SCIENTIFIC OASIS

Journal of Operational Intelligence

Journal homepage: www.jopi-journal.org
eISSN: 3009-4267

Prioritizing and Evaluating Risks of Ordering and Prescribing in the Chemotherapy Process Using an Extended SWARA and MOORA under Fuzzy Z-numbers

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ARTICLE INFO

Article history:
Received 11 October 2023
Received in revised form 13 November 2023
Accepted 17 November 2023
Available online 18 November 2023

Keywords: Risk assessment; Risk prioritization; Dispensing process; Ordering process; Clinical chemistry; Failure mode and effects analysis (FMEA); Fuzzy SWARA; MOORA-Z method; Z-number theory; Process improvement; Process quality Risk reduction.

ABSTRACT

Assessing and prioritizing risks in the chemotherapy ordering and prescribing processes is crucial to improving their safety and quality. While FMEA is commonly used for this purpose, it has some limitations. To overcome these limitations, a three-stage approach was proposed in this study to enhance the FMEA method. The first stage involved using FMEA to identify and assign values to the RPN parameters. In the second stage, the fuzzy SWARA method and expert opinions were used to calculate the weights of the three factors. Finally, in the third stage, the risks were prioritized using the Z-MOORA approach, which provides more accurate results due to its consideration of different factor weights, uncertainty, and the use of the Z-number theory for reliability.

1. Introduction

Chemotherapy is a medical procedure used to treat cancer by administering drugs to the patient. Its primary objective is to cure cancer, increase the patient's lifespan, prevent the disease from spreading, and alleviate its symptoms. However, errors during the treatment process can lead to severe complications for the patient. Research has shown that a significant number of patients admitted to hospitals suffer harm due to medical errors, such as unnecessary surgeries, incorrect drug prescriptions, infections from treatments, and adverse medication effects. Examining and understanding the reasons for these errors can help reduce their occurrence and the related harm to patients.

To enhance the quality of medical services, it is necessary to monitor all stages of the process and accurately identify potential risks in order to prevent errors from occurring. One method used for this purpose is the Failure Modes and Effect Analysis (FMEA), which identifies possible errors, their

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https://doi.org/10.31181/jopi1120238

causes, and their consequences in a systematic way and proposes preventive measures. The aim of this technique is to increase safety and reduce risk through prevention. The Risk Priority Number (RPN) is used to prioritize potential errors, which is calculated based on the probability, severity, and detectability of potential errors. However, the RPN method has certain limitations, such as uncertainty in team decision-making, incomplete ranking of hazards, equal weighting of all hazardous factors, and lack of consideration for uncertainty. In order to overcome these limitations, various theories such as R-Number, G-Number, and Evidence Theory have been proposed to improve risk analysis. Therefore, new methods based on multi-criteria decision-making (MCDM) are needed to better prioritize identified errors in processes. Examples of these methods include combining FMEA with Base-Criterion Method (BCM) [1,2], Best-Worst Method (BWM) [3], Step-Wise Weight Assessment Ratio Analysis (SWARA) [4], MOORA [5], VIKOR [6], HECON [7], and TOPSIS [8].

Researchers are currently placing significant emphasis on using multi-criteria decision-making methods in complex decision-making processes, particularly in healthcare. For instance, Mardani et al. [9] found that multi-criteria decision-making methods were effective techniques for evaluating healthcare facilities and services, reducing uncertainty, and facilitating complex decision-making processes in various hospital and healthcare settings. Hassieh et al. [10] were the first to use multi-criteria decision-making methods to reduce medication errors, using the Analytic Hierarchy Process (AHP) and the Best-Worst Method (BWM) to evaluate vital human factors associated with medication errors. Researchers have also proposed various approaches to reduce medication errors, including the Lean Six Sigma method [11], simulation-based learning [12,13], logistic regression [14], and qualitative studies [15]. Ismailpourshirvani et al. [16] demonstrated that improving the medication management process in the women's surgery ward using the HFMEA method increases patient safety, particularly for patients requiring chemotherapy. Lisa Weber et al. [17] used the FMEA method to evaluate and prioritize risks related to the chemotherapy preparation process. In a study of two different centers, potential failure modes were identified, and corrective actions were implemented to reduce the risk of most failure modes, demonstrating that improving the chemotherapy preparation process increases patient safety and reduces the likelihood of medication errors. Robinson et al. [18] showed that the use of the FMEA method can guarantee the safety of pediatric cancer patients in hospitals. Sheridan et al. [19] demonstrated that the use of the FMEA method can significantly improve the quality of chemotherapy services and reduce the costs associated with medication errors. Given the importance of patient safety in chemotherapy, the use of the FMEA method to identify and rectify medication errors is critical.

The FMEA method has some limitations that can result in inaccurate outcomes, despite being widely used in different processes. As a solution, this research proposes a three-phase approach to address some of the drawbacks of the FMEA method. Firstly, the FMEA method is used to identify failure modes and determine the factors that contribute to the RPN. Secondly, the Z-SWARA method and expert opinions are used to calculate the weights of the triple factors [20]. Finally, the Z-MOORA method is utilized to prioritize failures while taking into account the obtained weights and uncertainty in triple factors. This approach not only assigns different weights to the triple factors but also considers uncertainty and uses the theory of Z-Number to improve reliability in the event of failure [21]. A review of previous research shows that the theory of fuzzy Z-numbers has been successfully used in scientific research to consider reliability of decisions [22-27]. The proposed approach has been tested in a hospital to evaluate and prioritize prescription and ordering risks in chemotherapy, and the results demonstrate that this method improves the process of prioritizing failures compared to traditional methods like FMEA and fuzzy MOORA [28]. By using the Z-SWARA and Z-MOORA methods while considering uncertainty in triple factors, this approach increases the accuracy of the risk prioritization process and can be an effective alternative to traditional methods in various processes [20].

In this study, the Z-SWARA and Z-MOORA methods of fuzzy group decision-making were utilized to assess and prioritize the risks involved in drug ordering and prescribing during chemotherapy. This approach combines both quantitative and qualitative information using fuzzy variables, resulting in higher precision and reliability when evaluating and ranking risks [21]. The following section introduces the Z-SWARA and Z-MOORA methods for prioritizing and assessing risks related to drug ordering and prescribing. It explains how a combination of quantitative and qualitative information is utilized through Z-NUMBER theory-based variables, ultimately leading to improved accuracy and reliability when evaluating and ranking risks. Consequently, this article offers novel and more precise methods for prioritizing and assessing risks associated with drug ordering and prescribing in chemotherapy, contributing to enhanced patient safety and treatment quality.

2. Methodology

The upcoming section will initially introduce the proposed approach and Z-number theory, and will present the initial definitions and mathematical formulas of Z-SWARA and Z-MOORA. Following this, the expert opinion transformation rules for ranking risk states using Z-numbers will be explored. It is important to mention that, for ease of understanding, the term "fuzzy number" will be used to refer to triangular fuzzy numbers.

2.1 Fuzzy sets theory

A Triangular Fuzzy Number (TFN) can be described as a fuzzy number that is characterized by a triplet of real numbers in the format of $F=(l,m,u)$. The highest possible value that the fuzzy number (F) can attain is indicated by the upper bound, represented by (u) [29]. Similarly, the lowest possible value that the fuzzy number (F) can attain is indicated by the lower bound, represented by (l).

Definition 1:

Based on this definition, the fuzzy set collected in the X reference set is identified as Eq. (1).

$$\tilde{A}=\left\{\left(x,\mu_A(x)\right)\middle|x\in X\right\} \tag{1}$$

Where $\mu_A(x):X\rightarrow[0,1]$ is the membership function set of $\tilde{A}$. The amount of membership function of $\mu_A(x)$ indicates the degree of dependence of $x\in X$ in the set $\tilde{A}$.

