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Patient waiting time management through fuzzy based failure mode and effect analysis

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Abstract. The amount of time patients spends on services to be delivered in clinics, still is a major problem of some health centers. To solve this problem, various methods proposed by researchers. Failure Mode and Effects Analysis (FMEA) is one of the most used approaches to identify influential failure modes in prolongation of waiting time. In the FMEA method, numeric scores assign to failure modes, using the Risk Priority Number (RPN), but RPN criticized for its shortcoming and leads to unreal results. In this paper, to cover the conventional FMEA shortcoming, firstly, eleven risk factors result in prolongation of waiting time introduced by experts. Secondly, integration of the triangular fuzzy number (TFN) with the Best Worth Method (fuzzy-BWM) was utilized to determine the weights of effective criteria. In the following, failure modes ranked through fuzzy Multi-Objective Optimization by Ratio Analysis (fuzzy-MOORA). Finally, the ranks of eleven failure modes compared in three different methods (Conventional FMEA, conventional MOORA, and fuzzy-MOORA). The potential usage of this method is covering the shortcoming of previous methods and contribute certainty in identifying significant failure modes of the patient waiting time reduction in Out-Patient Departments (OPD). According to the analysis, three main failures for managing waiting time are: the patients never follow up for a later date by the center which can result in chaos in OPD, because of phone or in-person referrals. Secondly, unable to manage canceling/postponing an appointment in emergency cases, Thirdly, office visit not done in the estimated time, which results in a disordering in the center.

Keywords: Patient waiting time, out-patient departments, failure mode and effects analysis, fuzzy best-worst method, fuzzy multi-objective optimization by ratio analysis

1. Introduction

One of the important issues that out-patient departments (OPD) or any other section in health centers facing with is patient waiting time management [1]. The OPD is part of the hospital that clinical services are provided to patients who do not need to stay in the hospital over the night. In the last decade, reducing waiting time and service management were decisive factors in choosing a service sector [2]. Accurate time management, gaining patients' trust and produce profit, cost savings and market share benefits [3, 4]. On the contrary, long patient waiting time not only results in dissatisfaction of patients, but also the effects on the quality of services [5, 6]. This is the reason why health service sectors in many countries focus on service time management and finding a definite solution to overcome this problem.

There have been numerous studies to investigate the best solution of reducing the waiting time in OPD [7, 8]. Among all, one of most used methods, is recognition the failure modes and their effects on patient

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waiting time. For instance, Zhu et al. [9], used a simulation study to analyze the factors influencing the prolongation of the waiting time in OPDs. Mahesh et al. [10] assessed factors result on the patient waiting time in the cardiology department by using of DMAIC (Define, Measure, Analyze, Improve, and Control) methodology. Alkuwaiti et al. [5] applied cross section study to analyze effective variables on the patient's satisfaction.

Historically, the FMEA method is one of the most well-known methods for failure modes evaluation [11]. The FMEA is a team-based systematic tool and pre-occurrence prevention principle which can be used to identify risks, cause of the occurrence, and impacts of potential risks. FMEA is often applied to either validate or to improve a process [12]. FMEA determines the risk priorities of failure modes of an organization through the risk priority number (RPN).

RPN is calculating through the multiplication of occurrence (O: indicates failure frequency), severity (S: indicates the seriousness of the effect of the failure) and detection (D: indicates the possibility of failure detection before its effects) of potential failures [13]. The higher the RPN, the more urgently corrective action is required, because of the higher probability of future failure risks [14].

The FMEA is used to support decision maker to solve various challenges in the healthcare industry such as preventing medication errors in hospitals [15], analyzing the effects of chemotherapy for both patient and nurses [16], assessing failures at a healthcare diagnosis service [17], improving medication management process to reduce risks and errors [18], discovering risks in the intensive care unit and reduce or eliminate them [19]. However, besides many advantages of FMEA, its main weakness is being team-motivated, that leads to uncertainty in considering the determination of RPN [20]. Therefore, for achieving more robust results against the opinions of different individuals, it is vital to prioritize the risks with regard to uncertainties inherent in these criteria. In addition, the shortage of full ranking (the distinction between various risk priorities) and the assumption of the equal importance of determinant factors are other shortcomings of traditional RPN [21]. Consequently, researchers have tried to cover some of the drawbacks of the RPN by utilizing alternative approaches, including MCDM [22].

Throughout the last decades, various MCDM methods presented and used in a different field. Some of the well-known methods are Technique for the Order of Preference by Similarity to Ideal Solution (TOPSIS) [23, 24], Analytic Hierarchy Process (AHP) [25, 26], Multi-Objective Optimization on the basis of Ratio Analysis (MOORA) and Multi-MOORA [27], and Analytic Network Process (ANP) [28], and Best Worth Method (BWM) [29–31]

Under the situation where data cannot be expressed quantitatively, fuzzy set theory can be used. The fuzzy set theory has enabled doing various studies in health care management. For more information, one can refer to [27] for the use of fuzzy -MOORA and –Multi-MOORA techniques, and [32] for the use of fuzzy AHP in health service management and patient safety.

