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A New Extended Approach to Reduce Admission Time in Hospital Operating Rooms Based on the FMEA Method in an Uncertain Environment

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ABSTRACT

Operating rooms (ORs) are one of the essential hospital resources and optimal management can result in efficient OR usage. The admission time reduction before surgery in the ORs can lead to on-time surgery and efficient use of ORs. This study addresses this issue by identifying the main failure modes that cause delays in ORs. The conventional methodology known as Failure Mode and Effects Analysis (FMEA) represents one of the prevailing techniques utilized for the purpose of ascertaining failure modes within a given process. This involves the assignment of numerical scores to each failure mode, with the intention of utilizing the resultant Risk Priority Number (RPN) to facilitate the identification of said failure modes. However, RPN scoring has been criticized for some deficiencies. This study proposes a three-phase approach to address some of the shortcomings of the FMEA method. The initial stage involves utilizing the FMEA approach to recognize failure modes and assess the crucial elements of RPN. Following this, the second stage employs the Z-BWM technique and expert insights to determine the weights of the five essential factors. Lastly, in the third phase, risks are prioritized using the proposed Z-ARAS method based on the outputs of the previous phases. This approach considers the uncertainty in the determining factors and assigns different weights to them, while also taking into account the reliability of the risks through the Z-Number theory. Finally, comparing the proposed approach with other traditional approaches, reinforces the usefulness of the proposed method in evaluating failure modes in OR management.

1. Introduction

Operating rooms (ORs), such as casualty rooms, are one of the most productive sectors in hospitals [1]. Delays in the ORs can negatively affect efficiency and the working environment [2]. Late start indicates a noticeable wait time for staff and patients and a waste of resources [3]. Its efficient utilization requires multidisciplinary teamwork, particularly the significant role of supporting services

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in decreasing OR delays [4]. Human errors and system deficiencies are the main reasons for any OR delay. Delays can potentially happen both before and during the scheduled surgery, which may involve delays in reaching the operating rooms and during the actual procedure. However, solutions for inefficiencies in the ORs can only be organized if the reasons for delays are better understood [5], [6].

Addressing this issue is achievable through a better understanding of the flow in the ORs [7]. Reducing the lead time between surgeries in ORs is a critical element that increases access to care for patients and surgeon [8]. One way of raising OR time is by declining non-operative time, ideally without further capital or human resources. Decreasing admission time before the surgery can play an essential role in managing time and minimizing delays, which can reduce start time delays in OR [9].

There are various methods to reduce preoperative delays in ORs, such as optimization method [10], multivariate regression analysis [11], logic model based on Benders' methods [12], multi-objective model based on decision-making style [13], meta-heuristic approach [13], genetic algorithm [14], simulation [15], [16], machine learning [17], Answer Set Programming (ASP) [18], and Six Sigma [19].

Failures and adverse events are one of the most significant challenges to health systems at the international level [20]. Thus, delay in preoperative admission is a set of failure modes in the process [21]. The FMEA is a proactive and systematic method that assesses a process to define where and how it might fail [22-24]. The FMEA method is commonly used and highly regarded in the healthcare industry [25-27], especially healthcare waste management [27-29]. Prioritizing the failure modes is done by a Risk Priority Number (RPN), which is as follows:

$RPN=S\times O\times D$

O shows failure occurrence or frequency, S is the failure severity, and D shows the detection before its effects of possible failures [30]. Nevertheless, besides the many advantages of FMEA, team motivation, lack of full ranking, and the presumption of the same importance of determinant criteria are the main weaknesses [31].

To address the shortcomings in RPN scoring, the application of Multiple Criteria Decision Making (MCDM) has emerged as an effective approach [32]. In recent times, there has been a growing interest among researchers in utilizing MCDM techniques for complex decision-making processes [33-35]. For instance, Moons et al. applied the Analytic Network Process (ANP) to measure the performance of the ORs supply chain. Supporting hospital logistics managers is the main aim of this study [36]. Momen et al. utilized Fuzzy Best-Worst Method (FBWM) for prioritizing factors that may cancel surgical operations in ORs to consider both the consequences of surgical cancellation on hospitals and patients [37]. Hamid et al. utilized the DEA method to improve the efficiency of any healthcare system. This problem is addressed through the minimization of the waiting time of elective patients, overutilization and underutilization costs of ORs, and the total completion time of surgeries [38]. Cappanera et al. addressed the conflict of stakeholders' priorities in surgical scheduling based on goal programming (GP); the proposed method lets specify the quantity and type of surgeries scheduled in each OR [39]. Li et al. employed the GP method intending to schedule surgeries in OR with regards to the limited sources; the result of this study is scheduling elective surgeries optimally according to the surgeon accessibility and operating rooms over a planning horizon [40]. O'Neill and Dexter found out that DEA is an appropriate tool to improve the efficiencies of OR concerning financial data and market growth. Also, it is concluded that DEA is a proper technique for hospitals to discover the potential to grow different specialties of inpatient surgery [41]. Ozkarahan scheduled surgeries in OR based on GP, addressed by minimizing idle time and overtime and enhancing surgeon, patient, and staff satisfaction [42]. Reducing patients' time waiting for surgery in the operating room is a significant concern. Unfortunately, this issue has been the minimal focus in the current literature. By identifying potential problems in the admission process, we can decrease the average lead time in the operating room and improve efficiency.

This research has focused on finding the main failure modes in the admission process in OR. The main contribution is to provide a procedure-based typical FMEA method. The proposed integrated approach covers the deficiencies of the typical RPN method. The inclusion of cost and time criteria in RPN scoring aims to effectively minimize the duration of the admission process in operating rooms (ORs). Essentially, prolonging surgeries in ORs can result in increased costs and time consumption. In this study, ten primary failure modes that contribute to lead time in the admission process were initially identified based on expert opinions. To assign weights to the five criteria of RPN, a combination of Z-number and Best Worst Method (ZBWM) was employed. The BWM method, introduced by [43], was specifically chosen to overcome the limitations of previous MCDM methods. The BWM method has been used in different areas [44], [45] and extended by various fuzzy sets and numbers [46], [47].

The Z-number theory is valuable in improving the credibility of research findings, particularly those related to the COVID-19 pandemic [48]. Z-number is also combined with MCDMs to consider the uncertainty and reliability of the RPN criteria values for each failure mode [49]. By assigning varying weights to the criteria of Risk Priority Number (RPN) based on their significance, the limitations of conventional Failure Mode and Effects Analysis (FMEA) can be resolved. In the subsequent phase, an extended version of the Additive Ratio Assessment, known as Z-ARAS (which incorporates Z-number theory to account for reliability and uncertainty), is employed to rank nine failure modes. This approach effectively addresses the issues and incorporates a more comprehensive evaluation process. The addictive ratio assessment (ARAS) approach was primarily introduced by Zavadskas and Turskis [50]. ARAS method can be used in various areas, including environmental and healthcare issues. ARAS approach is used to decrease greenhouse gas emissions [51]. Sen 2017 [52] employed the ARAS-G method to address the problem of hospital location for healthcare management.