Definition 2:

A triangular fuzzy number is represented by three values, namely l, m, and u, and its degree of membership is given by a mathematical equation described as equation (2) and visualized in Figure (1). In simpler terms, a triangular fuzzy number is a way to represent uncertainty or imprecision in a numerical value by using a range of possible values and a degree of membership for each value.

$$\mu_{\tilde{A}}(x)=\begin{cases}0 & x\in(-\infty,l)\\ \dfrac{x-l}{m-l} & x\in[l,m]\\ \dfrac{u-x}{u-m} & x\in[m,u]\\ 0 & x\in(u,\infty)\end{cases} \tag{2}$$

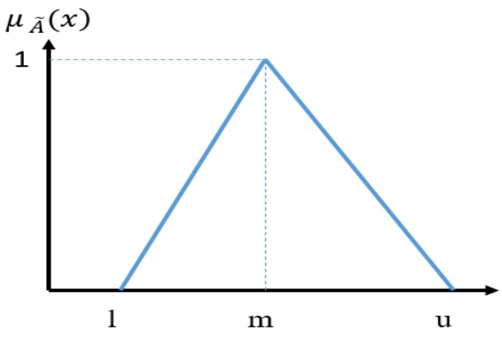

Figure 1. Triangular Fuzzy Number

Definition 3: Triangular fuzzy numbers are computationally efficient because they involve simple mathematical operations. This means that it is easy to perform mathematical operations, such as addition, subtraction, multiplication, and division, on triangular fuzzy numbers like F1 and F2. The simplicity of these operations make triangular fuzzy numbers a popular choice in fuzzy logic and fuzzy mathematics for representing uncertain or imprecise values and performing calculations on them:

$$F_1 = (l_1, m_1, u_1) \tag{3}$$
$$F_1 * F_2 = (l_1 * l_2, m_1 * m_2, u_1 * u_2) \tag{4}$$
$$\frac{F_1}{F_2} = (\frac{l_1}{u_2}, \frac{m_1}{m_2}, \frac{u_1}{l_2}) \tag{5}$$
$$F_1^{-1} = (\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}) \tag{6}$$
$$K * F = (K * l, K * m, K * u) \tag{7}$$

Definition 4: Assuming $\tilde{B} = (l_2, m_2, u_2), \tilde{A} = (l_1, m_1, u_1)$ are two positive triangular fuzzy numbers, the distance between $\tilde{A}$ and $\tilde{B}$ is defined according to equation (8):

$$d\left(\tilde{A}, \tilde{B}\right) = \sqrt{1/3\left(\left(l_1 - l_2\right)^2 + \left(m_1 - m_2\right)^2 + \left(u_1 - u_2\right)^2\right)} \tag{8}$$

2.2. Z-Numbers

Zadeh [30] introduced the concept of Z-Numbers as a means to handle uncertainty when dealing with less-than-reliable numerical data. A Z-Number comprises two fuzzy numbers, denoted as Z = (A, B). Here, A represents a fuzzy subset within a specific domain X, while B is a fuzzy subset within the unit interval that quantifies the reliability of component A. To illustrate, in the context of a Z-Number representing an incorrect detection, the first component might indicate a high level of uncertainty, while the second component can express a lack of confidence. A Z-Valuation, expressed as (X, A, B), is a three-part definition that assigns values to X and is calculated using Equation (9). Essentially, Z-Numbers provide a versatile framework for addressing uncertainty and vagueness in computations by making use of fuzzy sets and their associated reliability levels.

$$\mathrm{Pr}ob\left(x\ is\ A\right) is\ B \tag{9}$$

The probability distribution function that represents a constraint on the system is referred to as a "probability restriction." This function can be mathematically expressed using equation (10). In essence, the equation defines the probability distribution of a system's output given its input and any constraints that are imposed on the system.

$$R(X): X \text{ is } A \rightarrow Poss(X = u) = \mu_A(u) \tag{10}$$

The provided equation includes a membership function labeled as $\mu_{\tilde{A}}$, associated with A, and a general value denoted as u for X. $\mu_{\tilde{A}}$ can be interpreted as a limitation on $R(x)$, indicating the degree to which it aligns with u. Consequently, X is a stochastic variable characterized by a probability distribution, which can potentially impose constraints on X. Likely limitations and their corresponding probability density function are defined in equations (11) and (12), respectively. Essentially, these equations allow us to express restrictions on a system with respect to their probability distribution functions.

$$R(x): X \text{ is } p \tag{11}$$

$$R(x): X \text{ is } p \rightarrow \mathrm{Pr}ob(u \le X \le u + du) = p(u)du \tag{12}$$

In equation (12), the expression "du" signifies the derivative of the variable "u." This means it represents how quickly the probability density function changes as "u" undergoes variations.

2.3. Z- SWARA

Keršuliene rt al. [4] put forward the step-wise weight assessment ratio analysis (SWARA) approach. Decision making can be uncertain due to various factors like inadequate, unquantifiable, or unavailable information, as well as partial ignorance. Conventional multiple attribute decision making (MADM) methods are often insufficient in handling imprecise information, leading to the development of fuzzy multiple attribute decision making methods. The techniques mentioned aim to handle the vagueness in evaluating the comparative significance of characteristics and the ratings of alternatives concerning these characteristics [31, 32]. To tackle this problem, this study seeks to expand the SWARA method to encompass Z-SWARA. The study assumes that all criteria are autonomous. The process of calculating the relative weights of criteria using the Z-SWARA approach is identical to that of the SWARA method and includes these steps:

Step 1. Involves arranging the evaluation factors in a decreasing order of anticipated importance.

Step 2. Pertains to the regulations for transforming z-numbers and linguistic variables.

The subsequent step requires converting the linguistic variables linked with factors depicted as Z-Numbers into triangular fuzzy linguistic variables. This process of conversion can be explained as below:

Consider a Z-Number denoted as Z = (A, B), where A is the linguistic variable described in Table 1, and B is the linguistic variable defined in Table 2. Let's assume that $\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) | x \in [0,1]\}$ and $\tilde{B} = \{(x, \mu_{\tilde{B}}(x)) | x \in [0,1]\}$ are triangular membership functions. In this case, equations (13) and (14) are employed to convert the reliability aspect of the Z-Number into an exact numerical value.

$$\alpha = \frac{\int x\mu_{\tilde{B}}(x)dx}{\int \mu_{\tilde{B}}(x)dx} \tag{13}$$

$$\tilde{Z}^{\alpha} = \left\{ (X, \mu_{\tilde{A}^{\alpha}}) \mid \mu_{\tilde{A}^{\alpha}}(x) = \alpha \mu_{\tilde{A}} \, , X \in [0,1] \right\} \tag{14}$$

The equations presented above utilize a to signify the weight of reliability, $\mu_{\tilde{B}}(x)$ to indicate the level of dependence on $x \in X$ in B, and $\mu_{\tilde{A}^{a}}(x)$ to indicate the level of dependence of $x \in X$ in A^{a}.

To use the Z-SWARA method, the next step involves merging the Linguistics variable used to assess the factors (Table 1) with the linguistics variable conversion rules for reliability (Table 2). This combination helps determine the procedure for converting the verbal variables provided by the decision-makers into Z-Numbers.

Table1
Conversion directions for linguistic variables

Linguistic forms	Membership function
Equally Influential (EI)	(1,1,1)
Weakly Influential (WI)	(2/3,1, 3/2)
Fairly Influential (FI)	(2/5,1/2,2/3)
Very Influential (VI)	(2/7,1/3,2/5)
Absolutely Influential (AI)	(2/9,1/4,2/7)

Table 2
Conversion directions of reliability

Linguistic forms	Membership function
Remarkably Low (RL)	(0,0,0.3)
Low (L)	(0.1,0.3,0.5)
Medium (M)	(0.3,0.5,0.7)
High (H)	(0.5,0.7,0.9)
Remarkably High (RH)	(0.7,1,1)

For instance, let us consider a Z-Number $Z = (A, B)$ where the first component is denoted as $\tilde{A} = (MOL)$ and the second component is denoted as $\tilde{R} = (H)$.This results in $Z = \left[\left(1, \frac{2}{5}, \frac{2}{3}\right), (0.5,0.7,0.9)\right]$. Initially, the second component of the Z-Number is converted to a crisp value using equations (13) and (14). Equation (13) provides the value of a as 0.7, which is then used in Equation (14) to obtain $\tilde{Z}^{a} = \left(1, \frac{2}{5}, \frac{2}{3}; 0.7\right)$ Subsequently, the Z-number weight is transformed into a triangular fuzzy number using Equation (14), which yields $\tilde{Z}' = \left(1 * \sqrt{0.7}, \frac{2}{5} * \sqrt{0.7}, \frac{2}{3} * \sqrt{0.7}\right) = (0.837,0.335,0.561)$. Other conversions are presented in Table 3 based on the information provided in Tables 1 and 2.