With regards to the gaps like not considering certainty in managing patient waiting time at OPDs and the weakness of existing approaches, the contribution of this study is aimed to provide a new full score ranking method to improve and cover the deficiencies of traditional methods. The proposed approach is extended version of the FMEA, and fuzzy-BWM and fuzzy-MOORA are utilized in suggested method. Therefore, in the first place, risk factors that play an important role in the prolongation of waiting time are defined by experts. Secondly, BWM in fuzzy environment is used for weighing the triple factors (SOD), considering uncertainty in the group decision-making process and solving the problem in assigning different weights to the three factors. Fewer paired wise comparison and including certainty in decision making are some of the advantages of the proposed method in comparison with conventional methods. In third place, for ranking failure modes, fuzzy-MOORA is utilized. In the proposed approach, failure modes are decision making alternatives and factors that weighted by fuzzy-BWM, are failure assessment criteria. In this paper, by considering certainty in both weighting criteria and ranking failure modes, full prioritization is possible. The advantage of full prioritization is the facilitation of identifying significant failure modes and implementing appropriate action to solve problems.

The rest of this study organized as follows: In Section 2, fuzzy set and triangular fuzzy number (TFN) explained and all steps of transferring BWM and MOORA to fuzzy-BWM and fuzzy-MOORA, respectively, presented. In Section 3, Proposed approach explained in detail. In Section 4, the results presented, analysis and discussion are described, and the final results of the proposed method compared with conventional FMEA and MOORA method. Finally, the conclusion presented and corrective actions to reduce waiting time in

OPD or any other section of the healthcare center explained.

2. Methodology

In this section, as prerequisite methods, a brief explanation of fuzzy sets theory, fuzzy BWM and fuzzy MOORA approach, presented. The list of terminologies used in this article are as follows:

A	Set
$\tilde{A}, \tilde{B}$	Fuzzy sets
C_n	Criteria for n-th component
a	Lower bound of fuzzy set
b	Middle bound of fuzzy set
c	Upper bound of fuzzy set
$\mu_{\tilde{A}}(x)$	Membership function
X	Reference set
TM_k	k-th decision maker group
C_B	Best criteria
C_W	Worst criteria
$\tilde{P}_B$	Best-to-Others vector
$\tilde{P}_W$	Others-to-Worst vector
$\tilde{w}$	Fuzzy weight of criteria
W	Worst criteria
B	Best criteria
$\tilde{y}_i$	Performance value
$\tilde{v}_{ij}$	Weighted normalized decision fuzzy matrix

2.1. Fuzzy set theory

The fuzzy set theory can solve the ambiguous and imprecise conceptual problems as a practical tool in uncertain conditions and environment [33]. The fuzzy theory is a framework that has the ability to model reality as it is. It tries to bring the model and reality closer together and reduce the gap between modeling and human thinking. This framework provides a suitable opportunity for the definition of fuzzy terms such as low, medium, and high, which corresponds well with human thinking and feelings [34].

A fuzzy set represents elements' membership degrees in the defined interval, [0,1], which is specified as a membership function. To define the basic fuzzy set, consider a set A defined in reference X as

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) | x \in X\} \quad (1)$$

where $\mu_{\tilde{A}}(x) : X \to [0, 1]$ is the membership function of the set $\tilde{A}$. The membership value represents the degree of dependency of $x \in X$ in A and $\tilde{A}$ is called a fuzzy set.

2.1.1. The TFN

A TFN represents by three real numbers, the upper bound (c) as the maximum value, the lower bound (a) as the minimum value, and the medium value (b) of TFN like $\tilde{A} = (a, b, c)$. The membership function of a TFN is:

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-a}{b-a} & a \leq x \leq b \\ \frac{c-x}{c-b} & b \leq x \leq c \\ 0 & \text{otherwise} \end{cases}$$

Consider $\tilde{A} = (a_1, b_1, c_1)$, $\tilde{B} = (a_2, b_2, c_2)$ as two positive TFN, the basic operations for TFNs are as followed:

$$\tilde{A} \oplus \tilde{B} = (a_1 + a_2, b_1 + b_2, c_1 + c_2),$$

$$\tilde{A} \ominus \tilde{B} = (a_1 - c_2, b_1 - b_2, c_1 - a_2),$$

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$$\tilde{A} \otimes \tilde{B} = (a_1 a_2, b_1 b_2, c_1 c_2),$$

$$\tilde{A} \oslash \tilde{B} = \left(a_1/c_2, b_1/b_2, c_1/a_2\right),$$

$$\lambda\tilde{A} = (\lambda a_1, \lambda b_1, \lambda c_1),\ \lambda \geq 0,$$

2.2. Fuzzy BWM

One of the powerful methods of the MCDM technique for determining the weights of the criteria is BWM [29]. When the comparison system is fully consistent with every criterion, or there are two or more criteria in the MCDM, the BWM method can be used to lead the decisions into to a single solution [35].

