

Comprehensive fuzzy FMEA model: a case study of ERP implementation risks

Adil Baykasoğlu¹ · İlker Gölcük^{1,2}

Received: 5 October 2016 / Revised: 5 June 2017 / Accepted: 14 July 2017
© Springer-Verlag GmbH Germany 2017

Abstract Failure mode and effects analysis (FMEA) is a prominent engineering technique for eliminating the potential failures emerged from various systems such as products, processes, designs, or systems. In the traditional FMEA, for each risk factor, severity, occurrence, and detectability ratings are multiplied and risk ranking number (RPN) is calculated. However, traditional FMEA has been subject of severe criticism in the literature and significant efforts have been made to overcome the shortcomings of the RPN. The present paper aims to put a step forward to enhance fuzzy FMEA by proposing a hybrid multi-attribute decision making model by combining fuzzy preference programming, fuzzy cognitive maps, and fuzzy graph-theoretical matrix approach. Fuzzy preference programming method is used to derive ratings of risk factors from incomplete, imprecise, and reciprocal pairwise comparison judgments. The causal dependencies among failure modes are modelled via fuzzy cognitive maps in order to capture the long term influences. Finally, fuzzy graph-theoretical matrix approach is employed to calculate risk priority indices of failure modes by taking into account interactions among risk factors. Although the FMEA method has been implemented in variety of technical problems, its potential in analyzing complex information systems have not been fully explored. Therefore, the proposed model is implemented in evaluating enterprise resource planning implementation risks in a real life case study.

✉ Adil Baykasoğlu
adil.baykasoglu@deu.edu.tr; baykasoglu@gmail.com;
<http://web.deu.edu.tr/baykasoglu>

¹ Department of Industrial Engineering, Faculty of Engineering, Dokuz Eylül University, Izmir, Turkey

² The Graduate School of Natural and Applied Sciences, Dokuz Eylül University, Izmir, Turkey

Keywords Fuzzy FMEA · Fuzzy preference programming · Fuzzy cognitive maps · Fuzzy graph-theoretical matrix approach · Enterprise resource planning · Risk management

1 Introduction

Failure mode and effects analysis (FMEA) is a commonly employed engineering technique for identifying and eliminating known and/or potential failures, problems, errors and so on from system, design, process and/or service before they reach the customer (Stamatis 1995). The major concern of FMEA is to assess the risk of potential failure modes in a proactive way that the appropriate corrective actions can be taken before the failure happens. The origins of FMEA technique dates back to early 1960s, firstly developed by aerospace industry with their obvious reliability and safety requirements (Bowles and Pelaez 1995; Teoh and Case 2005). Then, manufacturing industry adopted FMEA technique as quality improvement and risk assessment tool. After many standardization efforts such as Military Standard (MIL-STD) 1629A, International Organization for Standardization (ISO) 9000 series, and the Society of Automotive Engineers (SAE) standard J1739_199407, FMEA has become one of the most extensively employed safety and reliability analysis tools in general (Liu et al. 2015). FMEA technique has been broadly applied in a wide variety of areas such as automotive, mechanical, chemical, electronics, and medical industries (Liu et al. 2013).

In traditional FMEA studies, priority of a potential failure is determined through risk priority number (RPN), which is defined as the product of severity, occurrence, and detectability of a failure. Three risk factors (RFs) are evaluated by using the ratings from 1 to 10. Despite its inherent simplicity, RPN number has been criticized in terms of various aspects (Chang et al. 2001, 2014; Gargama and Chaturvedi 2011; Gilchrist 1993; Pillay and Wang 2003): (1) different sets of severity, occurrence, and detectability ratings might yield the same RPN value. Thus, RPN may not detect a highly risky potential failure. (2) The rationale behind the multiplication of severity, occurrence, and detectability ratings is unknown. (3) Relative importance degrees of severity, occurrence, and detectability are ignored. (4) In the rating tables, the conversion of scores is different for severity, occurrence, and detectability. (5) There are many holes in the RPN distribution that makes it difficult to interpret different RPN numbers. (6) Small variations in one of the RFs produce vastly different effects on the RPN value. (7) Ratings of RFs are very difficult to precisely determine. (8) Possible interdependencies among failure modes (FMs) are ignored. (9) Interactions among RFs are neglected.

In the literature, a variety of approaches have been proposed in order to overcome the shortcomings of the traditional RPN-based failure prioritization. Fuzzy set theory (Zadeh 1965) is one of these approaches widely used within FMEA studies. Fuzzy rule based models employ fuzzy if-then rules to model experts' field knowledge regarding the problem. Bowles and Pelaez (1995) proposed a fuzzy rule based model for prioritizing the FMs. Puente et al. (2002) evaluated 125 fuzzy rules

in order to rank the risks of potential causes of failure. Xu et al. (2002) developed a fuzzy expert system for diesel engine gas turbocharger. Zafiroopoulos and Dialynas (2005) proposed a fuzzy rule based FMEA model for power electronic devices. Although there are many applications of the fuzzy inference models being used to enhance FMEA methodology, they suffer from several drawbacks (Liu et al. 2013; Tay and Lim 2010; Yang et al. 2008; Zhang and Chu 2011): (1) there is a combinatorial rule explosion problem. In order to improve the accuracy of the fuzzy FMEA model, large number of rules are required. (2) Building a fuzzy if–then knowledge base is cognitively demanding and requires vast number of expert judgements. (3) Fuzzy if–then rules having different antecedents but the same consequents cannot be distinguished which hinder complete ranking of FMs. (4) There are some information loss during the inference calculations. (5) Analysis requires dedicated software packages.

Apart from fuzzy rule based models, multi-attribute decision making (MADM) models have been used to improve traditional RPN. Zammori and Gabrielli (2012) employed analytical network process (ANP), and RPN is calculated based on the pairwise comparisons. Selim et al. (2016) and Braglia et al. (2003) implemented fuzzy TOPSIS method in prioritizing FMs. Geum et al. (2011) proposed a service specific FMEA model based on grey relation analysis. Seyed-Hosseini et al. (2006) adopted DEMATEL method for linking causes of failures with the FMs. Liu et al. (2012) used fuzzy VIKOR method to prioritize FMs. Similar studies can be found in the detailed literature review of FMEA (Liu et al. 2013). The main drawback of the MADM methods is that possible interdependencies among FMs are neglected. Moreover, RFs are assumed to be preferentially independent of each other.

In this paper, a comprehensive fuzzy FMEA model is developed in order to overcome the above mentioned deficiencies of the FMEA technique. The proposed fuzzy FMEA model combines fuzzy preference programming (FPP) (Mikhailov 2003), fuzzy cognitive maps (FCMs) (Kosko 1986), and fuzzy graph-theoretical matrix approach (GTMA) (Baykasoglu 2014; Koulouriotis and Ketipi 2011). The proposed model exhibits some desirable features to overcome the drawbacks of the traditional FMEA and contributes to the literature in the following ways:

- In traditional FMEA, ratings of RFs are assigned based on the scale between 1 and 10 for each FM. However, decision makers' judgements are expressed in natural language that involve inherent uncertainties. Hence, fuzzy logic should be incorporated into the evaluation model. On the other hand, decision makers may not directly assign a rating value. Therefore, in this study, FPP is adopted to derive ratings of RFs for each FM. The main advantage of FPP is that it is able to derive priorities from the incomplete, fuzzy, and reciprocal pairwise comparison judgements. Furthermore, FPP is used to derive weights of RFs to deal with the assumption of equal importance of RFs.
- In traditional FMEA, FMs are regarded as independent entities and their possible influences on each other are neglected. However, a FM can cause the emergence of other FMs. This study adopts FCMs for modeling and solving causal dependencies among FMs. FCMs allow articulation of the dependencies through linguistic terms and are able to provide dynamic analysis.

- In traditional FMEA, ratings of RFs are multiplied to obtain RPN. However, rationale of using the multiplication operation is not clear, and resulting RPN does not produce accurate rankings. For that reason, this study employs fuzzy GTMA method for ranking of FMs. Instead of multiplying the ratings of RFs for each FM, fuzzy GMTA relies on the graph theory that takes into account all possible permutations of interactions among RFs and yields accurate rankings with no loss of information.

Although majority of the FMEA studies deal with the technical/engineering problems, we believe that FMEA has much to offer in complex, social and socio-technical problems. For that reason, the proposed model is realized in prioritizing potential failures in an Enterprise Resource Planning (ERP) implementation. The remainder of the paper is organized as follows: in Sect. 2, FPP, FCMs, and fuzzy GTMA are introduced. In Sect. 3, the proposed model is given. In Sect. 4, real life application of the proposed model is introduced. Concluding remarks are given in Sect. 5. Detailed computational steps regarding FPP method are given in “[Appendix A](#)”.

2 Methodology

In this section, FPP, FCMs, and fuzzy GTMA methods are introduced.

2.1 Fuzzy preference programming

Suppose that the pairwise comparisons with n criteria are conducted by means of fuzzy numbers. The total of m fuzzy comparison judgments are elicited from decision makers, which are represented by a set $F = \{\tilde{a}_{ij}\}$, where $m \leq n(n - 1)/2$. Each comparison judgement is represented as a triangular fuzzy number $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$.

FPP method aims to derive a priority vector $w = (w_1, w_2, \dots, w_n)^T$ in which the priority ratios are approximately within the scope of the initial fuzzy judgements as given in the Eq. 1.

$$l_{ij} \lesssim \frac{w_i}{w_j} \lesssim u_{ij} \quad (1)$$

where the symbol \lesssim represents “fuzzy less or equal to”.

Each resultant crisp priority vector satisfies the double-side inequality (Eq. 1) to some extent which is expressed by a membership function as in the Eq. 2.

$$\mu_{ij} \left(\frac{w_i}{w_j} \right) = \begin{cases} \frac{(w_i/w_j) - l_{ij}}{m_{ij} - l_{ij}}, & \frac{w_i}{w_j} \leq m_{ij} \\ \frac{u_{ij} - (w_i/w_j)}{u_{ij} - m_{ij}}, & \frac{w_i}{w_j} \geq m_{ij} \end{cases} \quad (2)$$

Note that the membership function in Eq. 2 coincides with the fuzzy triangular judgment $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$.