Table 3
Conversion directions of Z-Number to TFN

Linguistic forms	Membership function	Linguistic forms	Membership function
(EI, RL)	(1,1,1)	(FI, H)	(1,1,1)
(EI, L)	(1,1,1)	(FI, RH)	(1,1,1)
(EI, M)	(1,1,1)	(VI, RL)	(0.212,0.316,0.474)
(EI, H)	(0.367,0.548,0.822)	(VI, L)	(0.474,0.707,1.061)
(EI, RH)	(0.561,0.837,1.255)	(VI, M)	(0.636,0.949,1.423)
(WI, RL)	(0.126,0.158,0.212)	(VI, H)	(0.219,0.274,0.367)
(WI, L)	(0.283,0.354,0.474)	(VI, RH)	(0.335,0.418,0.561)

Linguistic forms	Membership function	Linguistic forms	Membership function
(WI, M)	(0.379,0.474,0.636)	(AI, RL)	(0.092,0.104,0.126)
(WI, H)	(0.159,0.181,0.219)	(AI, L)	(0.205,0.233,0.283)
(WI, RH)	(0.243,0.276,0.335)	(AI, M)	(0.275,0.313,0.379)
(FI, RL)	(0.069,0.079,0.092)	(AI, H)	(0.120,0.137,0.159)
(FI, L)	(0.155,0.177,0.205)	(AI, RH)	(0.184,0.209,0.243)
(FI, M)	(0.209,0.237,0.275)		

Step 3. Table 3 offers data about the relative importance of each factor in comparison to the previous factor (j-1) using Z-Numbers, allowing us to determine which factor holds greater significance. This procedure is reiterated for all factors until we reach the last one. Once all the experts have assessed the relative importance scores for each factor, these assessments are aggregated by employing the geometric mean of the respective scores.

Step 4. Calculate the coefficient $\tilde{k}_j$ using equation (15):

$$\tilde{k}_j = \begin{cases} \tilde{1} & j = 1 \\ \tilde{s}_j + \tilde{1} & j > 1 \end{cases} \tag{15}$$

Step 5. Compute the fuzzy weight $\tilde{q}_j$ using equation (16):

$$\tilde{q}_j = \begin{cases} \tilde{1} & j = 1 \\ \dfrac{\tilde{x}_{j-1}}{\tilde{k}_j} & j > 1 \end{cases} \tag{16}$$

Step 6. Compute the weights for the evaluation criteria relatively using equation (17):

$$\tilde{w}_j = \frac{\tilde{q}_j}{\sum_{k=1}^{n} \tilde{q}_k} \tag{17}$$

Here, $\tilde{w}_j = \left(w_j^l, w_j^m, w_j^u\right)$ represents the fuzzy weight of criterion j^{th} in relative terms, and n denotes the total number of evaluation criteria.

2.4. Z-MOORA

Brauers and Zavadskas [5] proposed the MOORA technique, which is a multi-objective optimization method used to make complex decisions in any area. Later, Akkaya et al. introduced the MOORA fuzzy approach to consider uncertainty in decision matrices. However, this approach neglects the reliability of the decision-making process, despite its improvement over the traditional MOORA method. This study employs Z-Numbers to enhance the dependability of expert decision-making. The inclusion of a reliability component in the decision-making matrix can impact the final ranking of options. There are three methods for problem-solving using Z MOORA: the Z-ratio method, Z-reference point approach, and full multiplicative form.

2-4-1. Z-Ratio method

In this section, we explore the Z-Ratio approach that employs fuzzy ratios and leverages the Z-Number theory. The steps involved in this approach are presented below:

Step 1. Below is the decision-making matrix consisting of Z-Number components. Here, m and n indicate the number of alternatives and criteria, respectively. Moreover, x_{ij} and y_{ij} represent the i^{th} criterion's value for j^{th} (the first component of the Z-Number) and the reliability of i^{th} for j^{th} (the second component of the Z-Number), respectively.

$$Z = \begin{bmatrix} [(x_{11}^l, x_{11}^m, x_{11}^u), (y_{11}^l, y_{11}^m, y_{11}^u)] & [(x_{12}^l, x_{12}^m, x_{12}^u), (y_{12}^l, y_{12}^m, y_{12}^u)] & \cdots & [(x_{1n}^l, x_{1n}^m, x_{1n}^u), (y_{1n}^l, y_{1n}^m, y_{1n}^u)] \\ \cdots & \cdots & \cdots & \\ \cdots & \cdots & \cdots & \\ [(x_{m1}^l, x_{m1}^m, x_{m1}^u), (y_{m1}^l, y_{m1}^m, y_{m1}^u)] & [(x_{m2}^l, x_{m2}^m, x_{m2}^u), (y_{m2}^l, y_{m2}^m, y_{m2}^u)] & \cdots & [(x_{mn}^l, x_{mn}^m, x_{mn}^u), (y_{mn}^l, y_{mn}^m, y_{mn}^u)] \end{bmatrix} \quad (18)$$

Step 2. Transformation guidelines for converting linguistic variables to Z-Numbers:

In the following phase, the elements of the decision-making matrix generated in the initial step are converted into triangular fuzzy numbers. This results in a decision-making matrix consisting of triangular fuzzy numbers. The conversion procedure can be outlined as follows:

When Z-Number Z = (A, B) and both $\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) | x \in [0,1]\}$ and $\tilde{B} = \{(x, \mu_{\tilde{B}}(x)) | x \in [0,1]\}$ have triangular membership functions, equations (19) and (20) can be utilized to obtain a precise numerical value for the second component, which represents Reliability.

$$\alpha = \frac{\int x \mu_{\tilde{B}}(x) dx}{\int \mu_{\tilde{B}}(x) dx} \quad (19)$$

$$\tilde{Z}^{\alpha} = \left\{(X, \mu_{\tilde{A}^{\alpha}}) | \mu_{\tilde{A}^{\alpha}}(x) = \alpha \mu_{\tilde{A}} \ , X \in [0,1]\right\} \quad (20)$$

The aforementioned equations use α as the weight of Reliability, where $\mu_{\tilde{B}}(x)$ represents the degree of dependency of $x \in X$ in B and $\mu_{\tilde{A}^{\alpha}}(x)$ represents the degree of dependency of $x \in X$ in A^{α}.

To utilize the Z-MOORA method, the linguistic variables applied to rank Risk modes (Table 4) and the transformation rules of linguistic variables for Reliability (Table 5) must be combined. This merging facilitates the determination of the procedure for converting the verbal variables provided by decision-makers into Z-Numbers.

Table 4
Linguistic variables for rating the risk modes

Linguistic variables	Remarkably Poor (RP)	Poor (P)	Medium Poor (MP)	Medium (M)	Medium High (MH)	High (H)	Remarkably High (RH)
TFNs	(0,0,1)	(0,1,3)	(1,3,5)	(3,5,7)	(5,7,9)	(7,9,10)	(9,10,10)

Table 5
Transformation rules of linguistics variables of reliability

Linguistic variables	Remarkably poor (RP)	Poor (P)	Medium (M)	High (H)	Remarkably High (RH)
TFNs	(0,0,0.3)	(0.1,0.3,0.5)	(0.3,0.5,0.7)	(0.5,0.7,0.9)	(0.7,1,1)

Assuming Z=(A,B) is a Z-Number, where A represents the first component and R represents the second component, denoted as $Z = [(5,7,9),(0.3,0.5,0.7)]$. Initially, Equations (19) and (20) are utilized to convert the second component of the Z-Number into a precise numerical value, with Equation (19) yielding α as 0.5 and Equation (20) producing $\tilde{Z}^{\alpha} = (5,7,9;0.5)$. The weight of the Z-Number is then transformed into a triangular fuzzy number using Equation (17), resulting in $\tilde{Z}' = (5 * \sqrt{0.5}, 7 * \sqrt{0.5}, 9 * \sqrt{0.5}) = (3.54,4,95,6,36)$. Other conversions based on Tables 4 and 5 are presented in Table 6.