Fuzzy BWM determines fuzzy weights from the fuzzy reference comparisons, and it is based on the best and the worst criteria [36]. The traditional BWM method uses crisp values for comparisons [29]. However, in uncertain and non-deterministic conditions, it cannot determine weights of criteria accurately. This is one of the reasons that BWM extended to fuzzy BWM [30, 31]. The fuzzy BWM has the outstanding features of the BWM method and yields the weight of the criteria based on TFN. Therefore, it leads to keep the originality of the information.

Weighting criteria by using fuzzy BWM included four steps.

Step 1: Building a set of decision criteria, including n components, $\{C_1, C_2, ..., C_n\}$.

Table 1
Linguistics variable and CIs for assessing the weight of risk factors

Linguistics terms	Fuzzy membership value	CIs
Equally important (EI)	(1,1,1)	3.00
Weakly important (WI)	(2/3,1, 3/2)	3.8
Fairly important (FI)	(3/2,2,5/2)	5.29
Important (I)	(5/2,3,7/2)	6.69
Very important (VI)	(7/2,4,9/2)	8.04

In this step, in order to assess the alternatives, the decision criteria system is built.

Step 2: Determining the best (C_B) and the worst (C_W) criteria based on the judgment of the k groups of decision-makers, $\{TM_1, TM_2, ..., TM_k\}$.

Step 3: Determining $\tilde{p}_{ij}$ as a fuzzy reference comparison.

In this step, the qualitative preferences of the best and worst criterion over every other criterion can be made by utilizing the linguistic terms in Table 1. After transforming linguistic variable to TFN, the obtained fuzzy Best-to-Others (BO) vector is:

$$\tilde{P}_B = (\tilde{p}_{B1}, \tilde{p}_{B2}, ..., \tilde{p}_{Bn}) \tag{2}$$

where $\tilde{p}_{Bj}$, j $= 1, 2, \ldots, n$ is the fuzzy preference of the best criterion, and $\tilde{p}_{BB} = (1, 1, 1)$.

In a similar way, we can determine the qualitative preference of the risk factors over the worst risk factor. Therefore, the fuzzy Others-to-Worst (OW) vector is:

$$\tilde{P}_W = (\tilde{p}_{1W}, \tilde{p}_{2W}, ..., \tilde{p}_{nW}) \tag{3}$$

where $\tilde{p}_{jW}$, $j = 1, 2, \ldots, n$, is the fuzzy preference of the worst criterion, and $\tilde{p}_{WW} = (1, 1, 1)$.

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

In this step, in order to obtain the constrained optimization problem for determining optimal fuzzy weights, (4) is used. The purpose of obtaining $\tilde{w}_n^*$ is to consider decision makers' preference in each criterion. The optimal weight for the criteria is the one where for each pair of $\frac{\tilde{w}_B}{\tilde{w}_j} = \tilde{p}_{Bj}$, and $\frac{\tilde{w}_j}{\tilde{w}_W} = \tilde{p}_{jW}$. With regards to sum condition for weights, the following problem results:

$$\min \max \left\{ \left| \frac{\tilde{w}_B}{\tilde{w}_j} - \tilde{p}_{Bj} \right|, \left| \frac{\tilde{w}_j}{\tilde{w}_W} - \tilde{p}_{jW} \right| \right\}$$

$$\text{s.t.} \begin{cases} \sum_{j=1}^{n} \tilde{w}_j = 1 \\ 0 \le a_j^w \le b_j^w \le c_j^w,\ j = 1, 2, ..., n \end{cases} \tag{4}$$

where $\tilde{p}_{jW} = (a_{jW}, b_{jW}, c_{jW})$ and $\tilde{p}_{Bj} = (a_{Bj}, b_{Bj}, c_{Bj})$.

The minimax model in (4) can be transferred to the nonlinear constrained optimization problem [37] as follows:

$$\min \tilde{\xi}$$

$$\text{s.t.} \begin{cases} \left| \frac{\tilde{w}_B}{\tilde{w}_j} - \tilde{p}_{Bj} \right| \le \tilde{\xi} \\ \left| \frac{\tilde{w}_j}{\tilde{w}_W} - \tilde{p}_{jW} \right| \le \tilde{\xi} \\ \sum_{j=1}^{n} \tilde{w}_j = 1 \\ 0 \le a_j^w \le b_j^w \le c_j^w,\ j = 1, 2, ..., n \end{cases} \tag{5}$$

where $\tilde{\xi}$ is a TFN.

Because $a^\xi \le b^\xi \le c^\xi$, we suppose that $\tilde{\xi}^* = (k^*, k^*, k^*)$, $k^* \le a^\xi$ then (5) can be transferred to (6):

$$\min \tilde{\xi}^*$$

$$\text{s.t.} \begin{cases} \left| \frac{(a_B^w, b_B^w, c_B^w)}{(a_j^w, b_j^w, c_j^w)} - (a_{Bj}, b_{Bj}, c_{Bj}) \right| \le (k^*, k^*, k^*) \\ \left| \frac{(a_j^w, b_j^w, c_j^w)}{(a_W^w, b_W^w, c_W^w)} - (a_{jW}, b_{jW}, c_{jW}) \right| \le (k^*, k^*, k^*) \\ \sum_{j=1}^{n} \tilde{w}_j = 1 \\ 0 \le a_j^w \le b_j^w \le c_j^w,\ j = 1, 2, ..., n \end{cases} \tag{6}$$

By solving the model in (6), the optimal fuzzy weights of all DMs $\tilde{w}_j^* = \left(\tilde{w}_1^*, \tilde{w}_2^*, ..., \tilde{w}_n^*\right)$ and optimal value of ξ^* are obtainable.

