comprehensive ranking, as the identified risks are categorized into only 14 groups instead of the total 18 risks. It is evident from this that the FMEA method-based prioritization is not comprehensive, lacking the ability to differentiate and address preventive measures for all the identified risks. Furthermore, FM17 and FM1 secure the top two spots in the MOORA technique, with scores of 0.048 and 0.035, respectively. Similarly, in the COPRAS method, FM17 and FM1 also consistently hold the first and second ranks. Moreover, FM11 consistently remains in the lowest rank across all the applied methods. Therefore, through a simultaneous and comprehensive comparison of the prioritization performed by the MOORA, COPRAS, and CoCoSo methods, it is possible to conclude that the essential risks identified remain consistent and unaffected by the choice of method. This observation further validates the proposed approach and its efficacy in accurately identifying and prioritizing the critical risks.

Moreover, an analysis has been carried out to compare the correlation between these three approaches and the FMEA method. In comparison to the COPRAS (0.9205) and MOORA (0.9252) approaches, the CoCoSo method has the highest correlation coefficient (0.9424) according to this analysis. This demonstrates the precision and dependability of the CoCoSo method's outputs. The correlation results between FMEA and the MOORA, COPRAS, and CoCoSo methodologies are shown graphically in Fig. 3. As a result, decision-makers can give key risks more attention and take action to address and mitigate them.

Table 11
Comparison of CoCoSo Method Results with Other Decision-Making Methods

FMs	FMEA		SF-CoCoSo		SF-MOORA		SF-COPRAS	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank
FM1	392.000	2	3.540	2	0.035	2	0.813	2
FM2	325.926	14	2.278	14	0.021	15	0.634	15
FM3	325.926	14	2.256	15	0.021	16	0.628	16
FM4	325.111	16	2.074	17	0.020	17	0.615	17
FM5	340.593	11	2.316	12	0.022	13	0.641	13
FM6	340.593	11	2.228	16	0.021	14	0.635	14
FM7	376.444	3	3.216	3	0.032	4	0.771	4
FM8	359.333	5	2.684	8	0.026	9	0.693	9
FM9	342.222	9	2.611	9	0.025	10	0.681	10
FM10	343.000	6	3.190	4	0.029	5	0.742	5
FM11	323.704	18	1.243	18	0.017	18	0.576	18
FM12	325.111	16	2.281	13	0.023	12	0.654	12
FM13	343.000	6	3.075	6	0.028	7	0.728	6
FM14	342.222	9	2.512	10	0.024	11	0.674	11
FM15	374.815	4	3.180	5	0.033	3	0.792	3
FM16	340.593	11	2.477	11	0.028	6	0.726	8
FM17	533.333	1	3.770	1	0.048	1	1.000	1
FM18	343.000	6	3.072	7	0.0286	8	0.727	7

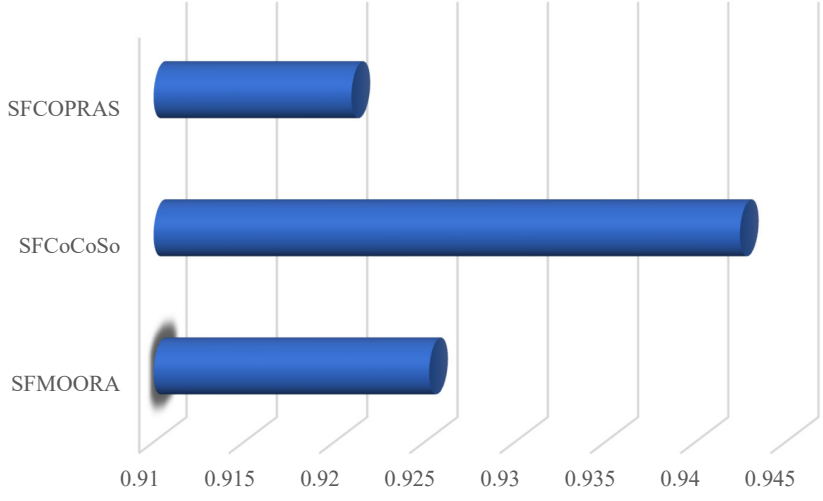

Fig. 3. Comparison of Correlation Degrees between CoCoSo, MOORA, and COPRAS Methods

Based on the research objectives, a thorough analysis was performed at the laboratory level using the FMEA method. As a result, eighteen primary risks were identified and assessed based on their RPN (Risk Priority Number) values. The severity, occurrence probability, and detectability factors were then weighted using the SF-BWM. Finally, the main risks were ranked and evaluated using the CoCoSo approach. This study underscores the criticality of hospital-related hazards and human errors, which can have far-reaching and irreparable consequences.