The solution of the FPP entails two assumptions. The first assumption is the existence of a non-empty fuzzy feasible area P on the $(n - 1)$ -dimensional simplex Q^{n-1} which is given in Eq. 3.

$$Q^{n-1} = \left\{ (w_1, \dots, w_n) \mid w_i > 0, \sum_{i=1}^n w_i = 1 \right\} \tag{3}$$

The fuzzy feasible area is defined as the intersection of the membership function. The membership function of the fuzzy feasible area is given by Eq. 4.

$$\mu_P(w) = \min \{ \mu_{ij}(w) \mid i = 1, \dots, n - 1; \quad j = 2, \dots, n; \quad j > i \} \tag{4}$$

The second assumption of the FPP states that the highest degree of membership in the aggregated membership function in Eq. 4 can be used to infer the priority vector. Because $\mu_P(w)$ is a convex set, there is always a priority vector $w^* \in Q^{n-1}$ that has a maximum degree of membership as given in Eq. 5.

$$\lambda^* = \mu_P(w^*) = \max_{w \in Q^{n-1}} \min_{ij} \{ \mu_{ij}(w) \} \tag{5}$$

The solution can be found based on the procedure of the maximin rule (Bellman and Zadeh 1970). The maximin problem can be transferred into a linear programming problem (Zimmermann 1990). The linear programming formulation of the maximin prioritization problem can be given as in the Eq. 6.

maximise: λ
 subject to:
 $\lambda \leq \mu_{ij}(w), \quad i = 1, 2, \dots, n - 1, \quad j = 2, 3, \dots, n, j > i \tag{6}$
 $\sum_{l=1}^n w_l = 1, w_l > 0, \quad l = 1, 2, \dots, n$

Considering the membership function in the Eq. 2, linear program given in the Eq. 6 can be transformed into the bilinear program as given in the Eq. 7.

maximise: λ
 subject to:
 $(m_{ij} - l_{ij})\lambda w_j - w_i + l_{ij}w_j \leq 0$
 $(u_{ij} - m_{ij})\lambda w_j + w_i - u_{ij}w_j \leq 0 \tag{7}$
 $\sum_{k=1}^n w_k = 1, w_k > 0, \quad k = 1, 2, \dots, n$
 $i = 1, 2, \dots, n - 1, \quad j = 2, 3, \dots, n, \quad j > i$

The optimal solution of the problem (λ^*, w^*) can be obtained by using an appropriate non-linear optimization solver. In the solution, w^* represents the priority vector that has the maximum degree of membership in the fuzzy feasible area, and λ^* gives the corresponding degree. If λ^* is positive, it can be said that the initial fuzzy judgements are quite consistent. In other words, the inequality given in Eq. 1 is completely satisfied. If λ^* is negative, the solution ratios approximately satisfy the all double-side inequalities. Hence, λ^* can be used to measure the consistency of the fuzzy judgements.

2.2 Fuzzy cognitive maps

Cognitive mapping was introduced by Axelrod (1976) for the analysis of the complex social systems. Despite many successful applications of the cognitive mapping, its inadequacy for modeling and describing much more complex systems was realized. In order to overcome the limited inference and knowledge representation capabilities of CMs, Kosko (1986) introduced FCMs. Methodological differences between CMs and FCMs can be found in (Özesmi and Özesmi 2004).

FCMs exhibit desirable properties of artificial neural networks (ANNs) and fuzzy logic. When compared with ANNs, FCMs are very easy to interpret. In the conventional ANNs, neurons and connections do not have specific meanings; on the contrary, concepts and connections have certain meanings in the FCMs (Tsadiras 2008). In parallel with this, the relationships among system variables are not only described by sign, but their strengths are also examined by means of fuzzy sets. Linguistic variables such as low, medium, high, etc., are used to quantify the degree of causal relationships among system variables.

In FCMs, concepts represent important elements of the system, and directed arcs represent the causal relationships (Papageorgiou and Salmeron 2014). There are three possible relationships as positive causality ($W_{ij} > 0$), negative causality ($W_{ij} < 0$), and no causality ($W_{ij} = 0$). The W_{ij} values represent how strongly concept C_i influences concept C_j (Kosko 1986). The causal dependencies are stored in the connection matrix and they are usually normalized into $[-1, +1]$.

The values of the concepts are being updated at each time step by the Eq. 8 (Xirogiannis et al. 2004):

$$C_i^{t+1} = f \left(C_i^t + \sum_{\substack{j=1 \\ j \neq i}}^n e_{ji} C_j^t \right) \quad (8)$$

where C_i^t is the value of concept C_i at time t , C_i^{t+1} represent the value of concept C_i at time $t + 1$, and e_{ji} is the weight of the relationship exerted from concept C_j to concept C_i . The symbol f is used to denote a transformation function. The most widely used transformation functions are bivalent, trivalent, unipolar sigmoid (logistic), and hyperbolic tangent functions (Bueno and Salmeron 2009; Tsadiras 2008). Applicability of the transformation functions considering nature of the

problem can be found in (Nikas and Doukas 2016). Network topology and inference scheme of an FCM are given in Fig. 1a, b, respectively.

An FCM is expected to converge one of the states: a fixed point, a limit cycle, or a chaotic behavior (Kosko 1997). In the fixed point state, concept vector remains the same for successive iterations. In a limit cycle, concept vector keeps repeating indefinitely. In chaotic behavior, concept vector keeps changing and exhibits a chaotic behavior.

2.3 Fuzzy graph-theoretical matrix approach

GTMA is based on graph theory and matrix permanents, and it exhibits desirable features for modeling interactions in MADM problems. GTMA is able to depict the problem in a visual form by means of graph theory. In addition, matrix representation makes computer processing straightforward. The main fabric of the GTMA relies on the permanent calculations.

Permanents belong to the branch of combinatorial mathematics, simultaneously introduced by Binet and Cauchy (Minc 1978). While their inception dates back to 1812, computation of a permanent is still a challenging task. Unlike determinant of a matrix, the permanent cannot be computed by using Gaussian elimination (Baykasoglu 2014). Computing the permanent of a binary matrix is #P-complete (Nourani and Andresen 1999).

Let $A = (a_{ij})$ be an $m \times n$ matrix, where $m \leq n$. The permanent of a matrix A is calculated by using Eq. 9 (Minc 1978).

$$Per(A) = \sum_{\sigma} a_{1\sigma(1)}a_{2\sigma(2)} \dots a_{m\sigma(m)} \tag{9}$$

where, the summation extends over all one-to-one functions from $\{1, \dots, m\}$ to $\{1, \dots, n\}$. The sequence $a_{1\sigma(1)}, \dots, a_{m\sigma(m)}$ represents the diagonal of matrix A and the product $a_{1\sigma(1)} \dots a_{m\sigma(m)}$ is a diagonal product of A . Therefore, permanent of A is the sum of all diagonal products of A (Baykasoglu 2014).

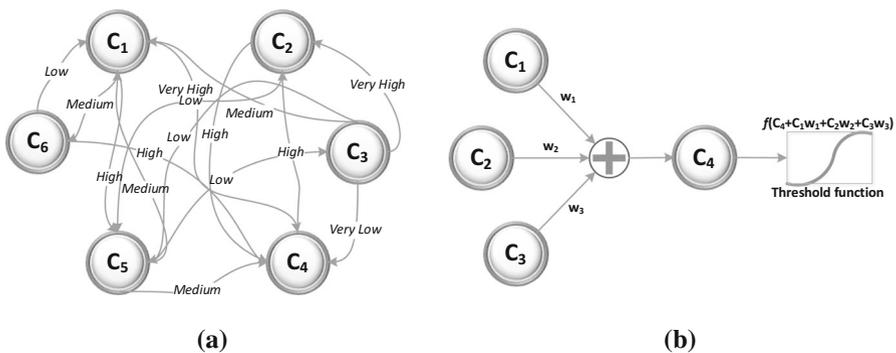


Fig. 1 FCM representation. **a** Network topology of an FCM. **b** Inference scheme in an FCM

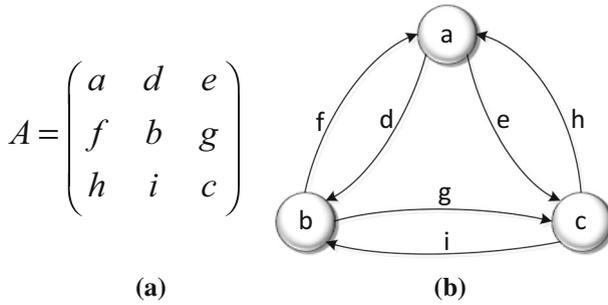


Fig. 2 Matrix and digraph representations of matrix A. **a** Matrix representation. **b** Digraph representation

In order to demonstrate the permanent calculation, let us consider the matrix A and its visual representation as seen in Fig. 2.

The permanent of the matrix A can be computed by using the Eq. 10 as follows:

$$Per(A) = abc + agi + beh + cdf + dgh + efi \tag{10}$$

where $Per(A)$ denotes the permanent of the matrix A. If the determinant of the same matrix is calculated, the result becomes as given in the Eq. 11.

$$Det(A) = abc - agi - beh - cdf + dgh + efi \tag{11}$$

where $Det(A)$ represents the determinant of the matrix A.

Note that the permanent is very similar to determinant except for the fact that all signatures are taken as positive in the permanent. In other words, signatures of the permutations are not taken into consideration and no negative sign appears in the permanent function (Baykasoğlu 2014; Rao and Padmanabhan 2006). Therefore, no information is lost in the permanents. Due to this property, interactions within all permutations in the graph are taken into account in the final ranking. Thereby, more accurate rankings are obtained.

In the context of risk assessment, RFs have considerable impact on the overall risk priorities. For instance, occurrence (O), severity (S), and detectability (D) are the most commonly used RFs in the FMEA. In traditional FMEA studies, ratings of the risk factors for each FM are multiplied. However, interactions among RFs should be taken into account when obtaining the rankings of FMs. Experts' knowledge and experience have pivotal role in this step. Decision makers' evaluations regarding the interrelationships among RFs are generally expressed in natural language, which are inherently vague and imprecise. For this reason, fuzzy sets are utilized to model decision makers' evaluations. Consequently, fuzzy GTMA needs to be resolved.

In fuzzy GTMA, RFs and their interrelations are modeled via fuzzy digraphs. Fuzzy digraph involves a set of nodes $\tilde{V} = (\tilde{v}_j)$, where $j = 1, 2, \dots, n$ and a set of direct edges $\tilde{E} = (\tilde{e}_{jk})$. A node \tilde{v}_j represents the fuzzy rating of the j th risk factor and \tilde{e}_{jk} represents the degree of influence the j th RF has over the k th RF. The matrix representation of the fuzzy digraph model is given in Eq. 12 as follows:

$$\tilde{A} = \begin{matrix} & RF_1 & RF_2 & RF_3 & \cdots & RF_n \\ RF_1 & \tilde{A}_1 & \tilde{a}_{12} & \tilde{a}_{13} & \cdots & \tilde{a}_{1n} \\ RF_2 & \tilde{a}_{21} & \tilde{A}_2 & \tilde{a}_{23} & \cdots & \tilde{a}_{2n} \\ RF_3 & \tilde{a}_{31} & \tilde{a}_{32} & \tilde{A}_3 & \cdots & \tilde{a}_{3n} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ RF_n & \tilde{a}_{n1} & \tilde{a}_{n2} & \tilde{a}_{n3} & \cdots & \tilde{A}_n \end{matrix} \quad (12)$$

where \tilde{A}_j represents fuzzy rating value of the j th RF, \tilde{a}_{jk} is the fuzzy value of the degree of influence RF_j has on the RF_k . The permanent of the matrix \tilde{A} is denoted by $Per(\tilde{A})$ and used to calculate the risk priority indices (RPIs). Details of the calculation steps of the fuzzy GMTA will be given in the next section.

3 Proposed evaluation model

This section presents the main framework of the proposed method used in this paper. The proposed methodology is introduced and the algorithmic steps are provided. The proposed methodology consists of the following procedures:

- Forming initial risk assessment matrix
- Modeling of interdependencies among failure modes
- Ranking of failure modes based on RPIs.