In order to calculate the consistency ratio (CR), ξ^* is used. The CR can be obtained according to $CR = {\xi^*}/{CI}$. This ratio is acceptable when $CR < 0.1$ [38]. The maximum possible value of consistency index (CI) in linguistic variables for fuzzy BWM, is given in Table 1.

Table 2
Linguistic variables for ranking failure modes

Linguistic variables	Very low (VL)	Low (L)	Slightly Low (SL)	Medium (M)	Slightly High (SH)	High (H)	Very High (VH)
TFNs	(0,0,1)	(0,1,3)	(1,3,5)	(3,5,7)	(5,7,9)	(7,9,10)	(9,10,10)

2.3. Fuzzy MOORA

The fuzzy MOORA is developed in three different approaches, the ratio method, reference point approach, and full multiplicative form [39]. In this study, the fuzzy ratio approach in [40] is considered for further investigation. In this method, linguistic variables in Table 2 are used for rating failure modes; for implementing this method, steps are as follow:

Step 1: A set of TFNs are used to create a decision matrix with *m* alternatives and *n* criteria:

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \dots & \tilde{x}_{2n} \\ & \dots & & \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \dots & \tilde{x}_{mn} \end{bmatrix} \tag{7}$$

where $\tilde{x}_{ij} = (a^x_{ij}, b^x_{ij}, c^x_{ij})$ is TFN and $i = 1, 2, \dots, m$, $j = 1, 2, \dots, n$

Step 2: Normalized elements of decision matrix:

$$t^{x*}_{ij} = \frac{t^x_{ij}}{\sqrt{\sum_{i=1}^{m} [(a^x_{ij})^2 + (b^x_{ij})^2 + (c^x_{ij})^2]}}, t = a, b, c \tag{8}$$

Step 3: The multiplication of $\tilde{w}_j$ by the normalized decision matrix results in the formation of the weighted normalized decision matrix as:

$$\tilde{v}_{ij} = (a^v_{ij}, b^v_{ij}, c^v_{ij}) = (a^w_j a^x_{ij}, b^w_j b^x_{ij}, c^w_j c^x_{ij}) \tag{9}$$

Step 4: The $\tilde{v}_{ij}$ is used to calculate the performance of the normalized value by subtracting the useless criteria from the total of useful criteria:

$$\tilde{y}_i = \sum_{j=1}^{g} \tilde{v}_{ij} - \sum_{j=g+1}^{n} \tilde{v}_{ij} \tag{10}$$

where $\tilde{y}_i$ is a TFN, $\sum_{j=1}^{g} \tilde{v}_{ij}$ and $\sum_{j=g+1}^{n} \tilde{v}_{ij}$ are beneficial and non-beneficial criteria, respectively; g and $n - g$ are numbers of beneficial and non-beneficial criteria, respectively.

Step 5: The best non-fuzzy performance (BNP) [41] is used to convert the fuzzy performance values that are normalized to a non-fuzzy value:

$$BNP_i(\tilde{y}_i) = y_i = \frac{(c^y_i - a^y_i) + (b^y_i - a^y_i)}{3} + a^y_i \tag{11}$$

The ranking of the failure modes can be performed using BNP when the values are sorted from the largest to the smallest. The largest value is considered to be the most important one.

3. Proposed approach

Using the fuzzy BWM for weighting criteria and fuzzy MOORA for ranking failure modes, the proposed method in this study is divided in three main stages.

In the first stage, five experienced clerks in the OPD section of a hospital, defined 11 key failure modes resulted in patient waiting time management, using brainstorming (see Table 3). The values of the three factors of RPN are also given in Table 4.

In the second step, the fuzzy BWM method is used to determine the importance of RPN factors and weigh them, such that at first, the best and worst criteria are determined and then paired comparisons are made based on the linguistic data. Consequently, by using the fuzzy BWM model in (6), the optimal weight of the criteria is determined.

In the third step, the ranking of failure modes for managing patient waiting time at OPD was performed by utilizing the fuzzy MOORA method using linguistic variables. The output of this model is to prioritize key criteria in managing patient waiting time at OPD. Finally, the results of the proposed method are compared with Conventional RPN, Conventional MOORA, and fuzzy MOORA.