The current study is structured as follows: Section 2 presents an explanation of the fundamental theorem of Z-number, along with a discussion on the BWM and ARAS methods and the transformation rules for Z-BWM and Z-ARAS. The third section outlines the research framework, which is focused on identifying nine primary failure modes that lead to MEs. In Section 4, the validation results of the proposed method are presented, which includes a comparison with conventional approaches such as FMEA and Fuzzy-ARAS. Finally, Section 5 includes suggested measures for mitigating or eliminating failure modes, as well as potential areas for future research.

2. Methodology

2.1 Preliminary Concepts

To explain the proposed approach, firstly, the fuzzy set theory is explained as a prerequisite concept for the proposed method. Then, the Z-number method was introduced as a way to improve reliability. The preliminary definitions and mathematical equations were presented too. Following that, transformation rules were thoroughly discussed based on the Z-Number theory. Finally, the steps for implementing Z-BWM and Z-ARAS were presented.

2.1.1 Fuzzy sets

In 1965, Zadeh established the concept of a fuzzy set [53]. A fuzzy set is defined by a membership function that assigns a value within the real unit range [54]. There are multiple definitions for fuzzy sets, some of which are outlined below.

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 $\mu_A(x): X \to [0,1]$ 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:

If the triangular fuzzy number (TFN) assigns a triple (l,m,u) value, in this case, m is middle bound, l and u denote the lower bounds and upper bounds [55]. Also, the membership function is specified by Eq. (2).

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

Definition 3: If $\tilde{A} = \{l_1, m_1, u_1\}$, $\tilde{B} = \{l_2, m_2, u_2\}$ be TFNs and λ defines as a fixed number it is higher than zero, the basic calculations are as follow:

$$\tilde{A} \oplus \tilde{B} = (l_1 + l_2, m_2 + m_2, u_1 + u_2) \tag{3}$$

$$\tilde{A} \otimes \tilde{B} = (l_1 l_2, m_2 m_2, u_1 u_2) \tag{4}$$

$$\tilde{A} - \tilde{B} = (l_1 - u_2, m_1 - m_2, u_1 - l_2) \tag{5}$$

$$\tilde{A} \,/\, \tilde{B} = (l_1 / u_2, m_2 / m_2, u_1 / l_2) \tag{6}$$

$$\tilde{A} \,/\, \tilde{B} = (l_1 / u_2, m_2 / m_2, u_1 / l_2) \tag{7}$$

And the arithmetic distance between $\tilde{A}$ and $\tilde{B}$ is calculated with relation (8).

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

2.1.2 Z-Number theory

The Z-number theory was suggested by Zadeh in 2011 [49]. Z-number is a general form of the uncertainty concept for calculating data reliability. Unlike fuzzy theory, Z-number considers the expert's self-confidence level in judging the subject under discussion. Combining this theory with MCDM approaches can produce more reliable and validated results. [31]. A Z-number is a couple of fuzzy numbers showed by $Z = (A, B)$, in which element A is a fuzzy subset of the range X , and the element B is indicating the reliability of the component. These fuzzy numbers are usually mentioned as linguisitc forms to solve the uncertainty problem. According to the Eq. (9), the triple set (X, A, B) is considered as Z-Number, namely a general constraint on X [49].

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

Present constraint is presented as a possible constraint that describes the probability distribution of X. Particularly, it can be represented as an Eq. (10).

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

Where, μ_A is membership function of A and a restriction linked to $R(X)$ and *u* shows a general value of *X*. Consequently, *X* is a random variable that have a probability distribution $R(X)$ which operates as a potential constraint on *X*. Potential constraint and *p* which is the probability density of *X*, are shown in Eqs. (11) and (12).

$$R\left(X\right) = X\ is\ p \tag{11}$$

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

In Eq. (12) the partial derivative of u is signed as du .

2.1.3 The graded mean integration representation

The graded mean integration representation, $R(\tilde{a})$ of a TFN, $\tilde{a}$ demonstrates the ranking [54, 55]. For completing the graded mean integration representation that defined as follows:

$$R(\tilde{a}) = \frac{(l_i + 4m_i + u_i)}{6} \tag{13}$$

Where $\tilde{a} = (l_i, m_i, u_i)$ and $R(\tilde{a})$ is TFN of $\tilde{a}$.

2.1.4 Conversion rules of Z-Number linguistic variables

Let a Z-number signifies as $Z = (A, B)$ and $\{\tilde{A} = (x, u_{\tilde{A}}) \mid x \in [0,1]\}, \{\tilde{B} = (x, u_{\tilde{B}}) \mid x \in [0,1]\}$ defines as triangular membership function, The reliability weight of Z-number names as α .

$$\alpha = \frac{\int x\mu_\beta\, dx}{\int \mu_\beta dx} \tag{14}$$

The weighted Z-Numbers define using the following formula:

$$\tilde{Z}^{\alpha} = \{(x, \mu_{\tilde{A}^{\alpha}}) \mid \mu_{\tilde{A}^{\alpha}}(x) = \alpha\mu_{\tilde{A}^{\alpha}}(x), x \in [0,1]\} \tag{15}$$

The final fuzzy form needs two components. The rules for transforming linguistic variables of the first component of the fuzzy number are shown in Table 1. The linguistic definition of selected criteria (SODCT) based on decision-makers (DMs) view are classified in five ranges.

Table 1
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)	(3/2,2,5/2)
Very Influential (VI)	(5/2,3,7/2)
Absolutely Influential (AI)	(7/2,4,9/2)

The second element can be conducted based on defined linguistic variables. Table 2 shows the conversion rules of reliability.

Table 2
Conversion directions of reliability

Linguistic forms	Membership function
Extremely Low (EL)	(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)
Extremely High (EH)	(0.7,0.9,1)

By combining Table 1 as a conversion rule for linguistic variables and Table 2 as conversion rules for linguistic variables, considering reliability, the conversion directions for Z-number linguistic variables are achieved. For instance, if the Z-Number defines as $Z = (A, B)$ and decision-maker determines Fairly Important (FI) by considering High (H) reliability, the Z-Number transforms as $Z = [(3\backslash 2, 2, 5\backslash 2), (0.5, 0.7, 0.9)]$. By using Eq. (14), crisp reliability is as follows:

$$\alpha = \frac{\int x\mu_\beta \, dx}{\int \mu_\beta dx} = 0.7$$

Then, based on Eq.15, the reliability weight is added to the constraint, and the result is as follow:

$$\tilde{Z}^{\alpha} = [(\sqrt{0.7} * 3\backslash 2, \sqrt{0.7} * 2, \sqrt{0.7} * 5\backslash 2)] = (1.26, 1.68, 2.10)$$

According to Table 1 and Table 2, all the members transformed, which is shown in Table 3.