The proposed hybrid method is depicted in Fig. 3.

3.1 Phase I: forming initial risk assessment matrix

This phase consists of problem structuring and obtaining initial priorities of the FMs and RFs. FPP models are constructed and non-linear mathematical models are solved in order to derive weights of FMs and RFs.

Step 1. Problem structuring In this step, decision makers are identified. The aim and the scope of the study are determined. With the help of expert opinions and extensive literature reviews, the potential failure modes are listed. Then, the list of risk factors is determined. Finally, linguistic variables and their associated fuzzy numbers are formed.

Step 2. Calculating ratings of the FMs In this step, ratings of the FMs are calculated by FPP method which allows imprecise and incomplete pairwise judgements. The ratings of the FMs are assessed by solving the non-linear mathematical programming models.

First, decision makers are asked to provide fuzzy pairwise comparisons of FMs with respect to RFs. Suppose that n FMs are determined in the previous step and the RFs are occurrence, severity, and detectability. Each decision maker makes use of linguistic variables to compare these n FMs with respect to severity, occurrence, and detectability, respectively. Then the majority rule is applied to

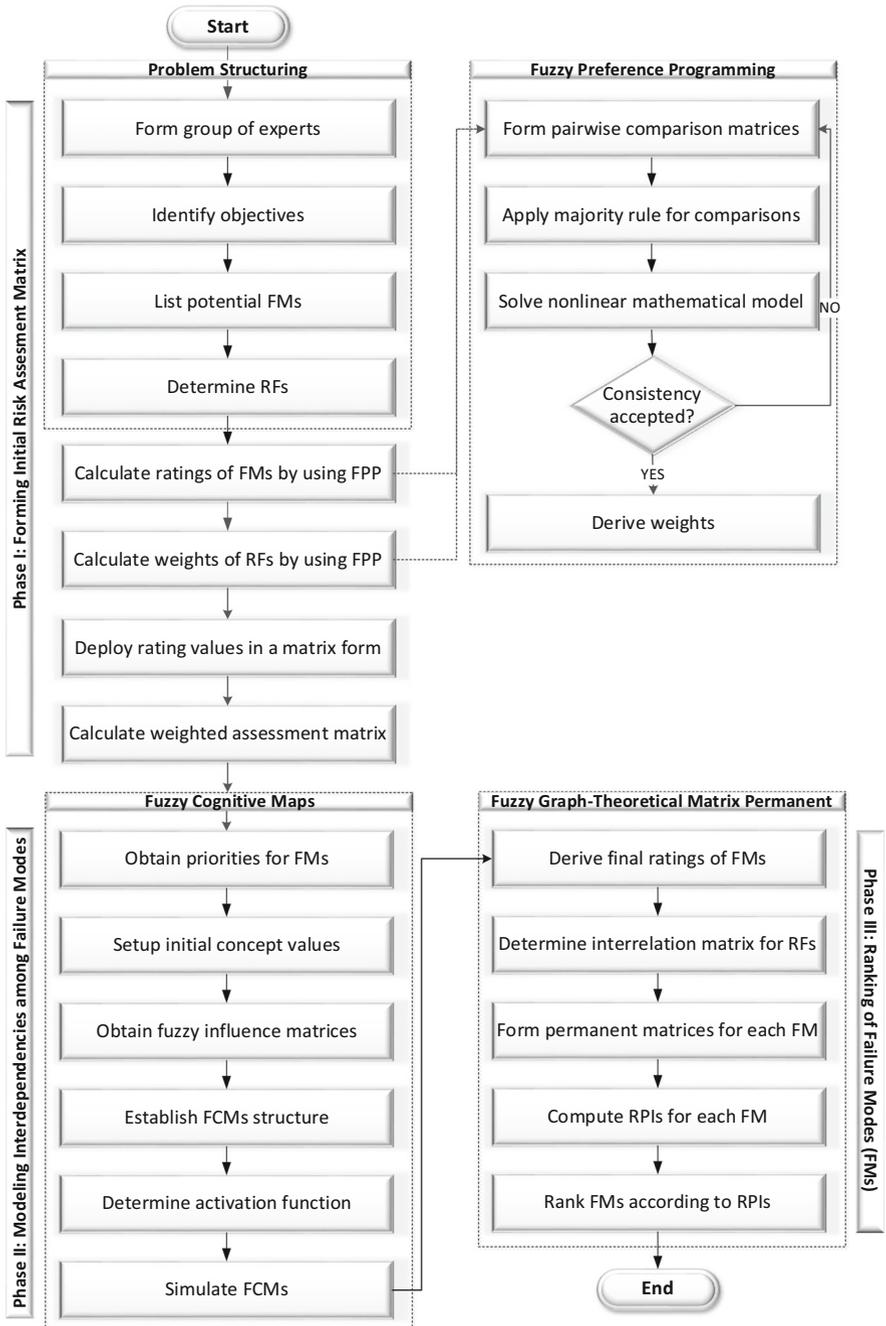


Fig. 3 Flowchart of the proposed model

form the group assessment. Here, if the linguistic label ‘‘High’’ is assigned to the pairwise comparison $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ by the majority of the decision makers, then the fuzzy number corresponding to the linguistic value ‘‘High’’ is used in the comparison matrix. If the decision makers cannot assign a linguistic variable to a pairwise comparison or the majority of the decision makers leave a particular comparison empty, then the comparison judgement is assumed to be empty. The FPP has a significant advantage that even if the some of the pairwise comparisons are missing, the algorithm can still find priorities of each FM. When the pairwise comparison matrices are formed, mathematical programming model given in the Eq. 7 is constructed. Then, an appropriate non-linear solver is employed and the rating of each FM is obtained as given in Eqs. 13–15.

$$FM^S = (FM_1^S, FM_2^S, \dots, FM_n^S) \tag{13}$$

$$FM^O = (FM_1^O, FM_2^O, \dots, FM_n^O) \tag{14}$$

$$FM^D = (FM_1^D, FM_2^D, \dots, FM_n^D) \tag{15}$$

where FM^S, FM^O, FM^D represent the rating vectors of n FMs with respect to severity, occurrence, and detectability, respectively. If consistency level of a pairwise comparison matrix has not found to be acceptable to decision makers, then the pairwise comparisons are adjusted and the algorithm is repeated.

Step 3. Calculating weights of RFs Each risk factor has different level of importance for decision makers. Thus, relative importance of each RF is calculated by using the FPP method. The same calculation procedures are applied as in the previous step. The relative importance of RFs are represented as in the Eq. 16:

$$W = (w_S, w_O, w_D) \tag{16}$$

where w_S, w_O, w_D represent relative importance of severity, occurrence, and detectability RFs, respectively.

When the relative importance of RFs and the rating values of the FMs are calculated, the initial risk assessment matrix is constructed as in the Table 1.

Step 4. Forming weighted risk assessment matrix In this step, risk assessment matrix is weighted by the relative importance of each RF as given in Eqs. 17–19.

$$FM_w^S = (FM_1^S \times w_S, FM_2^S \times w_S, \dots, FM_n^S \times w_S) \tag{17}$$

Table 1 Initial risk assessment matrix

FMs/RFs	Severity (w_S)	Occurrence (w_O)	Detectability (w_D)
FM_1	FM_1^S	FM_1^O	FM_1^D
FM_2	FM_2^S	FM_2^O	FM_2^D
\vdots	\vdots	\vdots	\vdots
FM_n	FM_n^S	FM_n^O	FM_n^D

$$FM_w^O = (FM_1^O \times w_O, FM_2^O \times w_O, \dots, FM_n^O \times w_O) \tag{18}$$

$$FM_w^D = (FM_1^D \times w_D, FM_2^D \times w_D, \dots, FM_n^D \times w_D) \tag{19}$$

where FM_w^S, FM_w^O, FM_w^D denotes weighted rating vectors of n FMs with respect to severity, occurrence, and detectability, respectively. Finally, weighted risk assessment matrix is constructed as seen in Table 2.

Here, $FM_{w_1}^S$ represents the weighted rating value of the FM_1^S .

3.2 Phase II: modeling interdependencies among failure modes

In the second phase of the evaluation model, FMs are evaluated by using FCMs. In traditional FMEA studies, FMs are assumed to be independent of each other. However, in many real life problems, various dependence and feedback relations exist among the FMs. For instance, a particular FM can precipitate unexpected consequences in the long term. Thus, ignoring such interdependencies can lead to erroneous results (Gölcük and Baykasoğlu 2016). FCMs are significant knowledge representation tools that allow modeling causal dependencies among FMs.

In a FMEA risk assessment framework, an FM can influence the other FMs in different degrees in terms of severity, occurrence, and detectability perspectives. For instance, an FM can have “High” influence on the occurrence, “Low” influence on the severity, and no influence on the detectability of another FM. Describing diverse causal influences among FMs can provide great benefits for understanding and analysis of the complex system.

Steps for modeling dependencies among FMs are as follows:

Step 5. Setting up initial concept values As mentioned in the previous section, concept nodes represent system variables and their interrelationships or causalities are characterized by directed arcs. In the presented FMEA model, each FM is described by concepts and causal dependencies among FMs are represented by directed arcs.

Initial concept values are derived from the risk assessment matrix. Initial concept values of the FCM that is developed in terms of severity is given in Eq. 20:

Table 2 Weighted risk assessment matrix

FMs/RFs	Severity (w_S)	Occurrence (w_O)	Detectability (w_D)
FM_1	$FM_{w_1}^S = FM_1^S \times w_S$	$FM_{w_1}^O = FM_1^O \times w_O$	$FM_{w_1}^D = FM_1^D \times w_D$
FM_2	$FM_{w_2}^S = FM_2^S \times w_S$	$FM_{w_2}^O = FM_2^O \times w_O$	$FM_{w_2}^D = FM_2^D \times w_D$
\vdots	\vdots	\vdots	\vdots
FM_n	$FM_{w_n}^S = FM_n^S \times w_S$	$FM_{w_n}^O = FM_n^O \times w_O$	$FM_{w_n}^D = FM_n^D \times w_D$

$$\begin{bmatrix} C_{FM_1^S}^{t=0} \\ C_{FM_2^S}^{t=0} \\ \vdots \\ C_{FM_p^S}^{t=0} \\ \vdots \\ C_{FM_n^S}^{t=0} \end{bmatrix} = \begin{bmatrix} FM_{w_1}^S \\ FM_{w_2}^S \\ \vdots \\ FM_{w_p}^S \\ \vdots \\ FM_{w_n}^S \end{bmatrix} \tag{20}$$

where $C_{FM_i^S}^{t=0}$ is the i th FM when $t = 0$. Similarly, the initial concept values of the FCMs developed in terms of occurrence and detectability are constructed as in the Eqs. 21 and 22, respectively.

$$\begin{bmatrix} C_{FM_1^O}^{t=0} \\ C_{FM_2^O}^{t=0} \\ \vdots \\ C_{FM_p^O}^{t=0} \\ \vdots \\ C_{FM_n^O}^{t=0} \end{bmatrix} = \begin{bmatrix} FM_{w_1}^O \\ FM_{w_2}^O \\ \vdots \\ FM_{w_p}^O \\ \vdots \\ FM_{w_n}^O \end{bmatrix} \tag{21}$$

$$\begin{bmatrix} C_{FM_1^D}^{t=0} \\ C_{FM_2^D}^{t=0} \\ \vdots \\ C_{FM_p^D}^{t=0} \\ \vdots \\ C_{FM_n^D}^{t=0} \end{bmatrix} = \begin{bmatrix} FM_{w_1}^D \\ FM_{w_2}^D \\ \vdots \\ FM_{w_p}^D \\ \vdots \\ FM_{w_n}^D \end{bmatrix} \tag{22}$$

where $C_{FM_i^O}^{t=0}$ and $C_{FM_i^D}^{t=0}$ are the i th FMs for occurrence and severity when $t = 0$, respectively.