Table 3
Selected failure modes

Failure Modes	Definitions
F_1	Long check-in time of patients in OPD
F_2	Postpone/cancel appointments due to emergency cases
F_3	Delay of the visit because of first new patient appointment.
F_4	Disturb others because of boring waiting time for patients results in disorder
F_5	Patient exit the office without checkout process
F_6	Completed visit but not within the expected time
F_7	Patient exit office, but lost to adjoin in primary care offices since no direction provided on location of checkout
F_8	Office visit completed but patient have not given any recommendations or booklet
F_9	Returned patients make disorder because they are familiar with the checkout office and the checkout process
F_{10}	Patients exit the office, considering receiving a phone call later
F_{11}	No entertainment or special space for kids results in chaos

Table 4
Traditional ratings for RPN factors [42]

Rating	S	O	D
10	Hazardous without warning	Very high: Almost failure is inevitable	Absolute uncertainty
9	Hazardous with warning		
8	Very high	High: repeated failures	High: repeated failures
7	High		
6	Moderate	Moderate: occasional failures	Moderate: occasional failures
5	Low		
4	Very low		
3	Minor	Low: relatively few failures	Low: relatively few failures
2	Very minor		
1	None	Remote: unlikely failure	Remote: failure is unlikely

Figure 1, illustrates a summary of the proposed method.

4. Results and discussion

In this section, the results of implementing the proposed approach in order to reduce the patient's waiting time presented and discussed. In the first step, according to the first phase of this approach, conventional RPN method, failure modes are identified by

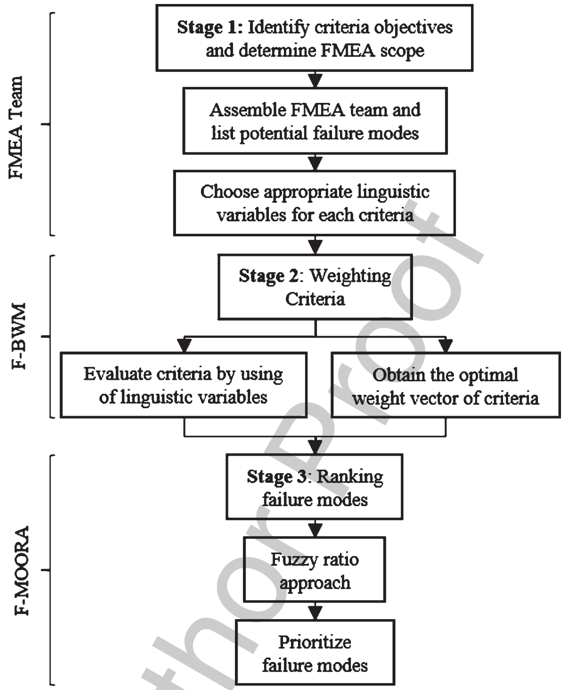

Fig. 1. Research Framework.

the FMEA team and the values of the three effective criteria SOD for each failure mode are determined (see Table 3).

Then, according to FMEA teams' opinions linguistic variables are assigned into each risk factors (Table 5) and consequently corresponding TFN in Table 2 are assigned to each linguistic variable.

Thereafter, the weights of the TFNs are determined using the fuzzy BWM method. For this purpose, the experts identified the best and worst factor in prolongation of waiting time due are identified based on experts' experience and their importance relative to other factors (paired comparisons) in the form of linguistic variables in Table 1 (see Table 6). For instance, for making first best vector, TM_1 identified O as a best criterion, then the importance of O compared with the other factors. The comparison results are written in fuzzy number and by using (6), all limitations are found and the BO and OW vectors are calculated as follows:

$$\tilde{P}_B = \left[(1, 1, 1), (3/2, 2, 5/2), (5/2, 3, 7/2)\right]$$

$$\tilde{P}_W = \left[(5/2, 3, 7/2), (3/2, 2, 7/2), (1, 1, 1)\right]$$

The mathematical programming model in (6) is updated as

Table 5
FMEA teams' opinions for risk factors scoring in managing patients' waiting time

Failure Modes	Severity (S)					Occurrence (O)					Detection (D)				
	TM No.														
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
F_1	1(L)	2(SL)	1(L)	1(L)	2(SL)	2(SL)	2(SL)	1(L)	2(SL)	1(L)	2(SL)	2(M)	1(L)	2(SL)	1(SL)
F_2	7(H)	9(H)	9(VH)	9(H)	5(SH)	7(H)	5(SH)	9(H)	8(H)	7(SH)	7(H)	5(H)	9(SH)	8(H)	7(SH)
F_3	2(SL)	1(L)	1(L)	2(SL)	2(SL)	1(L)	2(SL)	2(SL)	1(L)	2(SL)	1(L)	2(VL)	2(L)	1(VL)	2(VL)
F_4	3(M)	5(SH)	7(SH)	3(M)	5(SH)	3(M)	2(SL)	3(M)	1(SL)	3(M)	3(M)	2(SH)	3(H)	1(SH)	3(SH)
F_5	5(SH)	3(M)	7(SH)	5(SH)	8(H)	2(SL)	3(M)	2(SL)	2(SL)	3(M)	2(SH)	3(H)	2(H)	2(SH)	3(SH)
F_6	7(SH)	3(M)	5(SH)	7(SH)	3(M)	3(M)	3(M)	3(M)	6(SH)	2(SL)	3(SH)	3(SH)	3(M)	6(SH)	2(M)
F_7	1(L)	2(SL)	2(SL)	3(M)	1(L)	2(SL)	3(M)	6(SH)	3(M)	3(M)	2(M)	3(M)	6(M)	3(SH)	3(M)
F_8	3(M)	6(SH)	3(M)	3(M)	2(SL)	3(M)	3(M)	3(M)	2(SL)	3(M)	3(SL)	3(SL)	3(SL)	2(SL)	3(L)
F_9	7(SH)	3(M)	2(SL)	3(M)	3(M)	3(M)	2(SL)	2(SL)	3(M)	2(SL)	3(L)	2(VL)	2(VL)	3(L)	2(VL)
F_{10}	5(SH)	9(H)	7(H)	7(SH)	8(H)	7(H)	9(VH)	7(H)	9(H)	8(H)	7(VH)	9(VH)	7(VH)	9(H)	8(H)
F_{11}	3(M)	7(SH)	2(SL)	3(M)	3(M)	7(SH)	3(M)	3(M)	2(SL)	3(M)	7(M)	3(SL)	3(SL)	2(M)	3(M)