Table 3
Conversion directions of Z-Number to TFN

Linguistic forms	Membership function	Linguistic forms	Membership function
(EI, EL)	(1,1,1)	(FI, H)	(1.26,1.68,2.10)
(EI, L)	(1,1,1)	(FI, EH)	(1.43,1.90,2.38)
(EI, M)	(1,1,1)	(VI, EL)	(0.79,0.95,1.11)
(EI, H)	(1,1,1)	(VI, L)	(1.37,1.641.92)
(EI, EH)	(1,1,1)	(VI, M)	(1.78,2.13,2.49)
(WI, EL)	(0,21,0.32,0.47)	(VI, H)	(2.10,2.52,2.94)
(WI, L)	(0.37,0.55,0.82)	(VI, EH)	(2.38,2.85,3.33)
(WI, M)	(0.47,0.71,0.82)	(AI, EL)	(1.11,1.26,1.42)
(WI, H)	(0.56,0.84,1.26)	(AI, L)	(1.92,2.19,2.47)
(WI, EH)	(0.63,0.95,1.43)	(AI, M)	(2.49,2.84,3.20)
(FI, EL)	(0.47,0.63,0.79)	(AI, H)	(2.94,3.36,3.78)
(FI, L)	(0.82,1.10,1.37)	(AI, EH)	(3.33,3.80,4.28)
(FI, M)	(1.07,1.42,1.78)		

2.1.4 Z-BWM Approach

The best-worst method (BWM) is a novel MCDM technique introduced by Rezaei in 2015 [43]. BWM is a valuable technique for specifying the decision criteria weights. BMW has a crucial feature that allows for more robust comparisons, even with minimal comparative data [56-58]. Two central problems are encountered using the pair comparison method [59]. The main issue is that the process could be shorter because many comparisons are needed to create a complete pairwise comparison matrix.

The second issue is the inconsistency in comparisons, which may arise due to insufficient information or lack of attention [60]. Therefore, similarly, pairwise comparison problems are reduced by using ZBWM. Another advantage of this method is that ZBWM uses a very structured method to collect the data needed for couple comparisons, which leads to very valid results that can be considered by the experts [61]. Afterward, the combination of Z-number theory with BWM, named Z-BWM, will be examined and evaluated. As stated, the Z-number method is combined with the BWM method to solve the reliability assessment problem of BWM. In this way, MCDM issues can be reliably evaluated. Some steps must be taken to implement the ZBWM method. In the following, the steps are examined comprehensively.

Step One: Forming the Decision Criteria

Decision criteria include a set of different criteria. For example, the decision criteria for n criteria will be $\{C_1, C_2, ..., C_n\}$.

Step Two: Determining the best and the worst criteria

The present step completes by determining the best and the worst decision criteria according to decision-makers' point of view. According to the definition, the best criterion known as the most favorable criterion (C_B), and the worst criterion known as the least favorable criterion (C_W)based on decision-makers (DMs).

Step Three: Implementation of the Z-Number reference comparing for the best and worst criteria Step three consists of two parts for best and worst criterion. For the best criterion, first paired comparison completes, where for $\tilde{a}_{ij}$ that i is the best component and in our study c_i is the best criterion (C_B) Second pairwise comparison completes, of $\tilde{a}_{ij}$ if *j* is the worst one. In this study c_j is the worst criterion (C_W) According to the DMs linguistic terms showed in Table 3, the Z-number priority of the best criteria can be calculated overall criteria. The fuzzy vector is as below:

$$\tilde{A}_B = (\tilde{a}_{B1}, \tilde{a}_{B2}, ..., \tilde{a}_{Bn}) \tag{16}$$

Where $\tilde{a}_{Bj}$ defines as the fuzzy priority of the best criterion over the criterion j, $j = (1, 2, ..., n)$. Similar above mentioned, the fuzzy preference of all criteria is determined by the worst criterion.

Therefore, the vector Eq. (17) is established for the worst criterion compared over others.

$$\tilde{A}_W = (\tilde{a}_{1W}, \tilde{a}_{2W}, ..., \tilde{a}_{nW}) \tag{17}$$

Where $\tilde{a}_{iW}$ defines as the fuzzy priority of the i $, i = (1, 2, ..., n)$ over the worst criterion (C_W)

Step 4: Determining the fuzzy optimal weight $(\tilde{w}_1^*, \tilde{w}_2^*, ..., \tilde{w}_n^*)$

The optimal fuzzy weight obtains based on these two equations:

$$\tilde{W}_B / \tilde{W}_j = \tilde{a}_{Bj} \tag{18}$$

$$\tilde{W}_j / \tilde{W}_W = \tilde{a}_{jW} \tag{19}$$

To identify the optimal fuzzy weight, the Eq. (20) are presented.

$$Min\ Max\ \left\{ \left\| \frac{\tilde{W}_B}{\tilde{W}_j} - \tilde{a}_{Bj} \right\|, \left\| \frac{\tilde{W}_j}{\tilde{W}_W} - \tilde{a}_{jW} \right\| \right\}$$
$$s.t \begin{cases} \sum_{j=1}^{n} R(\tilde{W}_j) \\ l_j^W \le m_j^W \le u_j^W \\ l_j^W \ge 0 \\ j = 1, 2, ..., n \end{cases} \tag{20}$$

So that $\tilde{W}_B = \left(l_B^W, m_B^W, u_B^W\right)$. $\tilde{a}_{Bj} = \left(l_{Bj}, m_{Bj}, u_{Bj}\right)$ ، $\tilde{W}_W = \left(l_W^W, m_W^W, u_W^W\right)$ ، $\tilde{W}_j = \left(l_j^W, m_j^W, u_j^W\right)$ ، . $\tilde{a}_{jW} = \left(l_{jW}, m_{jW}, u_{jW}\right)$

The problem can be defined as nonlinear form as follows:

$$Min\ \tilde{\xi}$$

$$s.t. \begin{cases} \left|\dfrac{\tilde{W}_B}{\tilde{W}_j} - \tilde{a}_{Bj}\right| \le \tilde{\xi} \\ \left|\dfrac{\tilde{W}_j}{\tilde{W}_W} - \tilde{a}_{jW}\right| \le \tilde{\xi} \\ \sum_{j=1}^{n} R\left(\tilde{W}_j\right) = 1 \\ l_j^W \le m_j^W \le u_j^W \\ l_j^W \ge 0 \\ j = 1, 2, \ldots, n \end{cases} \tag{21}$$

Where $\tilde{\xi} = \left(l^{\xi}, m^{\xi}, u^{\xi}\right)$ and $l^{\xi} \le m^{\xi} \le u^{\xi}$. In this part, we assume that $\tilde{\xi}^* = \left(k^*, k^*, k^*\right), k^* \le l^{\xi}$. The final version of the equation is presented as follows:

$$\min \xi^k$$

$$s.t. \begin{cases} \left|\dfrac{\left(l_B^w, m_B^w, u_B^w\right)}{\left(l_j^w, m_j^w, u_j^w\right)} - \left(l_{Bj}, m_{Bj}, u_{Bj}\right)\right| \le \left(k^*, k^*, k^*\right) \\ \left|\dfrac{\left(l_j^w, m_j^w, u_j^w\right)}{\left(l_W^w, m_W^w, u_W^w\right)} - \left(l_{jW}, m_{jW}, u_{jW}\right)\right| \le \left(k^*, k^*, k^*\right) \\ \sum\limits_{j=1}^{n} R\left(\tilde{w}_j\right) = 1 \\ l_j^w \le m_j^w \le u_j^w \\ l_j^w \ge 0 \\ j = 1, 2, \ldots, n \end{cases} \tag{22}$$

Calculated and evaluated Results of the above equation are fuzzy optimum weights $\left(\tilde{w}_1^*, \tilde{w}_2^*, \ldots, \tilde{w}_n^*\right)$The value of each weight shows the importance of the intended criteria, which can influence the final results.