Step 6. Obtaining fuzzy influence matrices Fuzzy influence matrices represent the degree of causal dependency between each pair of FMs. The influence matrix of the FM_i^S which is elicited from the k th decision maker is denoted by \tilde{e}_{jik}^S . Similarly, influence matrices \tilde{e}_{jik}^O and \tilde{e}_{jik}^D are obtained.

Step 7: Forming augmented FCMs Fuzzy influence matrices which are elicited from K decision makers are aggregated, and the augmented FCM is formed. The augmented FCM calculations are given in Eqs. 23–25.

$$\tilde{e}_{ji}^S = \frac{\sum_{k=1}^K \tilde{e}_{jik}^S}{K}, \quad i = 1, \dots, n, \quad j = 1, \dots, n \tag{23}$$

$$\tilde{e}_{ji}^O = \frac{\sum_{k=1}^K \tilde{e}_{jik}^O}{K}, \quad i = 1, \dots, n, \quad j = 1, \dots, n \tag{24}$$

$$\tilde{e}_{ji}^D = \frac{\sum_{k=1}^K \tilde{e}_{jik}^D}{K}, \quad i = 1, \dots, n, \quad j = 1, \dots, n \tag{25}$$

where $\tilde{e}_{ji}^S, \tilde{e}_{ji}^O, \tilde{e}_{ji}^D$ are the aggregated fuzzy influence matrices constructed in terms of severity, occurrence, and detectability, respectively.

Step 8. Defuzzifying influence matrices The aggregated fuzzy influence matrices are defuzzified. Many defuzzification methods have been proposed in the literature (Broekhoven and Baets 2006; Chandramohan et al. 2006; Leekwijck and Kerre 2001; Mahdiani et al. 2013; Opricovic and Tzeng 2003). Center of gravity method is simple and practical, and it does not require preferences of decision makers (Hsieh et al. 2004). For this reason, center of gravity method is employed in this study. Defuzzification of a triangular fuzzy number $\tilde{N} = (l, m, r)$ is given by center of gravity method as seen in Eq. 26.

$$BNP = l + [(m - l) + (r - l)]/3 \tag{26}$$

where BNP is the non-fuzzy performance of the triangular fuzzy number.

Step 9. Simulating the FCMs The FCMs simulation with an appropriate threshold function is conducted in order to capture the long term influences among FMs. The threshold function can be selected as hyperbolic tangent, unipolar sigmoid, or bivalent function, etc. The FCM simulation is conducted by using Eq. 27.

$$C_{FM_i^S}^{t+1} = f \left(C_{FM_i^S}^t + \sum_{\substack{j=1 \\ j \neq i}}^n e_{ji}^S \times C_{FM_j^S}^t \right) \tag{27}$$

where $C_{FM_i^S}^t$ is the concept value of the i th FM_i^S at time step t . Similarly, the formulation related to dynamic analysis of the FCMs which are constructed in terms of occurrence and detectability are given in Eqs. 28 and 29, respectively.

$$C_{FM_i^O}^{t+1} = f \left(C_{FM_i^O}^t + \sum_{\substack{j=1 \\ j \neq i}}^n e_{ji}^O \times C_{FM_j^O}^t \right) \tag{28}$$

$$C_{FM_i^D}^{t+1} = f \left(C_{FM_i^D}^t + \sum_{\substack{j=1 \\ j \neq i}}^n e_{ji}^D \times C_{FM_j^D}^t \right) \tag{29}$$

where $C_{FM_i^O}^t$ is the concept value of the i th FM_i^O at time step t . The concept value of the i th FM_i^D at time step t is represented by $C_{FM_i^D}^t$.

When the causal dependencies among FMs are resolved by means of FCM simulation, steady-state concept values are considered for the next step.

3.3 Phase III: ranking of failure modes

In this phase, based on the final ratings of FMs and interactions among RFs, FMs are ranked by using the fuzzy GTMA. Because only three RFs are considered in this study, which are severity, occurrence, and detectability, formulations are given based on the considered RFs. The required computational steps are given as follows:

Step 10. Forming rating matrix In this step, the rating matrix is constructed based on the converged FCM concepts. The rating matrix for the i th FM Ψ_i is given as in the Eq. 30.

$$\Psi_i = \begin{bmatrix} C_{FM_i^s} & 0 & 0 \\ 0 & C_{FM_i^o} & 0 \\ 0 & 0 & C_{FM_i^p} \end{bmatrix} \tag{30}$$

where $C_{FM_i^s}, C_{FM_i^o}, C_{FM_i^p}$ represent the steady-state concept values of the FCMs which are constructed in terms of severity, occurrence, and detectability, respectively. In our approach, FCM weights are assumed to be positive as it is easier to collect information by means of linguistic variables given in Table 4. If there are more than one stable fixed points, then average of the fixed points can be used. In the case of chaotic behavior, decision makers can revise initial FCMs, stop FCM simulation after certain number of iterations, or change threshold functions and other parameters of the FCM. Note that each scenario helps decision makers better understand the nature of the system behavior.

Step 11. Generating interaction matrix Interactions among the RFs are collected. Decision makers are asked to determine degree of influence among RFs by means of linguistic variables given in Table 4. Then majority rule is employed to form interaction matrix $\tilde{\beta}$ which is given in the Eq. 31:

$$\tilde{\beta} = \begin{bmatrix} 0 & \tilde{r}_{12} & \tilde{r}_{13} \\ \tilde{r}_{21} & 0 & \tilde{r}_{23} \\ \tilde{r}_{31} & \tilde{r}_{32} & 0 \end{bmatrix} \tag{31}$$

where \tilde{r}_{ij} represents the influence of the i th RF over the j th RF.

Step 12. Forming risk ranking matrix After forming rating matrix (Ψ_i) and interaction matrix ($\tilde{\beta}$), the next step is to obtain risk ranking matrix which is given in Eq. 32.

$$\tilde{\xi}_i = \psi_i + \tilde{\beta} = \begin{bmatrix} C_{FM_i^s} & \tilde{r}_{12} & \tilde{r}_{13} \\ \tilde{r}_{21} & C_{FM_i^o} & \tilde{r}_{23} \\ \tilde{r}_{31} & \tilde{r}_{32} & C_{FM_i^p} \end{bmatrix} \tag{32}$$

where $\tilde{\xi}_i$ represents risk ranking matrix of the i th FM.

Step 13. Calculating permanent of the risk ranking matrix The permanent of the risk ranking matrix is calculated. For each FM, $per(\tilde{\xi}_i)$ is calculated and arranged in an descending order. The FM with the highest $per(\tilde{\xi}_i)$ value is considered as the most critical FM.

4 Case study

The role of information technologies on the business activities of the firms is rapidly expanding. In parallel with the increase in complexity of products, services, and customer expectations, the compelling market pressures lead firms to use sophisticated software to maintain their operations. ERP software is one of such solutions which help firms to integrate all the business functions for operational efficiency and effectiveness.

Despite the growing interest to the ERP solutions, there are numerous difficulties in the adoption process. Unfortunately, many enterprises have reported ERP implementation to be fraught with failures due to the variety of challenges. As the ERP implementations are such risky and difficult undertakings, firms should be supported with appropriate risk management tools in order to eliminate the potential failures during the implementation process. Evidently, awareness regarding the importance of ERP risk management tools for the success of implementation projects is growing. The company, which is contacted within the scope of this study, is well aware of the significance of such tools. Due to the firm policy, it is named as company A.

Company A is one of the largest software producers, heavily involved in business intelligence technologies, mobile solutions, ERP, and software-as-a-service applications. While penetrating into new market, company A is targeting absolute customer satisfaction to enhance the corporate image of the trademark. Company A is recently developing projects in order to decrease the chance of failures in ERP implementation of their customers. The authors of this study have recently collaborated with company A in order to identify the critical success factors of the ERP implementation. In parallel with these efforts, the proposed model is realized in collaboration with the experts of company A as an extension of the previous work.

Step 1 First, five experts from the company A are identified based on their professional backgrounds. Number of participants are reduced by assuring the heterogeneity of panel members. The experts consist of a team manager, an analyst, and three consultants who have more than 5 years of experience. After identification of the experts, participants are elucidated about the scope and details of the study. Then, the linguistic scales are determined. Linguistic scale, which is used for pairwise comparisons of the FPP, is given in Table 3.

Table 3 Linguistic variables for modeling pairwise comparisons

Linguistic variable	Fuzzy number	Reciprocal fuzzy number
Extreme importance (EXI)	(8, 9, 10)	(1/10, 1/9, 1/8)
Very strong importance (VSI)	(6, 7, 8)	(1/8, 1/7, 1/6)
Strong importance (SI)	(4, 5, 6)	(1/6, 1/5, 1/4)
Moderate importance (MI)	(2, 3, 4)	(1/4, 1/3, 1/2)
Equal importance (EI)	(1, 1, 2)	(1/2, 1, 1)

Similarly, the linguistic scale for the analysis of interactions (i.e., FMs, RFs) is given in Table 4.

A comprehensive literature review has been conducted in order to identify the FMs, their causes, and effects. There are numerous studies which provide review, classification, and analysis of factors in the ERP implementation success (Leyh and Crenze 2013; Leyh and Sander 2015; Ngai et al. 2008; Shaul and Tauber 2013; Yeh and Xu 2013). With the help of literature review, previous study results, and experts' views, FMEA table is constructed as in the Table 5.

The RFs are determined as severity, occurrence, and detectability for the practicality concerns.

4.1 Solution of pairwise comparisons

When the FMs and RFs are identified, the next step is to derive relative importance degrees by using the FPP.

Step 2 The decision makers are asked to compare FMs with respect to RFs. First, pairwise comparisons of FMs with respect to severity, occurrence, and the detectability are collected as given in Tables 6, 7 and 8, respectively.

The solution of the FPP method is given in Eqs. 33–35.

$$FM^S = (0.090, 0.104, 0.204, 0.081, 0.081, 0.052, 0.272, 0.115) \tag{33}$$

$$FM^O = (0.064, 0.060, 0.122, 0.040, 0.122, 0.061, 0.259, 0.273) \tag{34}$$

$$FM^D = (0.057, 0.031, 0.144, 0.038, 0.108, 0.074, 0.186, 0.361) \tag{35}$$

The corresponding λ values for the pairwise comparison matrices constructed with respect to severity, occurrence, and detectability are found as -4.714 , -5.476 , and -5.601 , respectively. Because matrices are relatively large and involve incomplete comparisons, λ values are accepted by the decision makers. Note that the FPP is able to find the relative importance of each FMs even if some of the pairwise comparisons are left blank.