Table 6
Best and worst of triple factors based on FMEA teams' opinions

No. of Team	BO vector of risk factors				OW vector of risk factors			
	Best	S	O	D	Worst	S	O	D
TM_1	O	EI	FI	I	D	I	FI	EI
TM_2	S	I	EI	WI	D	I	FI	EI
TM_3	O	EI	I	FI	D	FI	WI	EI
TM_4	S	FI	EI	I	D	VI	I	EI
TM_5	O	EI	FI	WI	S	VI	EI	WI

$$
Min = \xi
$$

$$
s.t. \begin{cases} -\xi c_2 \leq a_1 - 1.5c_2 \leq \xi c_2 \\ -\xi c_3 \leq a_1 - 2.5c_3 \leq \xi c_3 \\ -\xi c_3 \leq a_2 - 1.5c_3 \leq \xi c_3 \\ -\xi b_2 \leq b_1 - 2b_2 \leq \xi b_2 \\ -\xi b_3 \leq b_1 - 3b_3 \leq \xi b_3 \\ -\xi b_3 \leq b_2 - 2b_3 \leq \xi b_3 \\ -\xi a_2 \leq c_1 - 2.5a_2 \leq \xi a_2 \\ -\xi a_3 \leq c_1 - 3.5a_3 \leq \xi a_3 \\ -\xi a_3 \leq c_2 - 2.5a_3 \leq \xi a_3 \\ \dfrac{a_1 + 4b_1 + c_1}{6} + \dfrac{a_2 + 4b_2 + c_2}{6} + \dfrac{a_3 + 4b_3 + c_3}{6} = 1 \\ 0 \leq a_i \leq b_i \leq c_i \, , i = 1, 2, 3 \\ \xi \geq 0 \end{cases} \tag{12}
$$

Model (12) solved and the results are presented in Table 7. Given that the largest linguistic variable based on experts' opinion for the best factor is selected as Important (I), the CR calculated and all result showed the value smaller than 0.1, which verify that results are acceptable.

In the third phase of the proposed approach, based on the results of the first and second phases, risk scenario ranking is performed using the fuzzy MOORA method. Initially, the weighted normalized matrix is obtained by considering the weights of the three SOD factors (see Table 8).

As outlined in the proposed approach, in this section, the fuzzy ratio system approaches from the fuzzy MOORA method is implemented. Table 9 shows the results of the BNP, taking into account the uncertainty in the SOD factors.

The uncertainty of the SOD factors and weighing of these factors are considered, and failure modes have been re-ranked using RPN, conventional MOORA and fuzzy MOORA methods and the result is summarized in Table 10.

According to Table 10 and based on the traditional RPN, the risk of F_{10} with RPN = 720 has been addressed in the first priority. In addition, the risks F_1 and F_9 with RPN = 12 are jointly in the eighth priority and the risks F_7 and F_8 with RPN = 60 are jointly in the seventh priority. With a general review of the prioritization of risks based on traditional FMEA, it can be concluded that prioritization of risks has been

Table 7
Weights of factors listed as a TFN

No. of Team	S			O			D			ξ^*	*CR* *(CI = 6.69)*
	a	b	c	a	b	c	a	b	c		
TM_1	0.517	0.517	0.597	0.261	0.288	0.400	0.161	0.161	0.202	0.209	0.031
TM_2	0.267	0.282	0.338	0.418	0.489	0.597	0.216	0.216	0.216	0.438	0.065
TM_3	0.181	0.181	0.181	0.262	0.280	0.280	0.402	0.551	0.642	0.504	0.075
TM_4	0.123	0.148	0.148	0.222	0.444	0.556	0.370	0.444	0.444	0.228	0.028
TM_5	0.247	0.342	0.342	0.190	0.262	0.262	0.314	0.445	0.445	0.203	0.025
w_j^*	0.375	0.448	0.493	0.271	0.353	0.419	0.186	0.210	0.218		