Table 6
Transformation rules for z-number linguistics variables to fuzzy numbers

Linguistics Terms	Membership function	Linguistics Terms	Membership function
(RH,RH)	(8.54,9.49,9.49)	(RH,H)	(7.53,8.37,8.37)
(RH,M)	(6.36,7.07,7.07)	(RH,P)	(4.93,5.48,5,48)
(RH,RP)	(2.85,3.16,3.16)	(H,RH)	(6.64,8.54,9.49)
(H,H)	(5.86,7.53,8.37)	(H,M)	(4.95,6.36,7.07)
(H,P)	(3.84,4.93,5.48)	(H,RP)	(2.21,2.85,3.16)
(MH,RH)	(4.74,6.64,8.54)	(MH,H)	(4.18,5.86,7.53)
(MH,M)	(3.54,4.95,6.36)	(MH,P)	(2.74,3.84,4.93)
(MH,RP)	(1.58,2.21,2.85)	(M,RH)	(2.85,4.74,6.64)
(M,H)	(2.51,4.28,5.86)	(M,M)	(2.12,3.54,4.95)
(M,P)	(1.64,2.74,3.83)	(M,RP)	(0.95,1.58,2.21)
(MP,RH)	(0.95,2.85,4.74)	(MP,H)	(0.84,2.51,4.18)
(MP,M)	(0.71,2.12,3.54)	(MP,P)	(0.55,1.64,2.74)
(MP,RP)	(0.32,0.95,1.58)	(P,RH)	(0,0.95,2.85)
(P,H)	(0,0.84,2.51)	(P,M)	(0,0.71,2.12)
(P,P)	(0,0.55,1.64)	(P,RP)	(0,0.32,0.95)
(RP,RH)	(0,0,0.95)	(RP,H)	(0,0,0.84)
(RP,M)	(0,0,0.71)	(RP,P)	(0,0,0.55)
(RP,RP)	(0,0,0.32)		

Step 3: After completing the previous two steps, a decision-making matrix is created using triangular fuzzy components (Equation 21). The subsequent step involves normalizing the matrix. The matrix comprises "m" options, "n" criteria, and "d_mn" values that indicate the option's performance measurement for criterion "n" and alternative "m".

$$\widetilde{D} = \begin{bmatrix} (d_{11}^{l}, d_{11}^{m}, d_{11}^{u}) & (d_{12}^{l}, d_{12}^{m}, d_{12}^{u}) & \dots & (d_{1n}^{l}, d_{1n}^{m}, d_{1n}^{u}) \\ \dots & \dots & \dots & \\ \dots & \dots & \dots & \\ (d_{m1}^{l}, d_{m1}^{m}, d_{m1}^{u}) & (d_{m2}^{l}, d_{m2}^{m}, d_{m2}^{u}) & \dots & (d_{mn}^{l}, d_{mn}^{m}, d_{mn}^{u}) \end{bmatrix} \quad (21)$$

Step 4: At this point, a weighted normalized fuzzy decision matrix is created by using the criterion significance weights obtained through the FBWM (Fuzzy Best Worst Method). These weights are employed to determine the relative importance of each criterion in the decision-making process.

$$\begin{aligned}
&\tilde{d}_{ij}{}^{*} = \left(d_{ij}^{l*}, d_{ij}^{m*}, d_{ij}^{u*}\right) and \forall ij: \\
&d_{ij}^{l*} = \frac{d_{ij}^{l}}{\sqrt{\sum_{i=1}^{m}\left[\left(d_{ij}^{l}\right)^2 + \left(d_{ij}^{m}\right)^2 + \left(d_{ij}^{u}\right)^2\right]}} \\
&d_{ij}^{m*} = \frac{d_{ij}^{m}}{\sqrt{\sum_{i=1}^{m}\left[\left(d_{ij}^{l}\right)^2 + \left(d_{ij}^{m}\right)^2 + \left(d_{ij}^{u}\right)^2\right]}} \\
&d_{ij}^{u*} = \frac{d_{ij}^{u}}{\sqrt{\sum_{i=1}^{m}\left[\left(d_{ij}^{l}\right)^2 + \left(d_{ij}^{m}\right)^2 + \left(d_{ij}^{u}\right)^2\right]}}
\end{aligned} \tag{22}$$

By utilizing $p_{ij}^{l} = w_j d_{ij}^{l*}$, $p_{ij}^{m} = w_j d_{ij}^{m*}$, and $p_{ij}^{u} = w_j d_{ij}^{u*}$, $\widetilde{D}$ is converted into $\tilde{P}$, which denotes the normalized weighted matrix.

$$\tilde{P} = \begin{bmatrix} \left(p_{11}^{l}, p_{11}^{m}, p_{11}^{u}\right) & \left(p_{12}^{l}, p_{12}^{m}, p_{12}^{u}\right) & \cdots & \left(p_{1n}^{l}, p_{1n}^{m}, p_{1n}^{u}\right) \\ \cdots & \cdots & \cdots & \\ \cdots & \cdots & \cdots & \\ \left(p_{m1}^{l}, p_{m1}^{m}, p_{m1}^{u}\right) & \left(p_{m2}^{l}, p_{m2}^{m}, p_{m2}^{u}\right) & \cdots & \left(p_{mn}^{l}, p_{mn}^{m}, p_{mn}^{u}\right) \end{bmatrix} \tag{23}$$

Step 5: At this point, normalized performance values are computed by deducting the criteria that are not relevant to the problem type from the total number of relevant criteria [33].

$$\tilde{y}_i = \sum_{j=1}^{g} \tilde{p}_{ij} - \sum_{j=g+1}^{n} \tilde{p}_{ij} \tag{24}$$

In this scenario, $\sum_{j=1}^{g} \tilde{p}_{ij}$ denotes the benefit criteria, and $1,..,g; \sum_{j=g+1}^{n} \tilde{p}_{ij}$ denotes the cost criteria for $g+1,..,n$. The variable g represents the maximum number of criteria to be executed, while $(n-g)$ indicates the minimum number of criteria to be carried out.

Step 6: Given that the normalized performance values are in the form of fuzzy $\tilde{y}_i = \left(y_i^{l}, y_i^{m}, y_i^{u}\right)$, they need to be converted into precise numerical values by employing the optimal non-fuzzy performances indicated in equation (25):

$$BNP_i(y_i) = \frac{\left(y_i^{u} - y_i^{l}\right) + \left(y_i^{m} - y_i^{l}\right)}{3} + y_i^{l} \tag{25}$$

3. Proposed approach

In this section, the proposed strategy for prioritizing risk scenarios utilizing FMEA, Z-MOORA, and Z-SWARA methods is presented. The approach involves three stages, and the previous section provides a comprehensive overview of the Z-SWARA and Z-MOORA techniques. During the initial stage, the FMEA team identifies the risk modes within the scope of the risk assessment and assigns values to five factors based on Table 7. Additionally, the team evaluates the reliability of each risk mode identified in this phase.

Table 7
Traditional evaluations of SODCT factors

Rating	Severity (S)	Occurrence (O)	Detection (D)
10	Hazardous without warning	Very high: risk is almost inevitable	Absolute uncertainty
9	Hazardous with warning		
8	Very high	High: repeated risks	High: repeated risks
7	High		
6	Moderate	Moderate: occasional risks	Moderate: occasional risks
5	Low		
4	Very low		
3	Minor	Low: relatively few risks	Low: relatively few risks
2	Very minor		
1	None	Remote: risk is unlikely	Remote: risk is unlikely

The second stage of the proposed method involves the application of the Z-SWARA technique to determine the weights of the three criteria. Unlike the conventional SWARA method, Z-SWARA takes into consideration both the fuzzy values and the reliability of the three factors studied in this research. In the third phase, the risk scenarios that have been identified are ranked based on the significance of differences in the three factors using the Z-MOORA method. In contrast to the standard MOORA technique, Z-MOORA incorporates both the fuzzy values and the reliability of each factor and other factors for each risk under investigation. To execute this approach, a decision-making matrix is constructed, which contains the fuzzy and reliability values (Z-Numbers). These values are then transformed into fuzzy numbers with the help of Table 6, and the MOORA method is applied within a fuzzy context. The results of this model closely align with the initial prioritization of the risk scenarios identified in the first phase. The implementation process of this proposed method is depicted in Figure 2.