4. Conclusion

Today, the issue of hospital hazards and human errors has become a challenging and complex problem, with the number of incidents and their consequences increasing day by day, some of which are irreparable. Therefore, it is crucial and inevitable to pay attention to and manage these risks. In terms of laboratory safety, the presence of various chemicals, electrical equipment, and frequent utilization by students, professors, and staff make it imperative to manage these risks effectively. Additionally, the high monetary value of certain equipment further emphasizes the importance of risk management in laboratories. Consequently, it is necessary to identify, evaluate, and control the hazards present in laboratories using

appropriate methods. Among various risk identification and assessment methods, the FMEA method has gained significant attention and validation by most researchers in the healthcare field for controlling hospital risks and hazards. However, researchers have also recognized the limitations of this method and have sought improvements. In this study, we aimed to prioritize the identified risks in laboratories. To achieve this, we developed an integrated approach based on the BWM and CoCoSo methods in a fuzzy spherical environment to evaluate and prioritize laboratory risks.

In this research, we weighed the severity, detectability, and occurrence probability criteria using the fuzzy spherical BWM method, considering the nature of the identified issues. We then evaluated and prioritized the 18 identified risks in laboratories using the fuzzy spherical CoCoSo method, which helps reduce uncertainty. The results of the research indicate that FM17 and FM1 are the highest priorities. The implementation process of the FMEA method involves a team, which introduces the possibility of differing opinions among group members. Additionally, uncertainties arise in determining the factors of the Risk Priority Number (RPN), and the presence of ambiguous information further complicates the decision-making process. These limitations and uncertainties cannot be adequately addressed using precise numerical values alone. To overcome these challenges, we have employed the concept of fuzzy spherical sets, which are three-dimensional fuzzy sets that incorporate membership, non-membership, and hesitation degrees independently.

By utilizing fuzzy spherical sets, decision-makers can define membership functions within specific spherical regions and extend other components of the fuzzy set, allowing for the independent assignment of performance membership parameters across a broader domain. By adjusting the flexibility parameter, the fuzzy spherical set's degree of membership function accurately represents the decision-maker's knowledge and the range of information that was considered when making the decision. We have also compared the recommended methodology with two other decision-making procedures, MOORA and COPRAS, to verify the accuracy of the ranking results generated by our method. The comparative analysis, which demonstrates that the ranking results of our recommended method match those of the other approaches, provides more evidence for the consistency and dependability of our approach. A sensitivity analysis was performed to assess the $\boldsymbol{\lambda}$ parameter's influence on risk ranking in more detail. This demonstrates the robustness of the risk ranking methodology.

Based on these findings, it is possible to conclude that the proposed approach serves as a reliable multicriteria decision-making technique that effectively addresses the challenges faced by managers, stakeholders, and policymakers in assessing and managing risks. The use of fuzzy spherical sets and the robustness of the ranking results further enhance the applicability and trustworthiness of our approach in various decision-making scenarios

References

Astion, M. L., Shojania, K. G., Hamill, T. R., Kim, S., & Ng, V. L. (2003). Classifying laboratory incident reports to identify problems that jeopardize patient safety. *American journal of clinical pathology*, *120*(1), 18-26.

Bagheri, M., Alamdari, A., & Davoudi, M. (2016). Quantitative risk assessment of sour gas transmission pipelines using CFD. *Journal of Natural Gas Science and Engineering, 31,* 108-118.

Baker, G. R., Norton, P. G., Flintoft, V., Blais, R., Brown, A., Cox, J., ... & Tamblyn, R. (2004). The Canadian Adverse Events Study: the incidence of adverse events among hospital patients in Canada. *Cmaj*, *170*(11), 1678-1686.

Bonini, P., Plebani, M., Ceriotti, F., & Rubboli, F. (2002). Errors in laboratory medicine. *Clinical chemistry*, *48*(5), 691-698.

Bromiley, P., & Rau, D. (2016). A better way of managing major risks.

Carraro, P., & Plebani, M. (2007). Errors in a stat laboratory: types and frequencies 10 years later. *Clinical chemistry*, *53*(7), 1338-1342.

Carraro, P., Zago, T., & Plebani, M. (2012). Exploring the initial steps of the testing process: frequency and nature of pre-preanalytic errors. *Clinical chemistry*, *58*(3), 638-642.

Cui, Y., Liu, W., Rani, P., & Alrasheedi, M. (2021). Internet of Things (IoT) adoption barriers for the circular economy using Pythagorean fuzzy SWARA-CoCoSo decision-making approach in the manufacturing sector. *Technological Forecasting and Social Change*, *171*, 120951.

Ghoushchi, S. J., Bonab, S. R., Ghiaci, A. M., Haseli, G., Tomaskova, H., & Hajiaghaei-Keshteli, M. (2021). Landfill site selection for medical waste using an integrated SWARA-WASPAS framework based on spherical fuzzy set. *Sustainability, 13*(24), 13950.