Step 3 After obtaining the ratings of FMs, the relative importance of each RF is calculated. The pairwise comparison matrix of the RFs is given in Table 9.

Table 4 Linguistic variables for modeling interactions

Linguistic variable	Triangular fuzzy number
Very very high (VVH)	(0.8, 0.9, 1)
Very high (VH)	(0.65, 0.8, 0.9)
High (H)	(0.5, 0.65, 0.8)
Medium (M)	(0.35, 0.5, 0.65)
Low (L)	(0.2, 0.35, 0.5)
Very low (VL)	(0.1, 0.2, 0.35)
Very very low (VVL)	(0, 0.1, 0.2)

Table 5 FMEA table for ERP risks

No.	Failure modes	Causes of failure	Effects of failure
FM1	Failure to redesign business processes	Inadequate change management program, inadequate training and education	Budget and time excess, poor economic/financial performance
FM2	Failure to work as an effective team	Planning and problem solving experience of team members are inadequate, inadequate team formation	Poor team performance
FM3	Failure to gain top management support	Unclear strategic objectives, lack of leadership, insufficient resources	Poor business performance, low strategic goal fitting
FM4	Failure to build an effective software management methodology	Ineffective software engineering team, lack of training, poor communication, unclear objectives	Inadequate system reliability and stability, low degree of integration
FM5	Failure to ensure integration between enterprise-wide systems	Inadequate change management program, inadequate training of consulting company, lack of common understanding among departments	Project delay, low degree of flexibility, inadequate system stability
FM6	Failure to understand and respond changing customer requirements	Inadequate leadership, inadequate customer requirements planning system	Low strategic goal fitting, low degree of flexibility, poor performance
FM7	Failure to ensure key user involvement	Inadequate training, ineffective communication	Low user friendliness, poor business performance
FM8	Failure to maintain an effective project management	Inadequate leadership, inadequate use of project management tools, ineffective communication	Budget and time excess

The resulting weights of RFs are calculated as given in Eq. 36.

$$W = (w_S, w_O, w_D) = (0.516, 0.112, 0.372) \quad (36)$$

where λ is calculated as 0.612 which indicates that the pairwise comparison matrix of the RFs is quite consistent. Computational details are given in “Appendix A”.

Table 6 Pairwise comparisons of FMs with respect to severity

	FM1	FM2	FM3	FM4	FM5	FM6	FM7	FM8
FM1	1	MI ⁻¹	EI ⁻¹	MI ⁻¹	EI	EI	EI ⁻¹	MI
FM2	MI	1	SI	VSI	MI ⁻¹	-	SI ⁻¹	-
FM3	EI	SI ⁻¹	1	VSI	EI	EI	-	VSI
FM4	MI	VSI ⁻¹	VSI ⁻¹	1	EI	EI	SI ⁻¹	-
FM5	EI ⁻¹	MI	EI ⁻¹	EI ⁻¹	1	EI	SI	MI ⁻¹
FM6	EI ⁻¹	-	EI ⁻¹	EI ⁻¹	EI ⁻¹	1	MI ⁻¹	MI ⁻¹
FM7	EI	SI	-	SI	SI ⁻¹	MI	1	EI
FM8	MI ⁻¹	-	VSI ⁻¹	-	MI	MI	EI ⁻¹	1

Table 7 Pairwise comparisons of FMs with respect to occurrence

	FM1	FM2	FM3	FM4	FM5	FM6	FM7	FM8
FM1	1	SI	VSI	EI	SI ⁻¹	SI	EI ⁻¹	MI ⁻¹
FM2	SI ⁻¹	1	MI	-	MI ⁻¹	-	MI ⁻¹	-
FM3	VSI ⁻¹	MI ⁻¹	1	VSI	EI	EI	-	MI
FM4	EI ⁻¹	-	VSI ⁻¹	1	MI	MI ⁻¹	SI ⁻¹	-
FM5	SI	MI	EI ⁻¹	MI ⁻¹	1	EI	EI ⁻¹	SI ⁻¹
FM6	SI ⁻¹	-	EI ⁻¹	MI	EI ⁻¹	1	VSI ⁻¹	MI ⁻¹
FM7	EI	MI	-	SI	EI	VSI	1	SI
FM8	MI	-	MI ⁻¹	-	SI	MI	SI ⁻¹	1

Table 8 Pairwise comparisons of FMs with respect to detectability

	FM1	FM2	FM3	FM4	FM5	FM6	FM7	FM8
FM1	1	VSI	VSI	EI	SI ⁻¹	SI	EI ⁻¹	MI ⁻¹
FM2	VSI ⁻¹	1	MI	-	SI ⁻¹	-	EI ⁻¹	-
FM3	VSI ⁻¹	MI ⁻¹	1	VSI	SI	EI	-	VSI
FM4	EI ⁻¹	-	VSI ⁻¹	1	-	MI ⁻¹	SI ⁻¹	-
FM5	SI	SI	SI ⁻¹	-	1	EI	MI ⁻¹	VSI ⁻¹
FM6	SI ⁻¹	-	EI ⁻¹	MI	EI ⁻¹	1	-	EI ⁻¹
FM7	EI	EI	-	SI	MI	-	1	SI
FM8	MI	-	VSI ⁻¹	-	VSI	EI	SI ⁻¹	1

Table 9 Pairwise comparisons of RFs

	S	O	D
S	1	SI	EI
O	SI ⁻¹	1	MI ⁻¹
D	EI ⁻¹	MI	1

Based on the results given in Eqs. 33–36, the initial risk assessment matrix is constructed as in the Table 10.

Step 4 The initial risk assessment matrix is weighted by the corresponding RF weights. The resulting weighted risk assessment matrix is given as in Table 11.

4.2 Resolving interdependencies

Traditional FMEA methods assume the independence of FMs. However, emergence of a FM can trigger the unfolding of other FMs with different levels of severity, occurrence, and detectability. For that reason, FCMs are built for each RF.

Step 5 The FCM is constructed and the initial concept values are established by using the weighted risk assessment matrix. The initial concept values of the FCM which is developed in terms of severity are given in Eq. 37.

$$\begin{bmatrix} C_{FM_1^s}^{t=0} \\ C_{FM_2^s}^{t=0} \\ \vdots \\ C_{FM_5^s}^{t=0} \\ \vdots \\ C_{FM_8^s}^{t=0} \end{bmatrix} = \begin{bmatrix} 0.046 \\ 0.054 \\ \vdots \\ 0.042 \\ \vdots \\ 0.059 \end{bmatrix} \quad (37)$$

In a similar fashion, initial concept values of the FCMs which are constructed based on the occurrence and detectability are established as in Eqs. 38 and 39, respectively.

$$\begin{bmatrix} C_{FM_1^o}^{t=0} \\ C_{FM_2^o}^{t=0} \\ \vdots \\ C_{FM_5^o}^{t=0} \\ \vdots \\ C_{FM_8^o}^{t=0} \end{bmatrix} = \begin{bmatrix} 0.007 \\ 0.007 \\ \vdots \\ 0.014 \\ \vdots \\ 0.031 \end{bmatrix} \quad (38)$$

Table 10 Result of the initial risk assessment matrix

FMs/RFs	Severity (0.516)	Occurrence (0.112)	Detectability (0.372)
FM1	0.090	0.064	0.057
FM2	0.104	0.060	0.031
FM3	0.204	0.122	0.144
FM4	0.081	0.040	0.038
FM5	0.081	0.122	0.108
FM6	0.052	0.061	0.074
FM7	0.272	0.259	0.186
FM8	0.115	0.273	0.361

Table 11 Result of the weighted risk assessment matrix

FMs/RFs	Severity	Occurrence	Detectability
FM1	$FM_{w_1}^S = 0.046$	$FM_{w_1}^O = 0.007$	$FM_{w_1}^D = 0.021$
FM2	$FM_{w_2}^S = 0.054$	$FM_{w_2}^O = 0.007$	$FM_{w_2}^D = 0.012$
FM3	$FM_{w_3}^S = 0.105$	$FM_{w_3}^O = 0.014$	$FM_{w_3}^D = 0.054$
FM4	$FM_{w_4}^S = 0.042$	$FM_{w_4}^O = 0.004$	$FM_{w_4}^D = 0.014$
FM5	$FM_{w_5}^S = 0.042$	$FM_{w_5}^O = 0.014$	$FM_{w_5}^D = 0.040$
FM6	$FM_{w_6}^S = 0.027$	$FM_{w_6}^O = 0.007$	$FM_{w_6}^D = 0.028$
FM7	$FM_{w_7}^S = 0.140$	$FM_{w_7}^O = 0.029$	$FM_{w_7}^D = 0.069$
FM8	$FM_{w_8}^S = 0.059$	$FM_{w_8}^O = 0.031$	$FM_{w_8}^D = 0.134$

$$\begin{bmatrix} C_{FM_1^D}^{t=0} \\ C_{FM_2^D}^{t=0} \\ \vdots \\ C_{FM_5^D}^{t=0} \\ \vdots \\ C_{FM_8^D}^{t=0} \end{bmatrix} = \begin{bmatrix} 0.021 \\ 0.012 \\ \vdots \\ 0.040 \\ \vdots \\ 0.134 \end{bmatrix} \tag{39}$$

Step 6 When the initial concept values are determined, the next step is to model relationships among FMs. In modeling of the relationships among FMs, fuzzy influence matrices are collected, aggregated, and defuzzified. In this step, the fuzzy influence matrices are collected.

Step 7 The fuzzy influence matrices are aggregated by employing Eqs. 23–25 in this step. The required modifications are discussed with the experts.

Step 8 The influence matrices are defuzzified by employing Eq. 26. The resulting FCM topologies are visualized in Fig. 4.

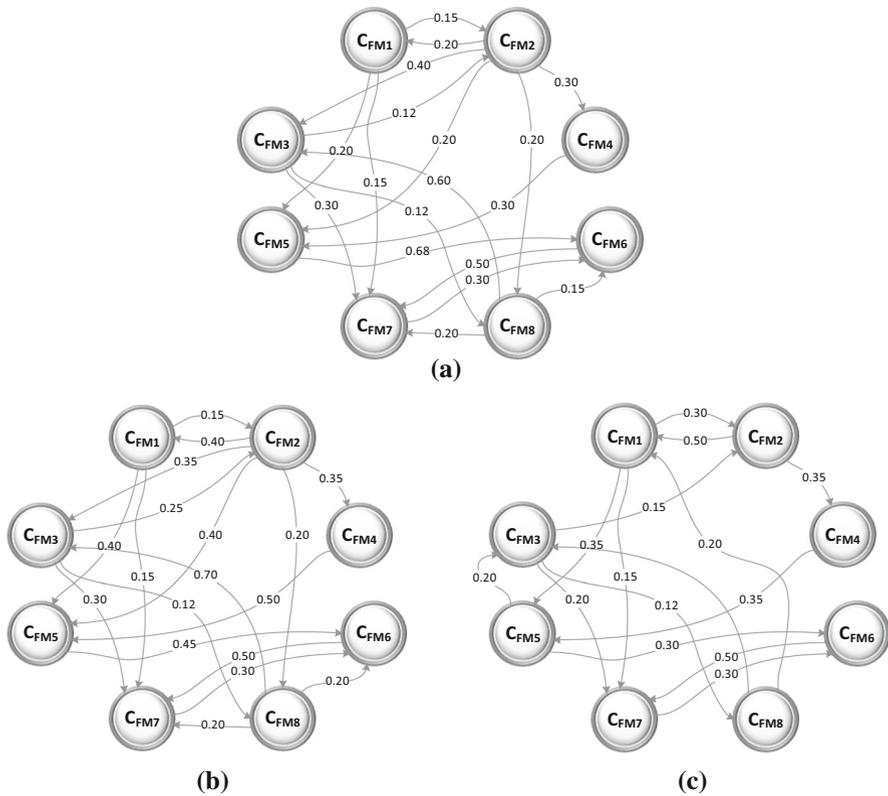


Fig. 4 FCM topologies with respect to risk factors. **a** Severity, **b** occurrence and **c** detectability

Step 9 FCMs are simulated in order to capture the long term effects of FMs. The hyperbolic tangent function is selected and the FCM simulation is conducted by employing Eqs. 27–29. Table 12 summarizes the changes in the concept values which are constructed in terms of severity of FMs.