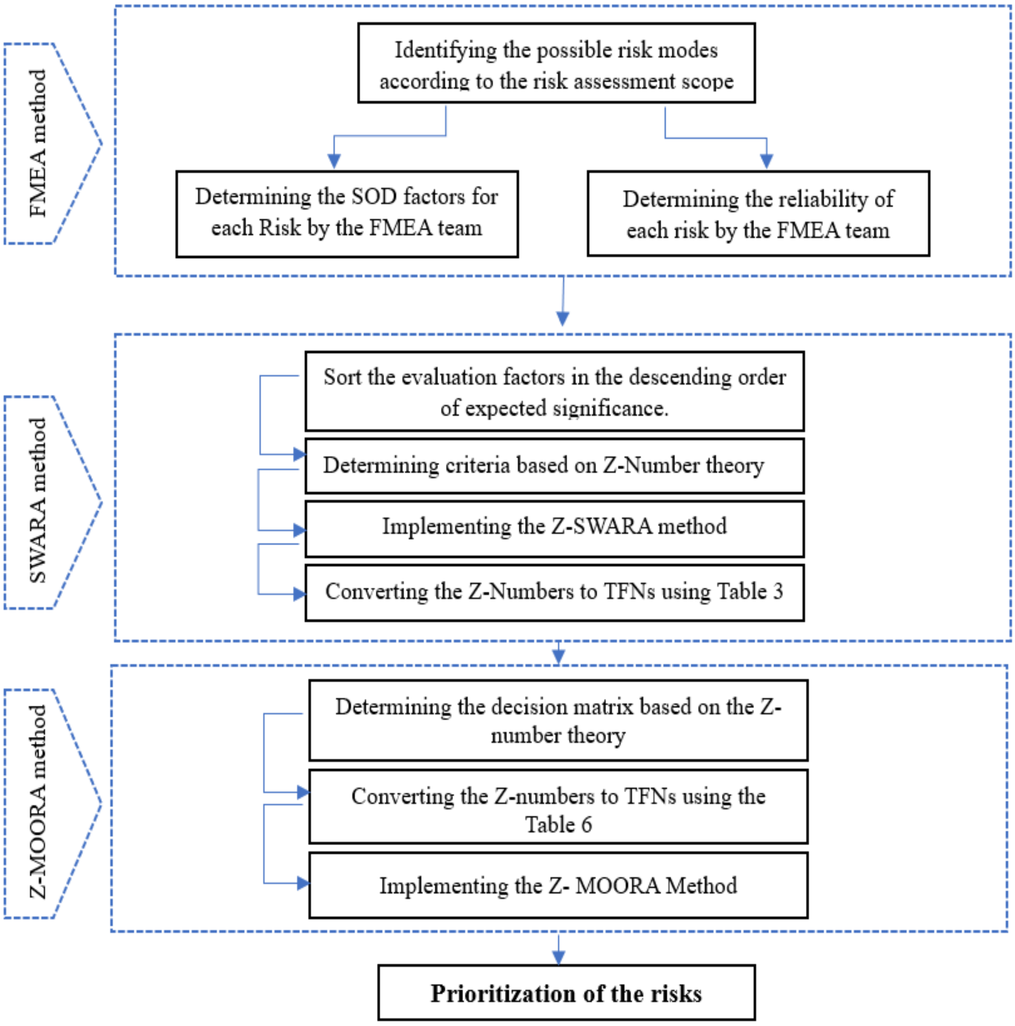

Figure 2. Proposed research approach to prioritize risks

4. Case Study

In this study, FMEA can be used for prioritizing risks associated with ordering and prescribing in the chemical treatment process in hospitals. In this method, initially an expert (head nurse) provided input, but using the proposed group decision-making approach and the collaboration of three expert physicians, the head nurse, and a university professor, the failures in the chemical treatment process in the hospital were identified and prioritized. This group approach, considering the different and specialized perspectives of these three experts, improved the accuracy in identifying and prioritizing existing failures in the chemical treatment process. For each failure, the severity, probability of occurrence, and detectability are calculated. Then, based on these parameters, risks are prioritized and corrective and preventive action plans are created for each risk. For example, it may be suggested to use multiple quality control checks to confirm the accuracy of orders during the drug prescribing phase, or to have automatic devices for drug injection to reduce the risk of human error.

Table 8
Risks identified in connection to drug identification and prescription during the chemotherapy process

	Risks mode	causes	Effects	S	O	D	RPN	Rank
R1	Premed missed before chemo	confusing premed line.	missed or incorrect medication	7	5	2	70	2
R2	Not using standard form	Dr. writing own order not using standard form.	incomplete orders with missing information	3	2	1	6	13
R3	Wt./height incorrect or missing for dosing	No current wt. or height on form	Delay wrong weight used for calculation	8	8	1	64	3
R4	Incomplete medication order	not all filled out	Delay, Errors in dosing	5	8	2	80	1
R5	legibility of the patient's prescription	poor handwriting, sloppy	errors or delays	8	5	1	40	7
R6	Methotrexate orders by OB are not complete	physician unfamiliar with calculating BSA	delay	7	8	1	56	4
R7	Incomplete checking of the physician's requested order by the RN	Form not filled out entirely, some chemo not related to BSA	errors or delay	7	8	1	56	4
R8	Incomplete order needs to be faxed back to office for completion	Nurse unable to take chemo orders over the phone.	Delay errors	3	5	3	45	6
R9	Nurse gets interrupted	Phone calls, other patients, questions etc. No quiet place for checking chemo orders	Loss of concentration	2	5	3	30	8
R10	Incomplete order already addressed by RN but pharmacist unaware	RN did not notify	Delay. Frustrating to physicians to get multiple calls	3	2	2	12	10
R11	Standard Protocol is not what the physician wants.	Changing doses based on prior reactions, other reasons not communicated. Rationale line not filled out on Chemo form	Delay while trying to find protocol or new information.	4	4	3	48	5
R12	calculations are incorrect (meds, solutions, amounts)	Human error	wrong dose or consent ration	10	1	1	10	11
R13	To much added to syringe, wrong size or needle for IM or SQ	Knowledge deficit	wrong dose or dilution. wrong route SQ instead of IM	6	2	1	12	10

	Risks mode	causes	Effects	S	O	D	RPN	Rank
R14	order Incompletely written by physician	not using standard guidelines for medication administration	Error in prescribing medication	3	2	3	18	9
R15	The incompleteness of the review of the technologies launched by two pharmaceutical companies	Haste and human error	Undetected errors	9	1	1	9	12
R16	Drug prescription and dosage regardless of the patient's medical history	The form is not completely filled out	wrong drug administration and wrong dose administration	4	3	1	12	10
R17	not paying attention to drug interactions in the prescription	Reaching the treatment goal faster	Error in prescribing medication	3	2	3	18	9

5. Analyzing the results

The following section examines and assesses the outcomes of implementing the proposed approach for risk assessment in the chemical treatment process. During the initial phase of the approach, the FMEA team identifies failure modes and establishes triple-factor values for each risk (Table 8).

To accommodate the uncertainty in these factors, the Z-Numbers theory is adopted. This theory takes into consideration both the fuzzy numerical uncertainty of the factors and their reliability. Based on the views of the FMEA team, Table 9 displays the Z-Number values of the triple factors for failure modes.