2.1.5 Z-ARAS method

The ARAS method is considered one of the most effective and applicable MCDM methods. This method was introduced by Zavadskas and Turskis [50]. When faced with real-world problems, it can be challenging to accurately determine the weight of alternative criteria and options based on those criteria [62]. The Fuzzy-ARAS method has been developed to cover the uncertainty. Data reliability was a significant issue unless Fuzzy-ARAS was used to solve various uncertainty problems. Therefore, combining Z-number with the ARAS method, which is more compatible with real-world cases, considers the reliability issue of data. The steps of the Z-ARAS method to reach a valid answer are as following ways:

Step one: Transforming linguistic variables

Selecting the linguistic variable by $\tilde{x}_{ij} : i = 1, 2, ..., m ; j = 1, 2, ..., n$ for other options according to the examined criteria. The linguistic variable is given in Table 4 for alternative options.

Table 4
Linguistic variables of failure modes

Linguistic variables	TFNs
Extremely Poor (EP)	(0,0,1)
Poor(P)	(0,1,3)
Medium Poor (MP)	(1,3,5)
Medium (M)	(3,5,7)
Medium Great (MG)	(5,7,9)
Great (G)	(7,9,10)
Extremely Great (EG)	(9,10,10)

The reliability of assigned linguistic variables for prioritizing the alternatives is determined based on Table 2. By using Table 4 and Table 2, all the members transformed into Table 5.

Table 5
Conversion of Z-number linguistic variables to TFNs based on Z-ARAS

LV	Membership function	LV	Membership function
(EG, EG)	(8.54,9.49,9.49)	(M, P)	(1.64,2.74,3.83)
(EG, G)	(7.53,8.37,8.37)	(M, EP)	(0.95,1.58,2,21)
(EG, M)	(6.36,7.07,7.07)	(MP, EG)	(0.95,2.85,4.74)
(EG, P)	(4.93,5.48,5.48)	(MP, G)	(0.84,2.51,4.18)
(EG, EP)	(2.85,3.16,3.16)	(MP, M)	(0.71,2.12,3,54)
(G, EG)	(6.64,8.54,9.49)	(MP, P)	(0.55,1.64,2.74)
(G, G)	(5.86,7.53,8.37)	(MP, EP)	(0.32,0.95,1.58)
(G, M)	(4.95,6.36,7.07)	(P, EG)	(0,0.95,2,85)
(G, P)	(3.84,4.93,5.48)	(P, G)	(0,0.84,2.51)
(G, EP)	(2.21,2.85,3.16)	(P, M)	(0,0.71,2.12)
(MG, EG)	(4.74,6.64,8.54)	(P, P)	(0,0.55,1,64)
(MG, G)	(4.18,5.86,7.53)	(P, EP)	(0,0.32,0.95)
(MG, M)	(3.54,4.95,6.36)	(EP, EG)	(0,0,0.95)
(MG, P)	(2.74,3.84,4.93)	(EP, G)	(0,0,0.84)
(MG, EP)	(1.58,2.21,2.85)	(EP, M)	(0,0,0.71)
(M, EG)	(2.85,4.74,6.64)	(EP, P)	(0,0,0.55)
(M, G)	(2.51,4.28,5.86)	(EP, EP)	(0,0,0.32)
(M, M)	(2.12,3.54,4.95)		

Step 2: Constructing a decision matrix:

ARAS method solves a problem based on m feasible options (rows) that are evaluated rely on n dimensions (columns). The primitive matrix based on expert opinion is created in the following way:

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{01} & \dots & \tilde{x}_{0j} & \dots & \tilde{x}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{x}_{i1} & \dots & \tilde{x}_{ij} & \dots & \tilde{x}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \dots & \tilde{x}_{mj} & \dots & \tilde{x}_{mn} \end{bmatrix}, \tag{23}$$

That $\tilde{x}_{ij}$ indicates the i alternative fuzzy value in terms of *j*. And $\tilde{x}_{0j}$ shows the optimum quantity of *j*.

Step 3: Ranking aggregation of alternative options according to each criterion ($\tilde{x}_{ij}$):

In this part the arithmetic mean is used to assemble and aggregate the rankings. To complete this part, we use the fuzzy-triangular numbers that, $\tilde{x}_{ijk} = \left(a_{ijk}, b_{ijk}, c_{ijk}\right), k = 1, 2, ..., K$ indicate the value of the i^{th}substitute according to the j^{th} criterion using the $k^{th}$of the expert or decision maker. We can define the final rating as:

$$\tilde{x}_{ij} = \left(a_{ij}, b_{ij}, c_{ij}\right), \qquad k = 1, 2, ..., K \quad , \tag{24}$$

Where is define:

$$a_{ij} = \frac{1}{K}\sum_{K=1}^{K} a_{ijk} \ , \ b_{ij} = \frac{1}{K}\sum_{K=1}^{K} b_{ijk} \ , \ c_{ij} = \frac{1}{K}\sum_{K=1}^{K} c_{ijk} \ . \tag{25}$$

Step 4: The optimum unknown amount of criterion *j*

By using Eqs. (26), (27) the optimal value can be determined as follows:

$$\tilde{x}_{oj} = \max_{i} \tilde{x}_{ij} \ ; The\ l\arg er,\ the\ better\ type, \tag{26}$$

$$\tilde{x}_{oj} = \min_{i} \tilde{x}_{ij} \ ; The\ smaller,\ the\ better\ type. \tag{27}$$

Step 5: Normalizing other decision matrices:

Normalization is used to prevent the problems of criteria with different dimensions. The optimal values or dimensionless weighted numbers are commonly in the closed range of 0 and 1. The final matrix of the normalization operations is determined as Eq. (28):

$$\tilde{\bar{X}} = \begin{bmatrix} \tilde{\bar{x}}_{01} & \dots & \tilde{\bar{x}}_{0j} & \dots & \tilde{\bar{x}}_{0n} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{\bar{x}}_{i1} & \dots & \tilde{\bar{x}}_{ij} & \dots & \tilde{\bar{x}}_{in} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{\bar{x}}_{m1} & \dots & \tilde{\bar{x}}_{mj} & \dots & \tilde{\bar{x}}_{mn} \end{bmatrix}, \tag{28}$$

The criteria for which the desired values are maxima are normalized based on Eq. (29).

$$\tilde{\bar{x}}_{ij} = \frac{\tilde{x}_{ij}}{\sum_{i=0}^{m} \tilde{x}_{ij}} \tag{29}$$

Step 6: Weighted normalized matrix

This step consists of (w_j) which is weights of criteria which is derived from Z-BWM and normalized fuzzy decision matrix, which is the result of the previous step. The equation is as follows:

$$\tilde{\hat{x}}_{ij} = \tilde{\bar{x}}_{ij} w_{j} \ . \tag{30}$$

Step 7: Optimality function

The optimality function is as follows:

$$\tilde{S}_i = \sum_{j=1}^{n} \tilde{\hat{x}}_{ij} \quad . \tag{31}$$

Where the maximum amount is the best, also minimum amount is the worst one.