Ghoushchi, S. J., Yousefi, S., & Khazaeili, M. (2019). An extended FMEA approach based on the Z-MOORA and fuzzy BWM for prioritization of failures. *Applied soft computing, 81*, 105505.

Haseli, G., Sheikh, R., Wang, J., Tomaskova, H., & Tirkolaee, E. B. (2021). A novel approach for group decision making based on the best–worst method (G-bwm): Application to supply chain management. *Mathematics, 9*(16), 1881.

ISO/TS 22367:2008. Medical laboratories- reduction of error through risk management and continual improvement.

Jafarzadeh Ghoushchi, S., Khazaeili, M., Amini, A., & Osgooei, E. (2019). Multi-criteria sustainable supplier selection using piecewise linear value function and fuzzy best-worst method. *Journal of Intelligent & Fuzzy Systems, 37*(2), 2309-2325.

Jafarzadeh Ghoushchi, S., Memarpour Ghiaci, A., Rahnamay Bonab, S., & Ranjbarzadeh, R. (2022). Barriers to circular economy implementation in designing of sustainable medical waste management systems using a new extended decision-making and FMEA models. *Environmental Science and Pollution Research, 29*(53), 79735-79753

Jahangoshai Rezaee, M., Salimi, A., & Yousefi, S. (2017). Identifying and managing failures in stone processing industry using cost-based FMEA. *The International Journal of Advanced Manufacturing Technology, 88*, 3329-3342.

Kalra, J. (2004). Medical errors: impact on clinical laboratories and other critical areas. *Clinical biochemistry, 37*(12), 1052-1062.

Kieu, P. T., Nguyen, V. T., Nguyen, V. T., & Ho, T. P. (2021). A spherical fuzzy analytic hierarchy process (SF-AHP) and combined compromise solution (CoCoSo) algorithm in distribution center location selection: A case study in agricultural supply chain. Axioms, 10(2), 53.

Kohn, L. T., Corrigan, J. M., & Donaldson, M. S. (2000). Errors in health care: a leading cause of death and injury. In To err is human: Building a safer health system. National Academies Press (US).

Kutlu Gündoğdu, F., & Kahraman, C. (2019). A novel VIKOR method using spherical fuzzy sets and its application to warehouse site selection. *Journal of Intelligent & Fuzzy Systems, 37*(1), 1197-1211.

Liu, C. C., Kanekiyo, T., Xu, H., & Bu, G. (2013). Apolipoprotein E and Alzheimer disease: risk, mechanisms and therapy. *Nature Reviews Neurology*, *9*(2), 106-118.

Ma, H., Chu, X., Xue, D., & Chen, D. (2019). Identification of to-be-improved components for redesign of complex products and systems based on fuzzy QFD and FMEA. *Journal of Intelligent Manufacturing, 30,* 623-639.

Makary, M. A., & Daniel, M. (2016). Medical error—the third leading cause of death in the US. *Bmj*, *353*.

Plebian, M. (2014). Laboratory-associated and diagnostic errors: a neglected link. *Diagnosis, 1*(1), 89-94.

Pradhan, S., Gautam, K., & Pant, V. (2022). Variation in Laboratory Reports: Causes other than Laboratory Error. *JNMA: Journal of the Nepal Medical Association, 60*(246), 222.

Ran, J., & Nedovic-Budic, Z. (2016). Integrating spatial planning and flood risk management: A new conceptual framework for the spatially integrated policy infrastructure. *Computers, Environment and Urban Systems, 57*, 68-79.

Rezaei, J. (2015). Best-worst multi-criteria decision-making method. *Omega*, *53*, 49-57.

Vincent, G. M., Guy, L. S., Perrault, R. T., & Gershenson, B. (2016). Risk assessment matters, but only when implemented well: A multisite study in juvenile probation. *Law and Human Behavior*, *40*(6), 683.

Yazdani, M., Zarate, P., Kazimieras Zavadskas, E., & Turskis, Z. (2019). A combined compromise solution (CoCoSo) method for multi-criteria decision-making problems. *Management Decision, 57*(9), 2501-2519.

Yousefi, S., Alizadeh, A., Hayati, J., & Baghery, M. (2018). HSE risk prioritization using robust DEA-FMEA approach with undesirable outputs: a study of automotive parts industry in Iran. *Safety Science, 102*, 144-158.

Zolfani, S. H., Chatterjee, P., & Yazdani, M. (2019, May). A structured framework for sustainable supplier selection using a combined BWM-CoCoSo model. In International scientific conference in business, management and economics engineering (pp. 797-804). Lithuania: Vilnius.