Table 8
Normalized fuzzy assessment matrix

Failure Modes	S			O			D		
F_1	0.02	0.07	0.14	0.01	0.05	0.11	0.04	0.09	0.15
F_2	0.20	0.27	0.31	0.21	0.26	0.29	0.18	0.24	0.28
F_3	0.02	0.07	0.14	0.02	0.07	0.12	0.00	0.01	0.05
F_4	0.07	0.14	0.20	0.12	0.18	0.24	0.15	0.21	0.26
F_5	0.02	0.07	0.14	0.15	0.21	0.26	0.17	0.23	0.28
F_6	0.10	0.16	0.23	0.12	0.18	0.24	0.12	0.18	0.24
F_7	0.10	0.16	0.23	0.03	0.08	0.14	0.10	0.16	0.22
F_8	0.08	0.15	0.22	0.09	0.15	0.21	0.02	0.08	0.14
F_9	0.06	0.12	0.19	0.09	0.15	0.21	0.00	0.01	0.05
F_{10}	0.24	0.30	0.33	0.18	0.24	0.28	0.24	0.28	0.30
F_{11}	0.10	0.16	0.23	0.09	0.15	0.21	0.07	0.12	0.18

Table 9
The value of BNP for each failure mode

Failure modes	$\tilde{y}_i$	y_i
F_1	(0.02, 0.07, 0.15)	0.078
F_2	(0.17,0.26, 0.34)	0.256
F_3	(0.01, 0.06, 0.13)	0.067
F_4	(0.09, 0.17, 0.26)	0.172
F_5	(0.08, 0.15, 0.24)	0.157
F_6	(0.09, 0.18, 0.27)	0.179
F_7	(0.06, 0.13, 0.22)	0.138
F_8	(0.06, 0.14, 0.22)	0.140
F_9	(0.05, 0.11, 0.19)	0.116
F_{10}	(0.19, 0.28, 0.34)	0.270
F_{11}	(0.07, 0.15, 0.24)	0.155

Table 10
Comparison of prioritized results

Failure Modes	Conventional FMEA		Conventional MOORA		Fuzzy MOORA	
	RPN	Rank	y_i	Rank	y_i	Rank
F1	12	8	0.152	9	0.078	10
F2	576	2	0.543	2	0.256	2
F3	4	9	0.109	10	0.067	11
F4	245	3	0.412	3	0.172	4
F5	224	4	0.412	3	0.157	5
F6	210	5	0.391	4	0.179	3
F7	60	7	0.282	6	0.138	8
F8	60	7	0.261	7	0.140	7
F9	12	8	0.195	8	0.116	9
F10	720	1	0.586	1	0.270	1
F11	125	6	0.326	5	0.155	6

done in a way that risks are grouped into eight categories. It indicates that the prioritization based on this traditional index is not fully ranked and confuses the decision-maker in risk management and corrective/preventive action planning.

Based on conventional MOORA method, F_{10} with $y_i = 0.586$, F_2 with $y_i = 0.543$ and F_4, F_5 with $y_i = 0.412$ are in first, second and third rank, respectively. The prioritization of failure modes based on conventional MOORA, are grouped in nine categories. Therefore, the aim of conventional MOORA utilization is partially improving the shortcoming of traditional FMEA, where the number of categories increased from eight to nine.

Using the fuzzy MOORA method, it is observed that all identified risks are in distinct priorities. In other words, the proposed method of this study, considering the uncertainty of the risk scenario, has tried to resolve some of the main deficiencies of the traditional RPN and the conventional MOORA method. In this method, the rank of $F_{10,}$ F_2 and F_4 has not changed in comparison of two other methods, but failure modes are fully ranked in 11 categories.

In summary, the non-interference weight of SOD factors, as well as the certainty in the process, is the result of conventional FMEA deficiencies. In the conventional MOORA method, contributing experts' ideas in the decision-making matrix results on increasing the number of categorizations from

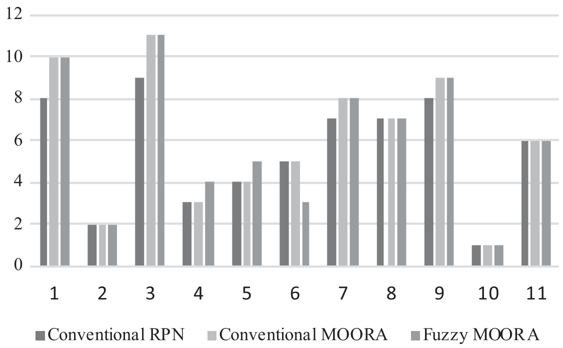

Fig. 2. Prioritized results from the proposed method.