Table 9
The decision matrix represented as Z-Numbers

Symbol	S			O			D		
	TM1	TM2	TM3	TM1	TM2	TM3	TM1	TM2	TM3
R1	H,H	H,H	MH,H	M,H	M,M	MP,H	MP,H	M,H	MP,H
R2	MP,H	P,RH	MP,RH	MP,RH	M,RH	MP,RH	MP,H	MP,RH	MP,H
R3	H,RH	MH,H	H,RH	H,M	H,M	MH,H	MP,H	MP,M	M,H
R4	MH,RH	H,M	MH,RH	H,RH	RH,RH	H,RH	M,RH	MP,H	MP,RH
R5	H,M	MH,M	MH,P	M,M	M,H	M,H	MP,M	MP,H	MP,H
R6	MH,M	MH,M	H,M	H,M	MH,M	MH,P	MP,M	MP,M	M,P
R7	MH,M	MH,H	H,M	H,H	MH,P	MH,RH	MP,H	MP,H	MPH
R8	MP,M	M,M	MP,H	M,H	M,H	MH,H	M,M	MP,M	MP,P
R9	MP,H	M,H	M,H	M,H	M,H	MH,H	M,H	MP,H	M,H
R10	M,RH	M,H	MP,H	MP,H	MP,RH	M,H	MP,H	MP,H	MP,RH
R11	M,H	M,H	MH,H	M,H	MH,H	M,M	M,H	MP,H	MP,M
R12	RH,H	RH,M	H,H	MP,H	M,H	MP,M	MP,H	MP,H	M,H
R13	MH,RH	M,H	M,H	MP,H	M,H	H,H	MP,RH	MP,H	MP,H
R14	M,M	MP,M	M,H	MP,H	MP,H	MP,RH	M,H	MP,M	MPH
R15	H,M	H,M	MH,M	MP,H	MP,H	M,H	MPH	MP,H	MP,H
R16	M,RH	M,H	MP,RH	M,H	MP,H	M,M	MP,M	MP,H	M,H
R17	M,P	M,M	MP,P	MP,H	M,P	MP,H	M,P	MP,P	MP,M

After the second phase of the proposed method, the weights of the five factors are determined using the Z-SWARA method. To achieve this, the FMEA team assesses the relative importance of each factor in relation to the previous factor using verbal descriptors, as outlined in Tables 10 and 11.

Table 10
Expert-determined values of risk factors presented in the format of Z-Numbers

TM1		TM2		TM3	
Risk Factor	Relative Important	Risk Factor	Relative Important	Risk Factor	Relative Important
S		S		S	
D	LI-M	O	VLI-H	D	MUL-M
O	VLI-H	D	MUL-H	O	MOL-H

Table 11
Significance weights of risk factors

Team		Comparative importance of average value $\tilde{s}_j$			Coefficient $\tilde{k}_j = \tilde{s}_j + \tilde{1}$			Recalculated weight $\tilde{q}_j = \frac{\tilde{x}_{j-1}}{\tilde{k}_j}$			Weight $\tilde{w}_j = \frac{\tilde{q}_j}{\sum_{k=1}^{n} \tilde{q}_k}$		
TM1	S				1	1	1	1.000	1.000	1.000	0.425	0.443	0.472
	D	0.335	0.418	0.561	1.335	1.418	1.561	0.641	0.705	0.749	0.272	0.312	0.353
	O	0.243	0.276	0.335	1.243	1.276	1.335	0.480	0.553	0.603	0.204	0.245	0.284
							sum	2.120	2.258	2.352			
TM2	S				1	1	1	1.000	1.000	1.000	0.403	0.411	0.425
	O	0.243	0.276	0.335	1.243	1.276	1.335	0.749	0.784	0.805	0.302	0.322	0.342
	D	0.184	0.209	0.243	1.184	1.209	1.243	0.603	0.648	0.679	0.243	0.267	0.289
							sum	2.352	2.432	2.484			
TM3	S				1	1	1	1.000	1.000	1.000	0.413	0.433	0.455
	D	0.155	0.177	0.205	1.155	1.177	1.205	0.830	0.850	0.866	0.343	0.367	0.394
	O	0.561	0.837	1.255	1.561	1.837	2.255	0.368	0.463	0.555	0.152	0.200	0.252
							sum	2.198	2.312	2.420			

Table 12
Ultimate weights of Risk Factors

Risk Factors	Final Weight		
S	0.414	0.429	0.451
O	0.219	0.256	0.293
D	0.286	0.315	0.345

Table 12 presents the factor weights in the format of triangular fuzzy numbers, which are listed as follows.
$\tilde{w}_S = (0.414, 0.429, 0.451)$,
$\tilde{w}_O = (0.219, 0.256, 0.293)$,
$\tilde{w}_D = (0.286, 0.315, 0.345)$,

In the third stage of the proposed method, the prioritization of risk scenarios is carried out using the newly developed Z-MOORA technique, based on the results obtained from the first and second phases. The initial step involves structuring the decision-making matrix for Z-MOORA in the form of Z-number strings, where rows represent the evaluated options (risk scenarios), and columns represent the assessment criteria or the five factors. The subsequent step is to transform the decision-making matrix into a decision matrix represented as triangular fuzzy numbers, employing the conversions specified in Table 6. The resulting matrix is presented in Table 13.

Table 13
Fuzzy collective evaluation matrix and consolidated fuzzy weights of Risk Factors

S									O								
T1			T2			T3			T1			T2			T3		
l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u
5.86	7.53	8.37	5.86	7.53	8.37	4.18	5.86	7.53	2.51	4.28	5.86	2.12	3.54	4.95	0.84	2.51	4.18
0.84	2.51	4.18	0	0.95	2.85	0.95	2.85	4.74	0.95	2.85	4.74	2.85	4.74	6.64	0.95	2.85	4.74
6.64	8.54	9.49	4.18	5.86	7.53	6.64	8.54	9.49	4.95	6.36	7.07	4.95	6.36	7.07	4.18	5.86	7.53
4.74	6.64	8.54	4.95	6.36	7.07	4.74	6.64	8.54	6.64	8.54	9.49	8.54	9.49	9.49	6.64	8.54	9.49
5.86	7.53	8.37	4.74	6.64	8.54	4.74	6.64	8.54	2.51	4.28	5.86	2.12	3.54	4.95	2.51	4.28	5.86
3.54	4.95	6.36	3.54	4.95	6.36	4.95	6.36	7.07	2.51	4.28	5.86	2.51	4.28	5.86	4.18	5.86	7.53
3.54	4.95	6.36	4.18	5.86	7.53	4.95	6.36	7.07	5.86	7.53	8.37	2.74	3.84	4.93	4.74	6.64	8.54
0.71	2.12	3.54	2.12	3.54	4.95	0.84	2.51	4.18	2.51	4.28	5.86	2.51	4.28	5.86	4.18	5.86	7.53
0.84	2.51	4.18	2.51	4.28	5.86	2.51	4.28	5.86	2.51	4.28	5.86	2.51	4.28	5.86	4.18	5.86	7.53
2.85	4.74	6.64	2.51	4.28	5.86	0.84	2.51	4.18	0.84	2.51	4.18	0.95	2.85	4.74	2.51	4.28	5.86
2.51	4.28	5.86	2.51	4.28	5.86	4.18	5.86	7.53	2.51	4.28	5.86	4.18	5.86	7.53	2.12	3.54	4.95
7.53	8.37	8.37	6.36	7.07	7.07	5.86	7.53	8.37	0.84	2.51	4.18	2.51	4.28	5.86	0.71	2.12	3.54
4.74	6.64	8.54	2.51	4.28	5.86	2.51	4.28	5.86	0.84	2.51	4.18	2.51	4.28	5.86	5.86	7.53	8.37
2.12	3.54	4.95	0.71	2.12	3.54	2.51	4.28	5.86	0.84	2.51	4.18	0.84	2.51	4.18	0.95	2.85	4.74
4.95	6.36	7.07	4.95	6.36	7.07	3.54	4.95	6.36	0.84	2.51	4.18	0.84	2.51	4.18	2.51	4.28	5.86
2.85	4.74	6.64	2.51	4.28	5.86	0.95	2.85	4.74	2.51	4.28	5.86	0.84	2.51	4.18	2.12	3.54	4.95
1.64	2.74	3.83	2.12	3.54	4.95	0.55	1.64	2.74	0.84	2.51	4.18	1.64	2.74	3.83	0.84	2.51	4.18