The FCM simulation has reached the steady-state after 25 iterations. The dynamic behavior of the FMs is given in Fig. 5.

It can be observed that failure to redesign business processes has been converged to relatively low concept values. The main reason is that only the failure to work as an effective team has small impact on the failure to redesign business processes. On the contrary, failure to ensure key user involvement has converged to higher concept values. This is due to the fact that severity of failure to ensure key user involvement has been influenced by failure to redesign business processes, failure to gain top management support, failure to understand and respond changing customer requirements, and failure to maintain an effective project management. Hence, severity of the failure to ensure key user involvement has increased in the long term.

The comparison of the initial and the steady-state concept values are depicted in Fig. 6. The most severe FM has found to be failure to ensure key user involvement

Table 12 Change of the concept values for the severity of failure modes

Failure modes								
Iteration	C_{FM1}	C_{FM2}	C_{FM3}	C_{FM4}	C_{FM5}	C_{FM6}	C_{FM7}	C_{FM8}
0	0.046	0.054	0.105	0.042	0.042	0.027	0.140	0.059
1	0.057	0.073	0.161	0.058	0.074	0.106	0.201	0.082
2	0.071	0.101	0.235	0.080	0.117	0.225	0.316	0.116
3	0.091	0.139	0.332	0.110	0.174	0.394	0.487	0.163
4	0.118	0.190	0.450	0.150	0.248	0.593	0.680	0.226
5	0.155	0.256	0.579	0.204	0.340	0.761	0.826	0.308
6	0.203	0.335	0.700	0.274	0.449	0.858	0.899	0.404
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
24	0.679	0.743	0.935	0.750	0.884	0.961	0.963	0.777
25	0.679	0.743	0.935	0.750	0.884	0.961	0.963	0.777

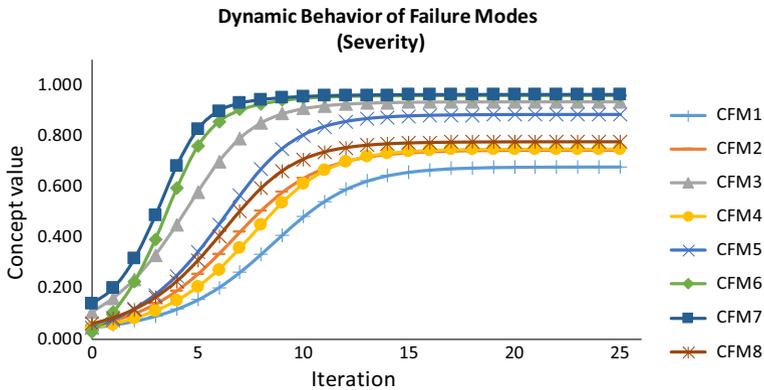


Fig. 5 Dynamic behavior of FMs with respect to severity

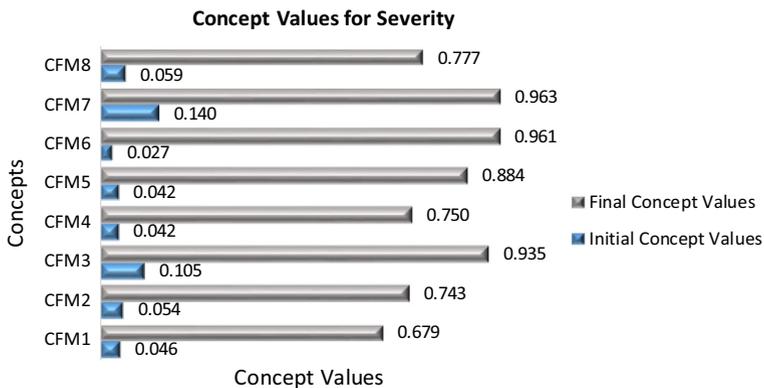


Fig. 6 Change of concept values with respect to severity

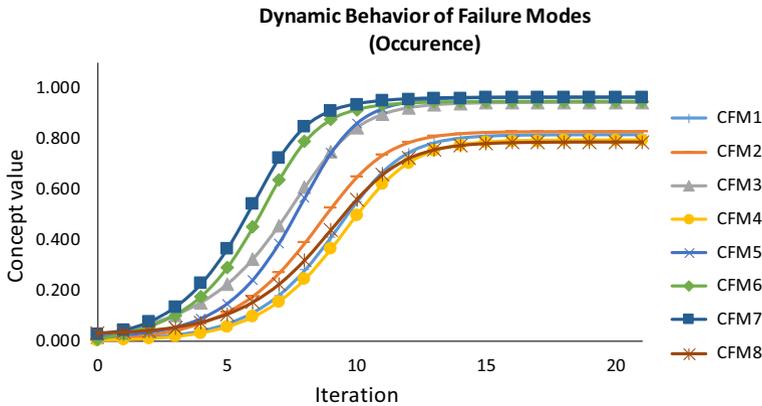


Fig. 7 Dynamic behavior of FMs with respect to occurrence

with the concept value 0.963. The second most severe FM is the failure to understand and respond changing customer requirements. Although failure to understand and respond changing customer requirements has a relatively small initial concept value, the integration problems between the enterprise-wide systems have considerable impact on it leading to increased severity in the long term. The third most severe FM has found as failure to gain top management support which ranks second according to initial concept values. The least severe FM has found to be failure to redesign business processes.

The dynamic behavior of FCM that is constructed in terms of occurrence is given in Fig. 7. It is observed that failure to ensure integration between enterprise-wide systems is the most frequent FM during the ERP implementation. Especially, failure to redesign business processes, failure to work as an effective team, and failure to build an effective software management methodology have considerable impact on the occurrence of enterprise-wide system integration. The FMs with the least concept value are failure to maintain an effective project management and failure to build an effective software management methodology.

Changes in the concept values with respect to occurrence of FMs are depicted in Fig. 8. Investigating the concept values, a drastic change has observed in the failure to main an effective project management. Despite its relatively high initial concept value, occurrence of the failure to maintain an effective project management has ranked eighth in terms of the final concept values. This is due the fact that only failure to work as an effective team and failure to gain top management support affect the occurrence of the failure to maintain an effective project management. The second interesting observation is that the occurrence of failure to understand and respond changing environment has ranked third in terms of steady-state concept values where it can only rank seventh in terms of initial concept value. This is due to the fact that flexibility of an organization in fulfilling customer expectations is highly influenced by enterprise-wide system integration, involvement of key users, and effective project management.

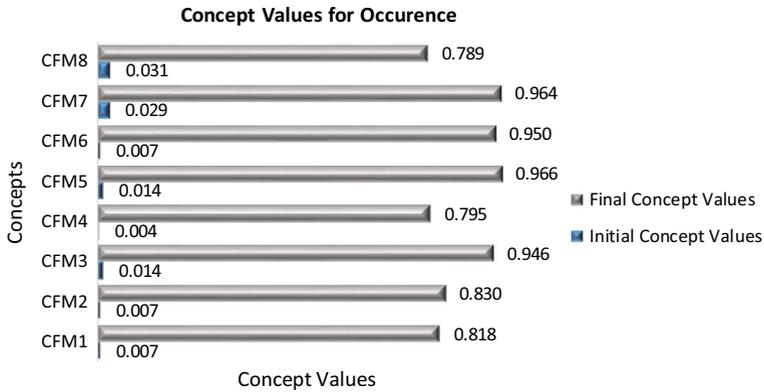


Fig. 8 Change of concept values with respect to occurrence

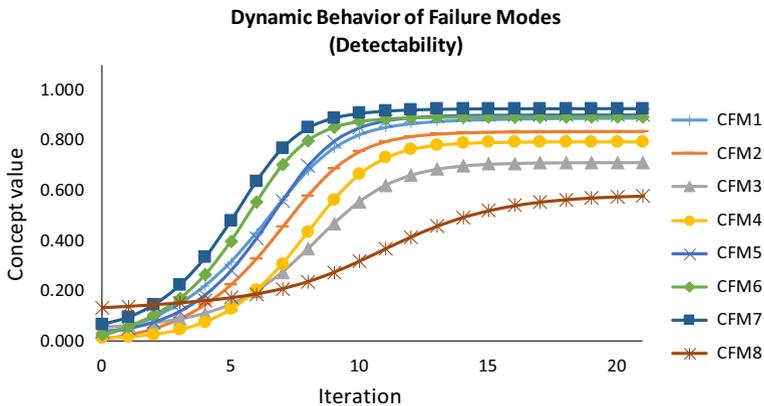


Fig. 9 Dynamic behavior of FMs with respect to detectability

As given in the Fig. 9, it takes 30 iterations to reach steady-state concept values of the FCM which is constructed in terms of detectability of the FMs. Failure to ensure key user involvement has reached to highest concept value which is 0.929. The FM with the second highest concept value is found to be failure to ensure integration between enterprise-wide systems. The most interesting observation is related to failure to maintain an effective project management. Although it has the highest initial concept value, failure to maintain an effective project management has converged to the lowest concept value. The main reason is that only failure to gain top management support makes it more difficult to detect the failure to maintain an effective project management. Other six FMs have no influence on the detectability of the failure to maintain an effective project management.

Evolution of the concept values from the detectability point of view is given in Fig. 10. The top ranked FMs with respect to detectability are failure to ensure key user involvement, failure to ensure integration between enterprise-wide systems,

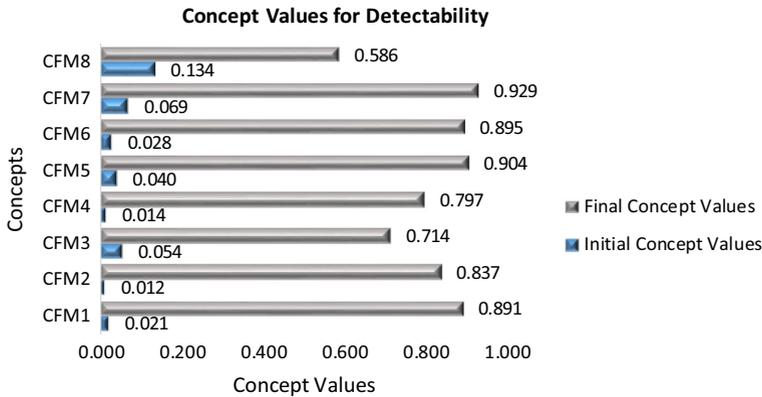


Fig. 10 Change of concept values with respect to detectability

and failure to understand and respond changing customer requirements. Despite having the third rank in terms of initial concept value, failure to gain top management support moves to rank seven with respect to detectability of the FMs. Another interesting observation is that failure to effective project management ranks first in terms of initial concept value. Because of the minor impacts received from other FMs, failure to effective project management has ranked eighth in terms of detectability. This is probably due to the fact that problems incurred from the ineffective project management are easier to detect and control.