Step 8: Defuzzification optimality function

Results of the previous stage are fuzzy numbers. Hence, for comparing the ranking of criteria, the results should be changed into crisp numbers. Best non-fuzzy performance method applied to transform fuzzy amounts to crisp numbers. The BNP result for the fuzzy number can be seen as follows:

$$BNP_i = \left[\left(U\tilde{S}_i - L\tilde{S}_i\right) + \left(M\tilde{S}_i - L\tilde{S}_i\right)\right] / 3 + L\tilde{S}_i \, . \tag{32}$$

Step 9: Utility degree (K_i)

The utility degree gain by comparing S_i with a best or maximum amount which defines as S_0:

$$K_i = \frac{S_i}{S_0} \tag{33}$$

Step 10: Ranking criteria

Finally, according to the decreasing order is arranged by K_i. The maximum K_i shows the importance of criteria.

3. Proposed approach

In order to assess and identify the risks associated with managing the admission time of OR, which is essential to reduce the human risks and costs of hospitals, it is necessary to identify significant Failure Modes (FMs) which result in malfunctions. There are main criteria that are important reasons for failure mode happening. In our study, the selected criteria are severity (S), occurrence (O), detection (D), cost (C), and time (T). The values of the quintuple criteria presented in Table 6.

Table 6
Rating for SODCT criteria

Rating	S	O	D	C	T
10	Hazardous with warning	Very high: almost inevitable failure	Absolute	Repair cost close to the original price	Repair time extremely high
9	Hazardous without warning	Very high: almost inevitable failure	uncertainty	The repair cost extremely high	Repair time extremely high
8	Very high	High: repeated failures	High: repeated failure	Repair cost high	Repair time high
7	High	High: repeated failures	High: repeated failure	Repair cost high	Repair time high
6	Moderate	Moderate: occasional failures	Moderate: occasional failures	The repair cost moderately high	Repair time moderate
5	Low	Moderate: occasional failures	Moderate: occasional failures	Repair cost moderate	Repair time moderate
4	Very low	Moderate: occasional failures	Moderate: occasional failures	The repair cost relatively low	Repair time moderate

Rating	S	O	D	C	T
3	Minor	Low: relatively few failures	Low: relatively few failures	Repair cost low	Repair time low
2	Very minor	Low: relatively few failures	Low: relatively few failures	The repair cost very low	Repair time low
1	None	Remote: failure is unlikely	Remote: failure is unlikely	Repair at nearly no cost	The repair cost very low

Finally, nine failure modes were selected for evaluation and ranking, as mentioned in Table 7. Then the reliability of failure modes is defined by three separate expert teams. The Z-BWM method was used for weighing criteria, and the Z-ARAS method was performed for ranking and evaluating failure modes. Eventually, the outcomes of Z-ARAS were compared with conventional FMEA and Fuzzy-ARAS. A conceptual framework of the suggested method of the present study is presented in Fig. 1.

Table 7
Failure modes of decrease admission time

Symbol	Failure Mode
FM_1	CRNA forgets to call report
FM_2	The patient arrives before the room is set up
FM_3	Monitor cable missing
FM_4	Missing supplies for a lab draw
FM_5	Physician delays in coming to room
FM_6	Tube not correctly placed
FM_7	Delay in obtaining postoperative chest X-ray
FM_8	Delay in when arterial ABG has drawn
FM_9	Delay in obtaining labs, delay in obtaining meds from pharmacy to replace electrolytes