D								
T1			T2			T3		
l	m	u	l	m	u	l	m	u
0.84	2.51	4.18	2.51	4.28	5.86	0.84	2.51	4.18
0.84	2.51	4.18	0.95	2.85	4.74	0.84	2.51	4.18
0.84	2.51	4.18	0.71	2.12	3.54	2.51	4.28	5.86
2.85	4.74	6.64	0.84	2.51	4.18	0.95	2.85	4.74
0.95	2.85	4.74	0.84	2.51	4.18	0.84	2.51	4.18
2.12	3.54	4.95	0.71	2.12	3.54	0.55	1.64	2.74
0.84	2.51	4.18	0.84	2.51	4.18	0.84	2.51	4.18
2.51	4.28	5.86	0.71	2.12	3.54	0.55	1.64	2.74
2.51	4.28	5.86	0.84	2.51	4.18	2.51	4.28	5.86
0.84	2.51	4.18	0.84	2.51	4.18	0.95	2.85	4.74
2.51	4.28	5.86	0.84	2.51	4.18	0.71	2.12	3.54
0.84	2.51	4.18	0.84	2.51	4.18	2.51	4.28	5.86
0.95	2.85	4.74	0.84	2.51	4.18	0.84	2.51	4.18
2.51	4.28	5.86	0.71	2.12	3.54	0.84	2.51	4.18
0.84	2.51	4.18	0.84	2.51	4.18	0.84	2.51	4.18
0.84	2.51	4.18	0.84	2.51	4.18	2.51	4.28	5.86
1.64	2.74	3.83	0.55	1.64	2.74	0.71	2.12	3.54

The utilization of the suggested Z-MOORA method is depicted in Table 14, showcasing the results in the context of uncertainty in risk factors and the reliability of risks. The achieved results are presented in Table 15.

Table 14

Standardized fuzzy evaluation matrix

Risks	Z-MOORA				
	$\tilde{y}_i$			$\bar{y}_i$	Rank
	l	m	u		
R1	0.052	0.108	0.180	0.113	5
R2	0.004	0.029	0.089	0.040	16
R3	0.078	0.152	0.232	0.154	2
R4	0.088	0.169	0.261	0.173	1
R5	0.049	0.109	0.194	0.117	4
R6	0.037	0.082	0.147	0.089	7
R7	0.048	0.102	0.176	0.108	6
R8	0.013	0.046	0.104	0.054	14
R9	0.017	0.065	0.139	0.073	11
R10	0.010	0.045	0.111	0.055	13
R11	0.025	0.073	0.147	0.081	10
R12	0.076	0.123	0.170	0.122	3
R13	0.027	0.077	0.154	0.085	8
R14	0.008	0.037	0.093	0.045	15
R15	0.036	0.078	0.136	0.083	9
R16	0.013	0.051	0.121	0.061	12
R17	0.006	0.025	0.062	0.030	17

Based on the proposed approach and Table 15, R4, R3, and R12 are the top three risks with values of 0.173, 0.154, and 0.122, respectively. These risks are considered serious and require planning for implementing corrective or preventive measures. On the other hand, R17 with a value of y ̄_i=0.030 is ranked last, and given the limited resources of the organization, no immediate corrective action is required. Overall, the proposed approach has successfully distinguished between different risk scenarios and provided a comprehensive prioritization that can assist decision-makers in focusing on the most critical risks. By prioritizing downtime and resource constraints, the implementation of corrective or preventive measures can lead to improved system performance.

Table 16 displays a comparison between the final risk ranking achieved using the Z-MOORA approach and other traditional techniques, such as fuzzy MOORA and standard FMEA.

Table 16
Contrasting the ranked outcomes from the proposed methodology with conventional techniques

Risks	Conventional FMEA		Fuzzy MOORA		Z-MOORA	
	RPN	Rank	$\bar{y}_i$	Rank	$\bar{y}_i$	Rank
R1	70	2	0.111	6	0.113	5
R2	6	13	0.032	17	0.040	16
R3	64	3	0.142	1	0.154	2
R4	80	1	0.141	2	0.173	1
R5	40	7	0.102	8	0.117	4
R6	56	4	0.127	4	0.089	7
R7	56	4	0.123	5	0.108	6
R8	45	6	0.058	12	0.054	14
R9	30	8	0.069	10	0.073	11
R10	12	10	0.048	16	0.055	13
R11	48	5	0.081	9	0.082	10
R12	10	11	0.127	3	0.123	3
R13	12	10	0.068	11	0.086	8

Risks	Conventional FMEA		Fuzzy MOORA		Z-MOORA	
	RPN	Rank	$\bar{y}_i$	Rank	$\bar{y}_i$	Rank
R14	18	9	0.049	15	0.046	15
R15	9	12	0.104	7	0.083	9
R16	12	10	0.056	13	0.062	12
R17	18	9	0.052	14	0.031	17

Table 16 reveals that based on the traditional Risk Priority Number (RPN), R4, R1, and R3 are ranked first, second, and third with RPN values of 80, 70, and 64, respectively. R6 and R7 are jointly placed in the fourth priority with an RPN of 56. The RPN-based prioritization categorizes the risks into thirteen groups, indicating an incomplete prioritization that can cause ambiguity for decision-makers in risk management and planning corrective/preventive measures. This may be due to the lack of assigning different weights to the SOD factors based on experts' opinions and organizational conditions, and the failure to consider the uncertainty in the values of these factors. The fuzzy MOORA method improves the prioritization by considering the uncertainty of three factors using fuzzy theory and the FBWM method to weight them. However, there is a problem with the reliability of decision making in this method. The proposed Z-MOORA method addresses this issue by combining the meanings of uncertainty and reliability of risk points using the Z-Number theory. According to the rankings based on the Z-MOORA method in Table 16, R4 is ranked first, followed by R3 in the second priority. These two risks have higher values of S and O, indicating that reducing their severity and probability of occurrence should be a priority. For example, the prescription for R4, which is an incomplete drug order, needs to be reviewed and rewritten, and complete drug order forms with patient information can be used to prevent R3, which requires weight/height for dosage.

Risk R12, ranked third, has a very high severity of occurrence, and independent double-checking should be performed to reduce its severity and probability of occurrence. By comparing the results of the Z-MOORA and conventional FMEA methods, risks that are more important in the most important factors of RPN are placed in higher priorities, resulting in a completer and more differentiated prioritization of risks (Figure 3).

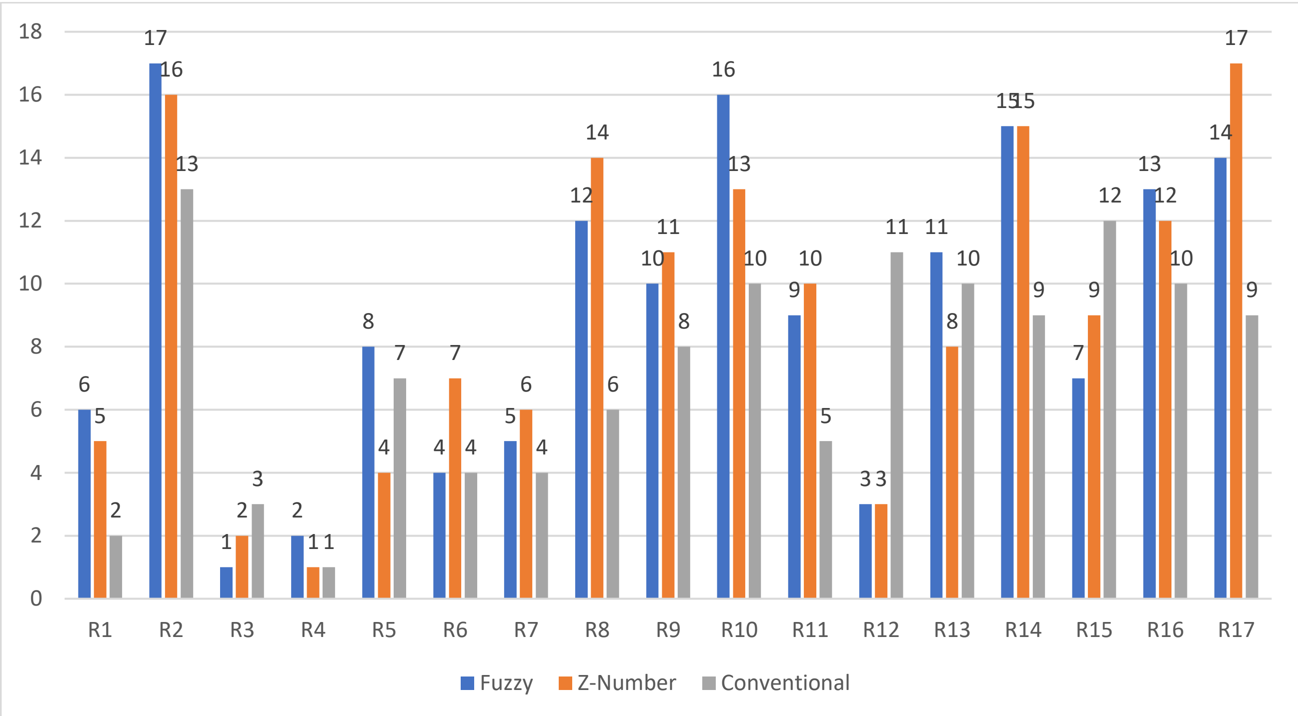

Figure 3. Evaluating the prioritization of HSE (Health, Safety, and Environment) risks