4.3 Ranking of failure modes

Step 10 The final concept values are used to form rating matrix. The rating matrices have the form as given in Eq. 40.

$$\begin{aligned}
 \Psi_1 &= \begin{bmatrix} 0.679 & 0 & 0 \\ 0 & 0.818 & 0 \\ 0 & 0 & 0.891 \end{bmatrix}, \\
 \Psi_2 &= \begin{bmatrix} 0.743 & 0 & 0 \\ 0 & 0.830 & 0 \\ 0 & 0 & 0.837 \end{bmatrix}, \dots, \\
 \Psi_8 &= \begin{bmatrix} 0.777 & 0 & 0 \\ 0 & 0.789 & 0 \\ 0 & 0 & 0.586 \end{bmatrix}
 \end{aligned} \tag{40}$$

Step 11 Interaction matrix is formed by means of linguistic variables. The interaction matrix is given in Eq. 41.

$$\begin{aligned}
 \tilde{\beta} &= \begin{bmatrix} 0 & H & M \\ VH & 0 & H \\ L & H & 0 \end{bmatrix} \\
 &= \begin{bmatrix} 0 & (0.50, 0.65, 0.80) & (0.35, 0.50, 0.65) \\ (0.65, 0.80, 0.90) & 0 & (0.50, 0.65, 0.80) \\ (0.20, 0.35, 0.50) & (0.50, 0.65, 0.80) & 0 \end{bmatrix}
 \end{aligned}
 \tag{41}$$

Step 12 Sum of the rating and interaction matrices is calculated, and the risk ranking matrices are obtained. For instance, risk ranking matrix for the FM₁ is calculated as given in Eq. 42.

$$\begin{aligned}
 \zeta_1 &= \begin{bmatrix} 0.679 & 0 & 0 \\ 0 & 0.818 & 0 \\ 0 & 0 & 0.891 \end{bmatrix} \\
 &+ \begin{bmatrix} 0 & (0.50, 0.65, 0.80) & (0.35, 0.50, 0.65) \\ (0.65, 0.80, 0.90) & 0 & (0.50, 0.65, 0.80) \\ (0.20, 0.35, 0.50) & (0.50, 0.65, 0.80) & 0 \end{bmatrix} \\
 &= \begin{bmatrix} (0.679, 0.679, 0.679) & (0.50, 0.65, 0.80) & (0.35, 0.50, 0.65) \\ (0.65, 0.80, 0.90) & (0.818, 0.818, 0.818) & (0.50, 0.65, 0.80) \\ (0.20, 0.35, 0.50) & (0.50, 0.65, 0.80) & (0.891, 0.891, 0.891) \end{bmatrix}
 \end{aligned}
 \tag{42}$$

The same calculations are performed and the risk ranking matrices are obtained as seen in Table 13.

Step 13 Permanent values of the risk ranking matrices are calculated to obtain RPIs. The fuzzy permanent values and their crisp equivalentents are given in Table 14.

Finally, calculated permanent values are sorted in a descending order. The most critical FMs are depicted in Fig. 11.

The most significant FM is found as failure to ensure key user involvement.

The yielded results have been compared with the traditional approach. In the traditional FMEA, RPN value of each FM is produced by multiplication of risk ratings. Because traditional FMEA employs a different rating scale, the produced results are compared with the case in which possible interdependencies in RFs and FMs are ignored. Based on the weighted risk assessment matrix given in Table 11, risk ratings are multiplied and the FMs are prioritized. Consequently, the most critical FM has been found as failure to ensure key user involvement (FM₇), which is in line with the produced result. The second critical FM in the traditional approach is failure to maintain an effective project management (FM₈). However, FM₈ has received relatively low influences from FM₂ and FM₃ only in the FCM. Therefore, overall influence exerted into FM₈ in the resulted FCM simulation is

Table 13 Risk ranking matrices of the failure modes

		S	O	D
FM1	S	(0.679, 0.679, 0.679)	(0.50, 0.65, 0.80)	(0.35, 0.50, 0.65)
	O	(0.65, 0.80, 0.90)	(0.818, 0.818, 0.818)	(0.50, 0.65, 0.80)
	D	(0.20, 0.35, 0.50)	(0.50, 0.65, 0.80)	(0.891, 0.891, 0.891)
FM2	S	(0.743, 0.743, 0.743)	(0.50, 0.65, 0.80)	(0.35, 0.50, 0.65)
	O	(0.65, 0.80, 0.90)	(0.830, 0.830, 0.830)	(0.50, 0.65, 0.80)
	D	(0.20, 0.35, 0.50)	(0.50, 0.65, 0.80)	(0.837, 0.837, 0.837)
FM3	S	(0.935, 0.935, 0.935)	(0.50, 0.65, 0.80)	(0.35, 0.50, 0.65)
	O	(0.65, 0.80, 0.90)	(0.946, 0.946, 0.946)	(0.50, 0.65, 0.80)
	D	(0.20, 0.35, 0.50)	(0.50, 0.65, 0.80)	(0.714, 0.714, 0.714)
FM4	S	(0.750, 0.750, 0.750)	(0.50, 0.65, 0.80)	(0.35, 0.50, 0.65)
	O	(0.65, 0.80, 0.90)	(0.795, 0.795, 0.795)	(0.50, 0.65, 0.80)
	D	(0.20, 0.35, 0.50)	(0.50, 0.65, 0.80)	(0.797, 0.797, 0.797)
FM5	S	(0.884, 0.884, 0.884)	(0.50, 0.65, 0.80)	(0.35, 0.50, 0.65)
	O	(0.65, 0.80, 0.90)	(0.966, 0.966, 0.966)	(0.50, 0.65, 0.80)
	D	(0.20, 0.35, 0.50)	(0.50, 0.65, 0.80)	(0.904, 0.904, 0.904)
FM6	S	(0.961, 0.961, 0.961)	(0.50, 0.65, 0.80)	(0.35, 0.50, 0.65)
	O	(0.65, 0.80, 0.90)	(0.950, 0.950, 0.950)	(0.50, 0.65, 0.80)
	D	(0.20, 0.35, 0.50)	(0.50, 0.65, 0.80)	(0.895, 0.895, 0.895)
FM7	S	(0.963, 0.963, 0.963)	(0.50, 0.65, 0.80)	(0.35, 0.50, 0.65)
	O	(0.65, 0.80, 0.90)	(0.964, 0.964, 0.964)	(0.50, 0.65, 0.80)
	D	(0.20, 0.35, 0.50)	(0.50, 0.65, 0.80)	(0.929, 0.929, 0.929)
FM8	S	(0.777, 0.777, 0.777)	(0.50, 0.65, 0.80)	(0.35, 0.50, 0.65)
	O	(0.65, 0.80, 0.90)	(0.789, 0.789, 0.789)	(0.50, 0.65, 0.80)
	D	(0.20, 0.35, 0.50)	(0.50, 0.65, 0.80)	(0.586, 0.586, 0.586)

Table 14 Permanent values of the failure modes

Failure mode	Fuzzy permanent	Crisp permanent (RPI)
FM1	(1.175, 1.796, 2.625)	1.865
FM2	(1.196, 1.819, 2.653)	1.889
FM3	(1.327, 1.971, 2.839)	2.045
FM4	(1.141, 1.754, 2.575)	1.823
FM5	(1.518, 2.192, 3.090)	2.267
FM6	(1.579, 2.263, 3.173)	2.338
FM7	(1.637, 2.329, 3.249)	2.405
FM8	(0.963, 1.538, 2.323)	1.608

quite low. Investigating the failure to understand and respond changing customer requirements (FM_6), relatively high influences are exerted into this FM in the FCM simulation. Hence, FM_6 is ranked second as a result of the proposed model. In the traditional approach, the third and fourth ranked FMs are FM_3 and FM_5 ,

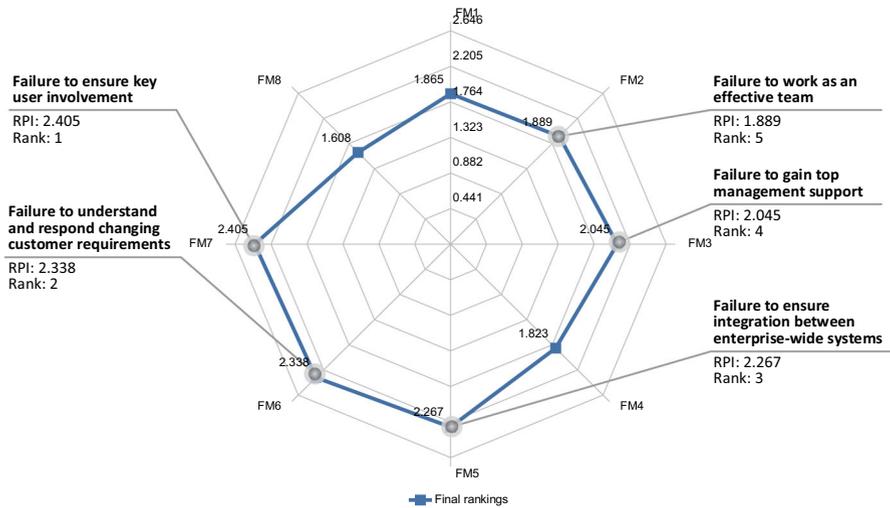


Fig. 11 Final rankings of the failure modes

respectively. On the other hand, in the proposed model, FM₅ is ranked third, and FM₃ is ranked fourth, respectively. As a result of the analysis, it can be said that priorities of the FMs may differ considerably if the causal dependencies are taken into consideration. The main advantage of the proposed model is that decision makers can better understand cause and effect relationships among FMs and interpret the results.

5 Concluding remarks

In this study, a new hybrid fuzzy FMEA model, which combines FPP, FCMs, and fuzzy GTMA, is proposed. The proposed model exhibits desirable properties that help overcome the drawbacks of the traditional FMEA and RPN. The proposed model is realized in a software company producing ERP products. The results have showed that the most critical risks among the potential failures are failure to ensure key user involvement, failure to understand and respond changing customer requirements, and failure to ensure integration between enterprise-wide systems. The results have been shared with the company, and several action plans are being generated to mitigate the ERP implementation failures.