CRNA: Certified registered nurse anaesthetics
ABG: Arterial blood gas

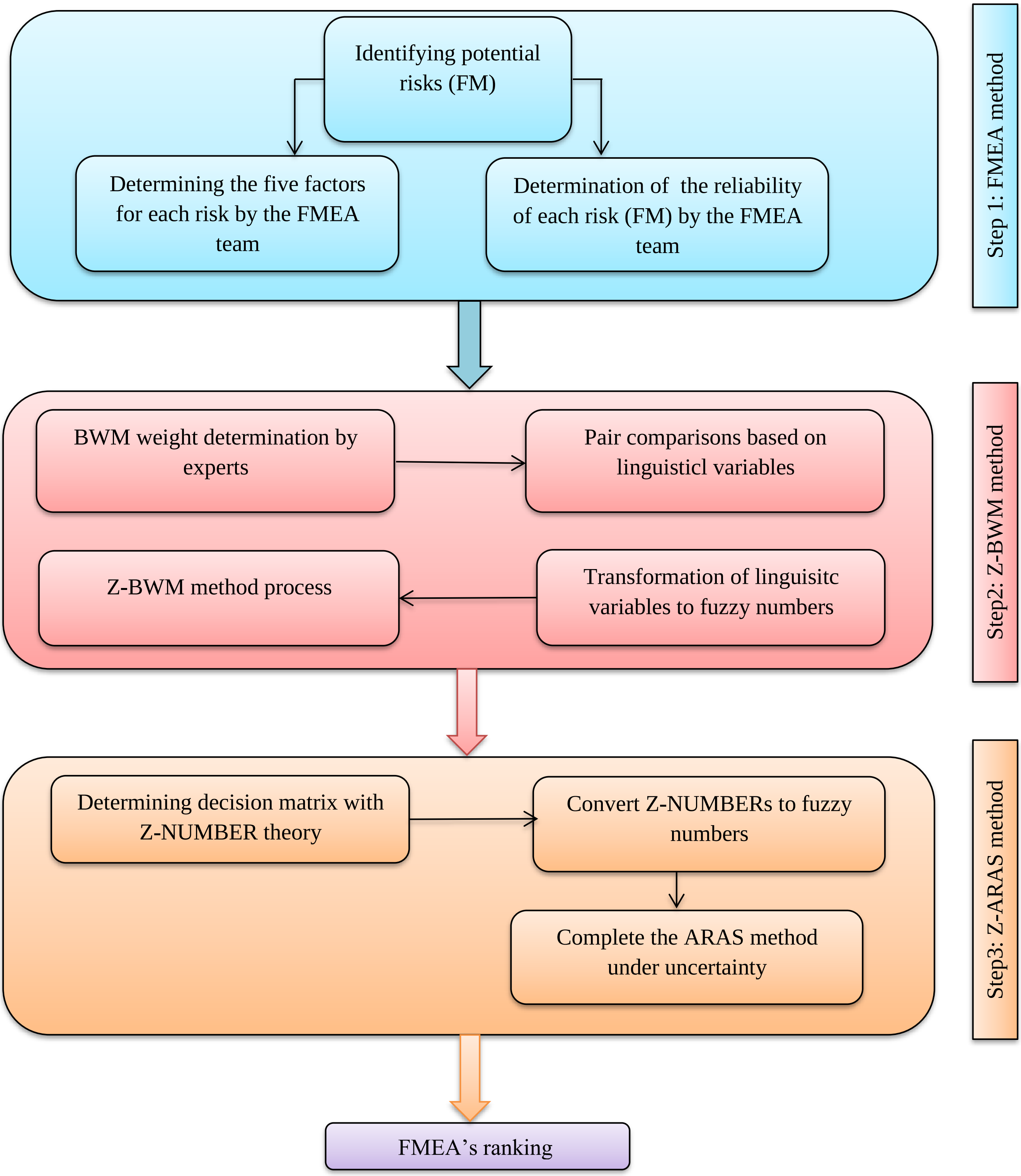

Fig. 1. Flowchart of the proposed approach

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4. Results

To implement the proposed approach for minimizing admission time in the ORs, initially, the values of the five criteria are determined by the experts who work in the FMEA team. The finding can be seen in Table 8.

Table 8

Scoring risk factors based on the FMEA team view

	S			O			D			C			T		
	DM1	**DM2**	**DM3**	**DM1**	**DM2**	**DM3**	**DM1**	**DM2**	**DM3**	**DM1**	**DM2**	**DM3**	**DM1**	**DM2**	**DM3**
FM_1	7	6	8	1	2	1	3	3	4	3	4	4	7	6	8
FM_2	6	5	7	5	4	6	2	3	1	3	5	4	8	6	7
FM_3	7	8	6	3	3	4	1	3	1	3	5	6	7	5	8
FM_4	8	7	9	6	5	6	2	2	1	3	5	4	7	6	7
FM_5	7	8	9	5	3	4	1	2	3	7	8	7	7	5	5
FM_6	9	7	8	3	4	4	6	5	5	4	5	4	6	7	6
FM_7	7	5	6	2	1	2	3	4	5	3	4	4	5	6	5
FM_8	6	8	7	4	5	3	4	5	6	3	2	1	7	5	6
FM_9	8	7	8	2	3	4	1	1	2	3	4	3	8	7	7

At this stage, the reliability of the indicators and the corresponding numbers obtained from decision-makers were first assessed by using the Z-number method. This step is for determining the decision-makers confidence level in numbers, and qualitative variables indicate the importance rate of indicators. After the complementation of a questionnaire by the teams and decision-makers, findings can be seen in Table 9.

Table 9

Linguistic variables for Z-Number forms of SODCT criteria

S	DM_1	(MG, G)	(MG,M)	(MG,M)	(G, EG)	(MG, EG)	(EG, EG)	(M, G)	(M, EG)	(G, G)
	DM_2	(G,G)	(MP,G)	(G,EG)	(MG,EG)	(MG,EG)	(M,M)	(MP,G)	(G,EG)	(M,EG)
	DM_3	(G,EG)	(M,EG)	(M,G)	(EG,M)	(G,M)	(MG,G)	(M,G)	(MG,M)	(G,G)
O	DM_1	(P,G)	(M,EG)	(P,EG)	(MG,EG)	(M,M)	(MP,EG)	(P,EG)	(M,EG)	(P,EG)
	DM_2	(MP,G)	(MP,G)	(P,M)	(M,G)	(P,G)	(M,M)	(EP,EG)	(M,G)	(MP,G)
	DM_3	(P,EG)	(MG,G)	(MP,M)	(MG,M)	(MP,EG)	(M,G)	(P,M)	(P,G)	(MP,M)
D	DM_1	(P,G)	(P,M)	(EP,G)	(P,M)	(P,G)	(MG,M)	(MP,G)	(MP,M)	(EP,M)
	DM_2	(MP,M)	(MP,G)	(MP,M)	(P,EG)	(P,G)	(M,EG)	(M,EG)	(M,EG)	(P,M)
	DM_3	(M,EG)	(EP,G)	(P,EG)	(EP,G)	(MP,EG)	(M,EG)	(M,M)	(MG,M)	(P,G)
C	DM_1	(MP,M)	(P,M)	(MG,M)	(MP,M)	(G,G)	(M,M)	(MP,M)	(MP,G)	(MP,EG)
	DM_2	(M,EG)	(M,EG)	(M,EG)	(MG,EG)	(EG,EG)	(MG,G)	(M,G)	(MP,M)	(M,EG)
	DM_3	(M,M)	(MP,G)	(MG,G)	(M,M)	(G,EG)	(M,M)	(M,EG)	(P,EG)	(MP,G)
T	DM_1	(G,G)	(G,G)	(MG,M)	(G,EG)	(MG,EG)	(MG,EG)	(M,M)	(MG,M)	(G,EG)
	DM_2	(MG,M)	(MG,M)	(M,M)	(MG,G)	(M,M)	(G,EG)	(MG,G)	(M,G)	(MG,G)
	DM_3	(G,EG)	(G,M)	(G,EG)	(G,M)	(M,G)	(MG,G)	(M,G)	(M,M)	(MG,M)

The next step is determining weights of quintuple criteria (SODCT) by using ZBWM method. In order to achieve this goal, the decision-makers determine best and worst criteria and their pairwise comparison and apply confidence level for their comparison (see Table 10).

Table 10
The value of Z-Number weights for SODCT

	Best	**S**	**O**	**D**	**C**	**T**
DM_1	S	(EI,EH)	(FI,EH)	(VI,M)	(AI,M)	(WI,EH)
DM_2	T	(WI,EH)	(I,M)	(AI,M)	(VI,M)	(EI,EH)
DM_3	S	(EI,EH)	(FI,M)	(AI,H)	(VI,M)	(WI,EH)
	Worst	S	O	D	C	T
DM_1	C	(AI,M)	(I,EH)	(FI,M)	(EI,EH)	(VI,L)
DM_2	D	(VI,M)	(I,M)	(EI,EH)	(WI,EH)	(AI,M)
DM_3	D	(AI,H)	(FI,M)	(EI,EH)	(WI,EH)	(VI,M)

At this stage, the weights related to the criteria are obtained by using Lingo 17.0 software. The lingo model based on the second DM's point of view is as follows. Finally, the optimal weights for the quintuple criteria can be seen in Table 11.