5.1. Sensitivity analysis

A sensitivity analysis was conducted by varying the weights of the criteria in three different scenarios (Table 17). Case 0 displays the precise weights of the criteria obtained through the Z-SWARA method in this study. To evaluate how the ranking of different positions changes under different conditions, the precise weights were assigned to the SOD factors and converted to cases 1 and 2. The results of the sensitivity analysis for ranking the 17 failure modes and different conditions are shown in Table 18.The collective decisions of three decision-making groups showed that the order of importance of SOD factors is S, O, and D, respectively. According to Table 18, R3 is ranked first in case 0 due to the high weight of S, while in cases 1 and 2, it is ranked second due to the low weight of S. In cases where R4 is ranked fifth in case 0, it is ranked first in cases 1 and 2 due to the high weights of D and O. The same trend can be observed for other criteria and failure modes. This shows that the weights of the criteria can significantly impact the final ranking of failure modes. Therefore, determining acceptable weights for the criteria based on the real situation, importance, and advantage is crucial for prioritizing different errors and subsequent treatment measures.

In summary, the sensitivity analysis reveals that the proposed Z-MOORA approach is sensitive to the weights of the criteria used in the decision-making process (Figure 4). It is essential to consider the real situation and the importance of each criterion to determine acceptable weights, which can lead to more accurate and reliable prioritization of risks.

Table 17
Factors' significance weights in relation to the analyzed scenarios

	S	O	D
Case 0	0.429951	0.255809	0.31552
Case1	0.379951	0.205809	0.41552
Case 2	0.329951	0.455809	0.21552

Table 18
Ranking outcomes of risk scenarios in connection to the assessed scenarios

	Case 0	Case 1	Case 2
R1	6	5	6
R2	17	17	17
R3	1	2	2
R4	5	1	1
R5	8	4	4
R6	3	7	7
R7	4	6	3
R8	12	15	12
R9	10	11	10
R10	16	13	14
R11	9	10	9
R12	2	3	5
R13	11	8	8
R14	15	16	16
R15	7	9	11
R16	13	12	13
R17	14	14	15

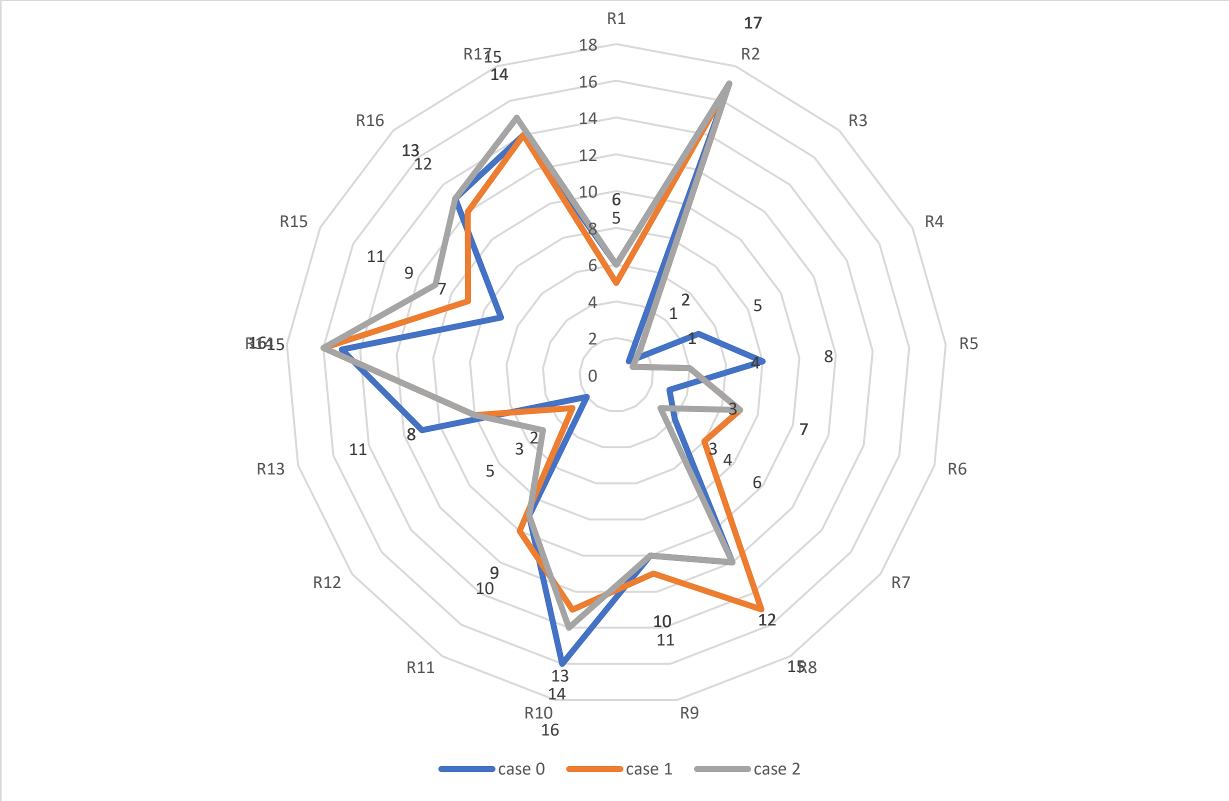

Figure 4. Sensitivity analysis for Z-MOORA

6. Conclusion

Nowadays, risk management and improving reliability in the pharmaceutical process, especially in the area of drug ordering and prescribing, are of particular importance. Incorrect drug prescription can cause serious side effects and even death for patients. The FMEA method is one of the most common and widely used risk analysis methods in various industries, which can also be used to identify and prioritize risk states in drug ordering and prescribing. However, the weaknesses and limitations of this method have led some researchers to seek to improve this common method. The proposed decision-making approach in this study combines the Z-SWARA and Z-WASPAS methods with the FMEA method to address some of the weaknesses of the RPN score. By using these methods, in addition to considering uncertainty in determining the weighting of factors and prioritizing failure modes, trustworthiness is also taken into account. In other words, since the views of different decision-making team members are not always certain in implementing the FMEA method, this approach uses both uncertainty and trustworthiness elements, which leads to a complete prioritization of failure modes. This method can provide decision-makers with a complete and reliable prioritization in examining risks related to drug ordering and prescribing. Generally, to improve the pharmaceutical process, it is necessary to require weight measurement for all patients, update or change the standard form, or use electronic ordering, create a quiet and calm environment, and perform independent double-checks. It should be noted that the lack of consideration of causality in failure modes is the main limitation of this study. In addition, the lack of importance-urgency calculation and uncertainty in decision-making and assessing the relative importance between experts are other issues that can be addressed in future research using the R, G, and evidence-based theory.

Author Contributions
Conceptualization, methodology, software, validation, formal analysis, investigation, S.J.G, and S.S.; resources, data curation, S.S.; writing—original draft preparation, writing—review and editing, S.J.G., and S.S.; supervision, S.J.G. All authors have read and agreed to the published version of the manuscript.

Funding
This research received no external funding.

Data Availability Statement
Data will be made available on request.

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.

Acknowledgement
This research was not funded by any grant.

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