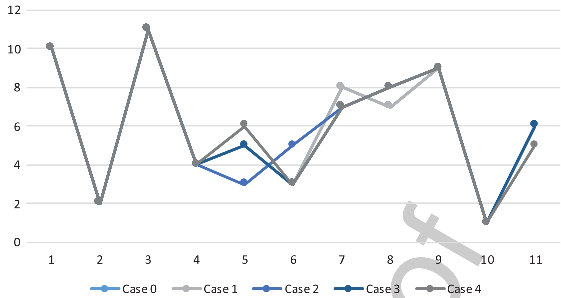

Fig. 3. Sensitivity analysis.

eight to nine groups. However, decisive decision-making matrix and uncertainty exist in the experts' decisions leads to imperfect ranking. To cover the deficiencies of above-mentioned traditional methods, in the fuzzy MOORA, the decision of the experts contributed in the TFN form and the weight of the SOD factors is obtained through the fuzzy BWM method.

4.1. Sensitivity analysis

In this article, for the uncertainty reduction in the obtained outputs, sensitivity analysis is used. In sensitivity analysis, weights of risk factors changed according to the fuzzy group matrix, such that, the obtained original weights from fuzzy BWM are used in case 0. However, in other cases (case 1, case 2, case 3 and case 4) different weights for risk factors are defined. Table 11 and Fig. 3 present the result of sensitivity analysis and indicate that the most important failure mode is F_{10} which is in the first place in all cases. Furthermore, due to the same values of SOD, in $F_1, F_2, F_3, F_4, F_9, F_{11}$ despite the weight changing, there was no change in failure mode ranking. However, ranking of F_5, F_6, F_7, F_8 was changed in various cases due to the different value of SOD.

According to the experts' opinions, in F_7, D criteria have more value than S and O, therefore, if weights of D criteria increases, F_7 will place in higher ranks. Contrariwise, in F_8, increment of D criteria's weight causes lower rank of this failure mode. In addition, there are big values of uncertainties in ranking F_5, F_6 factors which cause by the proximity of RPN's amount. The result of sensitivity analysis shows that weights of risk factors have a significant effect on the final ranking order. Consequently, appropriate weights based on hospital conditions and experts' opinions can result in accurate ranking and correct actions.

5. Conclusion

Patient waiting time is an essential factor in choosing health centers because of increasing demand for providing effective health service, and intensive competitiveness among health centers. In this

Table 11
Sensitivity analysis for different cases

Failure Modes	Case 0 $W_S = 0.35$ $W_O = 0.443$ $W_D = 0.207$	Case 1 $W_S = 0.2$ $W_O = 0.65$ $W_D = 0.15$	Case 2 $W_S = 0.2$ $W_O = 0.4$ $W_D = 0.4$	Case 3 $W_S = 0.3$ $W_O = 0.4$ $W_D = 0.3$	Case 4 $W_S = 0.5$ $W_O = 0.25$ $W_D = 0.25$
F_1	10	10	10	10	10
F_2	2	2	2	2	2
F_3	11	11	11	11	11
F_4	4	4	4	4	4
F_5	5	5	3	5	6
F_6	3	3	5	3	3
F_7	8	8	7	7	7
F_8	7	7	8	8	8
F_9	9	9	9	9	9
F_{10}	1	1	1	1	1
F_{11}	6	6	6	6	5

paper, to identify the failure modes for patient waiting time management, fuzzy-BWM presented for weighting criteria. Thereafter, failure modes ranked through fuzzy-MOORA method. The main purpose of these methods is to overcome the shortcoming of conventional FMEA (RPN index). In contrast, the fuzzy-MOORA contributes certainty and produce full prioritization of failure modes. The comparison of prioritization results through the proposed method and convention RPN, MOORA, prove the effectiveness of the proposed method.

Generally, in order to manage patient waiting time, the following three key scenarios are prioritized:

1) The main failure occurs when the patient completes office visit, and never receives a phone call from health center for the next session. Human errors are the main reason for this failure. Therefore, the patient referral in next days (in-person or phone) results in chaos in the OPD section and prolongation of other patients waiting time. The recommended action is that all other sections, direct patients to checkout station.

2) Postponing/canceling appointments due to emergency cases. The cause of failure is that patient feels rest less and may cancel the appointment and opt another hospital. The main effect is on the hospital reputation and number of patients would be reduced because of some disorders. The action proposed for this failure is engaging interactive activities for specialist clinics.

3) Failure happens when office visit completes but not in the estimated time. The possible effect is the patient's opinion changing about hospital. Preplanning appointments through online platforms can be helpful to prevent this failure occurrence.

5.1. Limitations and future scope

Overlooking the cause and effect relation of failure modes is the main limitation of this study. Future studies can address this problem through the cognitive map based on Z-number theory [43]. The proposed approach in this study can also use for qualitative assessment data in a complex decision-making environment based on Type II fuzzy sets, D-number [44], R-number [45], and G-number [46].

In addition, in order to manage patient waiting time efficiently in healthcare industry, we need to position the patients' order in the right place of the healthcare supply chain. The patient order penetration point [47–52] defines the stage in the healthcare value chain, where a personalized healthcare service such as treatment is linked to a specific patient order, such as organ transplants and the blood transfusion [53]. The challenge would be more critical for servicing and tracing the large scaled markets [54, 55].

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