$Min = Z;$ $\quad l_5 - 1.77*u_2 <= u_2*z;$
$l_5 - 0.63*u_1 <= u_1*z;$ $\quad l_5 - 1.77*u_2 >= -u_2*z;$
$l_5 - 0.63*u_1 >= -u_1*z;$ $\quad m_5 - 2.12*m_2 <= m_2*z;$
$m_5 - 0.95*m_1 <= m_1*z;$ $\quad m_5 - 2.12*m_2 >= -m_2*z;$
$m_5 - 0.95*m_1 >= -m_1*z;$ $\quad u_5 - 2.47*l_2 <= l_2*z;$
$u_5 - 1.43*l_1 <= l_1*z;$ $\quad u_5 - 2.47*l_2 >= -l_2*z;$

$l_5 - 2.49*u_4 <= u_4*z;$ $\quad l_1 - 2.49*u_3 <= u_3*z;$
$l_5 - 2.49*u_4 >= -u_4*z;$ $\quad l_1 - 2.49*u_3 >= -u_3*z;$
$m_5 - 2.84*m_4 <= m_4*z;$ $\quad m_1 - 2.84*m_3 <= m_3*z;$
$m_5 - 2.84*m_4 >= -m_4*z;$ $\quad m_1 - 2.84*m_3 >= -m_3*z;$
$u_5 - 3.20*l_4 <= l_4*z;$ $\quad u_1 - 3.20*l_3 <= l_3*z;$
$u_5 - 3.20*l_4 >= -l_4*z;$ $\quad u_1 - 3.20*l_3 >= -l_3*z;$

$l_2 - 1.77*u_3 <= u_3*z;$ $\quad l_4 - 0.63*u_3 <= u_3*z;$
$l_2 - 1.77*u_3 >= -u_3*z;$ $\quad l_4 - 0.63*u_3 >= -u_3*z;$
$m_2 - 2.12*m_3 <= m_3*z;$ $\quad m_4 - 0.95*m_3 <= m_3*z;$
$m_2 - 2.12*m_3 >= -m_3*z;$ $\quad m_4 - 0.95*m_3 >= -m_3*z;$
$u_2 - 2.47*l_3 <= l_3*z;$ $\quad u_4 - 1.43*l_3 <= l_3*z;$
$u_2 - 2.47*l_3 >= -l_3*z;$ $\quad u_4 - 1.43*l_3 >= -l_3*z;$

$l_1 + 4*m_1 + u_1 + l_2 + 4*m_2 + u_2 + l_3 + 4*m_3 + u_3 + l_4 +$
$4*m_4 + u_4 + l_5 + 4*m_5 + u_5 = 6;$
$l_1 <= m_1; m_1 <= u_1;\ l_2 <= m_2; m_2 <= u_2;\ l_3 <= m_3;$
$m_3 <= u_3;\ l_4 <= m_4; m_4 <= u_4;\ l_5 <= m_5; m_5 <= u_5;$
$z >= 0;$

Table 11
Final weights of (SODCT) criteria

	DM₁			DM₂			DM₃			Mean Value			Crisp value
	l	m	u	l	m	u	l	m	u	l	m	u	
S	0.263	0.342	0.363	0.276	0.300	0.311	0.350	0.353	0.393	0.350	0.353	0.393	0.359
O	0.185	0.231	0.250	0.147	0.175	0.194	0.171	0.182	0.221	0.171	0.182	0.221	0.187
D	0.100	0.104	0.117	0.089	0.096	0.099	0.096	0.096	0.108	0.096	0.096	0.108	0.098
C	0.086	0.095	0.095	0.091	0.119	0.130	0.105	0.105	0.116	0.105	0.105	0.116	0.107
T	0.196	0.249	0.249	0.287	0.320	0.320	0.213	0.240	0.306	0.213	0.240	0.306	0.247

According to Table 11, the crisp weights for five criteria is determined as $(0.349, 0.187, 0.098, 0.107, 0.247)$

4.1 Ranking of criteria using Z-ARAS method

As the first step in Z-ARAS method, the preliminary value matrix for Z-ARAS method is presented in Table 12.

Table 12
Preliminary values for Z-ARAS

	S			O			D			C			T		
FM₁	5.56	7.31	8.463	0.28	1.433	3.18	1.187	2.567	4.23	1.893	3.467	5.043	5.347	7.007	8.073
FM₂	2.41	4.067	5.727	2.623	4.37	6.117	0.28	1.073	2.38	1.23	2.653	4.313	4.783	6.28	7.267
FM₃	4.23	5.923	7.237	0.237	1.26	2.837	0.237	1.023	2.41	3.523	5.183	6.843	4.1	5.677	6.933
FM₄	5.913	7.417	8.367	3.597	5.29	6.92	0	0.553	1.937	2.523	4.1	5.677	5.257	6.92	8.03
FM₅	4.81	6.547	8.05	1.023	2.41	4.067	0.317	1.51	3.253	7.013	8.52	9.117	3.123	4.82	6.45
FM₆	4.947	6.297	7.323	1.86	3.557	5.183	3.08	4.81	6.547	2.807	4.313	5.81	5.187	7.013	8.52
FM₇	1.953	3.69	5.3	0	0.553	1.973	1.937	3.597	5.257	2.023	3.713	5.347	2.937	4.56	6.113
FM₈	4.343	6.077	7.497	1.787	3.287	5.003	2.367	3.937	5.513	0.517	1.86	3.523	2.723	4.257	5.723
FM₉	4.857	6.6	7.793	0.517	1.86	3.523	0	0.517	1.823	1.547	3.367	5.187	4.787	6.45	7.793

After passing multiple steps of Z-ARAS method according to Table 12, the findings of (l, m, u) for each failure mode is demonstrated in Table 13.

Table 13
Results of Z-ARAS method

Failure modes	l	m	u
FM₁	0.089	0.138	0.115
FM₂	0.078	0.209	0.105
FM₃	0.070	0.116	0.101
FM₄	0.121	0.264	0.128
FM₅	0.091	0.166	0.116
FM₆	0.118	0.216	0.128
FM₇	0.052	0.081	0.088
FM₈	0.087	0.185	0.110
FM₉	0.073	0.138	0.106
Max	0.160	0.292	0.149

In the next step, the mean indices of l , m and u of the previous step and K_i were calculated and recorded in Table 14. The ultimately ranking is based on K_i indices.

Table 14

K_i results

Failure modes	Mean value	K_i
FM_1	0.114	0.568
FM_2	0.131	0.652
FM_3	0.096	0.478
FM_4	0.171	0.852
FM_5	0.124	0.620
FM_6	0.154	0.769
FM_7	0.074	0.367
FM_8	0.127	0.634
FM_9	0.105	0.526
Max	0.200	1.000

The final ranking is stated in Fig.2 and Table 15. Finally, the results of the integrated approach that we proposed in compared with traditional FMEA and Fuzzy-ARAS is as follows. According to Table 15 and Fig. 2, the ranking accuracy of each method is obviously recognizable.

Table 15

Comparison of rankings obtained from three methods

Failure modes	RPN	Ranking	Fuzzy-ARAS	Ranking	Z-ARAS	Ranking
FM_1	441	7	0.553	6	0.567	6
FM_2	1680	4	0.679	3	0.652	3
FM_3	882	5	0.459	8	0.477	8
FM_4	2016	2	0.889	1	0.851	1
FM_5	1960	3	0.641	4	0.619	5
FM_6	3456	1	0.789	2	0.768	2
FM_7	540	6	0.402	9	0.367	9
FM_8	1680	4	0.539	7	0.634	4
FM_9	384	8	0.558	5	0.525	7

According to Table 15, in the conventional FMEA, the RPN=3465 for FM6 is the maximum among others, and FM6 is ranked first to consider as a more critical failure mode. FM4 with RPN=2016 is second, and FM5 with RPN=1960 is in the third rank. Conventional FMEA's fundamental problem is ranking both FM2 and FM8 as the fourth priority. This issue shows the unreliability of FMEA for experts because this ranking result may cause complications and confusion in the decision-making process. Obviously, the results should be accurate and distinct in healthcare issues related to human health quality. According to Fuzzy-ARAS, the results of ranking changes in which FM4 ranks as the priority and FM6, FM2, and FM5 are ranked second, third, and fourth priorities. Although using Fuzzy-ARAS, the results change because of uncertainty in the weighting process (SODCT), the reliability is not considered yet. Data reliability plays an essential role in MCDM problems; an expert view is fundamental to making a decision. By considering reliability, validation to obtain more realistic results can be provided. Accordingly, the Z-ARAS method is applied to better decision-making in decreasing the risks of OR. The results of the Z-ARAS method are similar to Fuzzy-ARAS in the three priorities. FM4 is in the fourth rank based on the Z-ARAS method, ranked seventh priority in Fuzzy-ARAS. This failure mode is defined as a delay when arterial blood gases (ABG) has drawn, which should be done on time. Delays in ABG has drawn can cause serious health problems for patients in OR. One reason for these changes is assigning weight for severity, which has an important role in the risks and failure modes of OR based on two teams of our decision-makers. Finally, the total rank of Fuzzy-ARAS and Z-ARAS is similar. The essential difference is in FM8 and FM9, which shows the importance of these two failure modes and considers reliability in decision-making. Our finding shows that the Z-ARAS method reveals rational and analytical results for ranking failure modes that can help OP managers make better and sound decisions, improving the quality of services and efficiency of OPs.

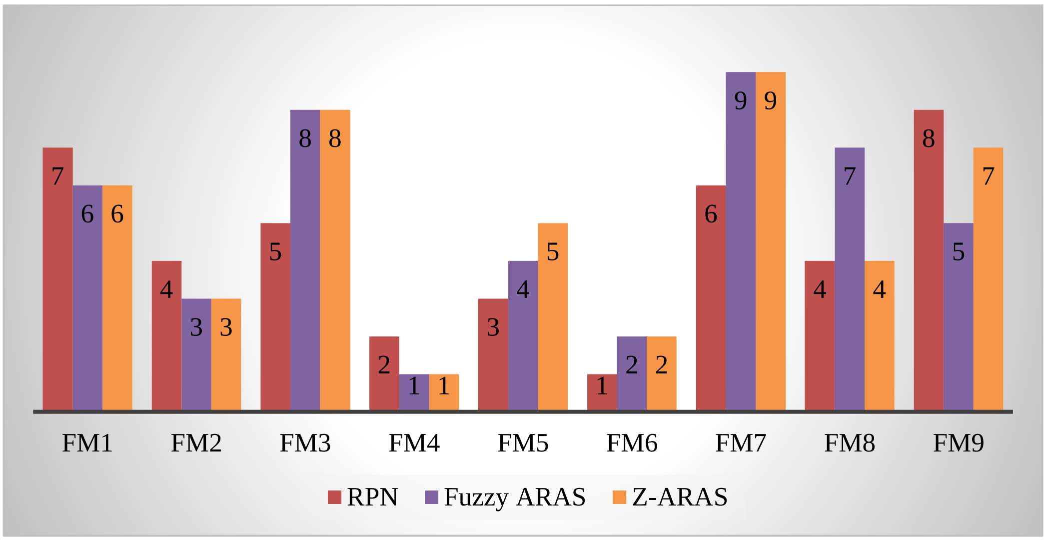

Fig. 2. Ranking for FMs with triple methods

5. Conclusion

The ORs are one of critical parts of healthcare units and hospitals. Hospital managers spend considerable costs on efficient and accurate workload ORs. Hence, time management of ORs is a challenging part of healthcare units that can improve healthcare service quality and efficiency. Lead time reduction is one of the essential elements of OR management based on its emergency nature. This study presents an integrated method based on FMEA for identifying the risks and failure modes that affect delays in ORs.

The MCDM methods used for ranking identified failure modes to eliminate or reduce them. This study's complete process was applying the Z-BWM method for weighting quintuple criteria (S, O, D, C, and T) and the Z-ARAS method for ranking nine determined failure modes according to the FMEA. This study aims to consider the uncertainty and reliability of data by using this integrated method, which is impossible to investigate with conventional FMEA. Using the Z-ARAS method makes it possible to rank failures ultimately so that critical failures can be identified with more incredible determination and certainty and reschedule the preventative and corrective actions. The final step is comparing the Fuzzy-ARAS method with the proposed integrated ARAS method, which makes it possible to determine the reliability of data. According to the findings, the proposed integrated method results are more valid and (have more) referral capability for decision-making. Finally, four failure modes (FMs) which are more important than others for increasing the efficiency of OR, are the result of our suggestion respectively.

1. (FM4) Missing supplies for lab draws: Insufficiently stocked rooms and lab supplies can cause this failure mode, which can affect delays in labs being run. The patients in our considered position are very acuity. Delays in treating labs such as blood counts and electrolytes can be devastating, and the practical actions can be completing checklists at the beginning of the day to ensure supplies are stocked.

2. (FM6) Tube not correctly placed: This failure mode can be the poor technique in placing the tube and/or securing it without adequate confirmation of the correct placement. This failure mode can aspirate the patient after extubating due to inadequate decompression and aspiration of stomach contents. Moreover, the suggested actions confirm tube placement by aspiration of stomach contents or audible air bolus on auscultation before a chest x-ray.

3. (FM2) Patient arrives before the room is set up: This can cause an insufficient time between the report and the patient being brought to the room; that OR room staff has to wait until the nurse completes room setup.

Efficient action is (estimated time of arrival) ETA given over report and communication if more time is needed.

4. (FM8) Delay in when arterial blood gases (ABG) have drawn: The respiratory staff, which is busy, can cause this failure mode that can affect the delayed treatment of the acid-based disorder. The vital action is electrolyte replacement in an efficient dose to minimize delays from the pharmacy. Future studies considering various failure modes based on the vast group of decision-makers can validate results. In this study, the lack of causal relationships between failures is one of the limitations, which can be investigated in future research using the Z-Number theory and other causal methods. Also, considering the importance of necessity by using R-Number or G-number methods can be another suggestion for future studies.

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Conflicts of Interest
The authors declare no conflicts of interest.

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