The main limitation of the presented study is that the results produced by the proposed model is highly dependent on the expert’s perceptions. Accordingly, results are difficult to be generalized. Secondly, experts are the ERP implementers of the company so that the results might represent single-sided views. Nevertheless, the presented study can be improved in terms of many aspects. The higher order uncertainties, such as type-2 fuzzy sets, hesitant fuzzy sets, etc. can be used in the survey processing stage. Also, other stakeholders’ views can be included. Different

RFs can be incorporated into the evaluation model. In future studies, these considerations will be at the top of our agenda.

Appendix A: Fuzzy preference programming solution

In this section, derivation of RF weights has been explained in detail. According to Table 9, pairwise comparisons of RFs can be written as in Eq. A.1.

$$\begin{bmatrix} \tilde{a}_{11} = (1, 1, 1) & \tilde{a}_{12} = (4, 5, 6) & \tilde{a}_{13} = (1, 1, 2) \\ \tilde{a}_{21} = (1/6, 1/5, 1/4) & \tilde{a}_{22} = (1, 1, 1) & \tilde{a}_{23} = (1/4, 1/3, 1/2) \\ \tilde{a}_{31} = (1/2, 1, 1) & \tilde{a}_{32} = (2, 3, 4) & \tilde{a}_{33} = (1, 1, 1) \end{bmatrix} \quad (\text{A.1})$$

Based on the bilinear program given in Eq. 7, mathematical model is constructed. Because the fuzzy pairwise comparison matrix is reciprocal, only the elements of the upper right part are used for building mathematical model. Therefore, we need to write constraints for the following judgements: \tilde{a}_{12} , \tilde{a}_{13} , and \tilde{a}_{23} . The resulting nonlinear optimization model is given in Eq. A.2.

$$\begin{aligned} & \text{Maximize: } \lambda \\ & \text{Subject to} \\ & \left. \begin{aligned} (5 - 4)\lambda w_2 - w_1 + (4)w_2 &\leq 0 \\ (6 - 5)\lambda w_2 + w_1 - (6)w_2 &\leq 0 \end{aligned} \right\} \text{ constraints for } \tilde{a}_{12} \\ & \left. \begin{aligned} (1 - 1)\lambda w_3 - w_1 + (1)w_3 &\leq 0 \\ (2 - 1)\lambda w_3 + w_1 - (2)w_3 &\leq 0 \end{aligned} \right\} \text{ constraints for } \tilde{a}_{13} \\ & \left. \begin{aligned} (1/3 - 1/4)\lambda w_3 - w_2 + (1/4)w_3 &\leq 0 \\ (1/2 - 1/3)\lambda w_3 + w_2 - (1/2)w_3 &\leq 0 \end{aligned} \right\} \text{ constraints for } \tilde{a}_{23} \\ & w_1 + w_2 + w_3 = 1 \\ & w_1 \geq 0, w_2 \geq 0, w_3 \geq 0 \end{aligned} \quad (\text{A.2})$$

Note that for each judgement in the upper right part of the comparison matrix, two constraints have been added to the model. If a judgement has been left blank by decision maker, then no constraint has been written instead. Solution of the above model has already been given in Eq. 36, Sect. 4.1.

References

- Axelrod R (1976) Structure of decision: the cognitive maps of political elites. Princeton University Press, Princeton
- Baykasoğlu A (2014) A review and analysis of “graph theoretical-matrix permanent” approach to decision making with example applications. *Artif. Intell. Rev.* 42:573–605
- Bellman RE, Zadeh LA (1970) Decision-making in a fuzzy environment. *Manage. Sci.* 17:B-141–B-164

- Bowles JB, Pelaez CE (1995) Fuzzy-logic prioritization of failures in a system failure mode, effects and criticality analysis. *Reliab Eng Syst Saf* 50:203–213
- Braglia M, Frosolini M, Montanari R (2003) Fuzzy TOPSIS approach for failure mode, effects and criticality analysis. *Qual Reliab Eng Int* 19:425–443
- Broekhoven EV, Baets BD (2006) Fast and accurate center of gravity defuzzification of fuzzy system outputs defined on trapezoidal fuzzy partitions. *Fuzzy Sets Syst.* 157:904–918
- Bueno S, Salmeron JL (2009) Benchmarking main activation functions in fuzzy cognitive maps. *Expert Syst. Appl.* 36:5221–5229
- Chandramohan A, Rao MVC, Arumugam MS (2006) Two new and useful defuzzification methods based on root mean square value. *Soft. Comput.* 10:1047–1059
- Chang CL, Liu PH, Wei CC (2001) Failure mode and effects analysis using grey theory. *Integr Manuf Syst* 12:211–216
- Chang KH, Chang YC, Lai PT (2014) Applying the concept of exponential approach to enhance the assessment capability of FMEA. *J. Intell. Manuf.* 25:1413–1427
- Gargama H, Chaturvedi SK (2011) Criticality assessment models for failure mode effects and criticality analysis using fuzzy logic. *IEEE Trans. Reliab.* 60:102–110
- Geum Y, Cho Y, Park Y (2011) A systematic approach for diagnosing service failure: service-specific FMEA and grey relational analysis approach. *Math. Comput. Model.* 54:3126–3142
- Gilchrist W (1993) Modelling failure modes and effects analysis. *Int J Qual Reliab Manag* 10:16–23
- Gölcük İ, Baykasoğlu A (2016) An analysis of DEMATEL approaches for criteria interaction handling within ANP. *Expert Syst. Appl.* 46:346–366
- Hsieh T-Y, Lu S-T, Tzeng G-H (2004) Fuzzy MCDM approach for planning and design tenders selection in public office buildings. *Int. J. Project Manage.* 22:573–584
- Kosko B (1986) Fuzzy cognitive maps. *Int. J. Man Mach. Stud.* 24:65–75
- Kosko B (1997) Fuzzy engineering. Prentice Hall, Upper Saddle River
- Koulouriotis DE, Ketipi MK (2011) A fuzzy digraph method for robot evaluation and selection. *Expert Syst. Appl.* 38:11901–11910
- Leekwijck WV, Kerre EE (2001) Continuity focused choice of maxima: yet another defuzzification method. *Fuzzy Sets Syst.* 122:303–314
- Leyh C, Crenze L (2013) ERP system implementations vs. IT projects: comparison of critical success factors. In: Poels G (ed) Enterprise information systems of the future: 6th IFIP WG 8.9 working conference, CONFENIS 2012, Ghent, Belgium, 19–21 September 2012, Revised Selected Papers. Springer, Berlin, pp 223–233. doi:10.1007/978-3-642-36611-6
- Leyh C, Sander P (2015) Critical success factors for ERP system implementation projects: an update of literature reviews. In: Sedera D, Gronau N, Sumner M (eds) Enterprise systems strategic, organizational, and technological dimensions, lecture notes in business information processing, vol 198. Springer, Berlin, pp 45–67
- Liu HC, Liu L, Liu N, Mao LX (2012) Risk evaluation in failure mode and effects analysis with extended VIKOR method under fuzzy environment. *Expert Syst. Appl.* 39:12926–12934
- Liu HC, Liu L, Liu N (2013) Risk evaluation approaches in failure mode and effects analysis: a literature review. *Expert Syst. Appl.* 40:828–838
- Liu HC, You JX, Shan MM, Shao LN (2015) Failure mode and effects analysis using intuitionistic fuzzy hybrid TOPSIS approach. *Soft. Comput.* 19:1085–1098
- Mahdiani HR, Banaian A, Haji Seyed Javadi M, Fakhraie SM, Lucas C (2013) Defuzzification block: new algorithms, and efficient hardware and software implementation issues. *Eng. Appl. Artif. Intell.* 26:162–172
- Mikhailov L (2003) Deriving priorities from fuzzy pairwise comparison judgements. *Fuzzy Sets Syst.* 134:365–385
- Minc H (1978) *Permanents*. Addison-Wesley, Reading
- Ngai EWT, Law CCH, Wat FKT (2008) Examining the critical success factors in the adoption of enterprise resource planning. *Comput. Ind.* 59:548–564
- Nikas A, Doukas H (2016) Developing robust climate policies: a fuzzy cognitive map approach. In: Doumpos M, Zopounidis C, Grigoroudis E (eds) Robustness analysis in decision aiding, optimization, and analytics. Springer, Cham, pp 239–263
- Nourani Y, Andresen B (1999) Exploration of NP-hard enumeration problems by simulated annealing—the spectrum values of permanents. *Theoret. Comput. Sci.* 215:51–68
- Opricovic S, Tzeng G-H (2003) Defuzzification within a multicriteria decision model. *Int J Uncertain Fuzziness Knowl Based Syst* 11:635–652

- Özesmi U, Özesmi SL (2004) Ecological models based on people's knowledge: a multi-step fuzzy cognitive mapping approach. *Ecol. Model.* 176:43–64
- Papageorgiou EI, Salmeron JL (2014) Methods and algorithms for fuzzy cognitive map-based modeling. In: Papageorgiou EI (ed) *Fuzzy cognitive maps for applied sciences and engineering*. Intelligent systems reference library, vol 54. Springer, Berlin, pp 1–28
- Pillay A, Wang J (2003) Modified failure mode and effects analysis using approximate reasoning. *Reliab Eng Syst Saf* 79:69–85
- Puente J, Pino R, Priore P, Fuente D (2002) A decision support system for applying failure mode and effects analysis. *Int J Qual Reliab Manag* 19:137–150
- Rao RV, Padmanabhan KK (2006) Selection, identification and comparison of industrial robots using digraph and matrix methods. *Robot Comput Integr Manuf* 22:373–383
- Selim H, Yunusoglu MG, Balaman SY (2016) A dynamic maintenance planning framework based on fuzzy TOPSIS and FMEA: application in an international food company. *Qual Reliab Eng Int* 32:795–804
- Seyed-Hosseini SM, Safaei N, Asgharpour MJ (2006) Reprioritization of failures in a system failure mode and effects analysis by decision making trial and evaluation laboratory technique. *Reliab Eng Syst Saf* 91:872–881
- Shaul L, Tauber D (2013) Critical success factors in enterprise resource planning systems: review of the last decade. *ACM Comput. Surv.* 45:1–39
- Stamatis DH (1995) *Failure mode and effect analysis: FMEA from theory to execution*. ASQC Press, New York
- Tay KM, Lim CP (2010) Enhancing the failure mode and effect analysis methodology with fuzzy inference techniques. *J Intell Fuzzy Syst* 21:135–146
- Teoh PC, Case K (2005) An evaluation of failure modes and effects analysis generation method for conceptual design. *Int. J. Comput. Integr. Manuf.* 18:279–293
- Tsadiras AK (2008) Comparing the inference capabilities of binary, trivalent and sigmoid fuzzy cognitive maps. *Inf. Sci.* 178:3880–3894
- Xirogiannis G, Stefanou J, Glykas M (2004) A fuzzy cognitive map approach to support urban design. *Expert Syst. Appl.* 26:257–268
- Xu K, Tang LC, Xie M, Ho SL, Zhu ML (2002) Fuzzy assessment of FMEA for engine systems. *Reliab Eng Syst Saf* 75:17–29
- Yang Z, Bonsall S, Wang J (2008) Fuzzy rule-based Bayesian reasoning approach for prioritization of failures in FMEA. *IEEE Trans. Reliab.* 57:517–528
- Yeh CH, Xu Y (2013) Managing critical success strategies for an enterprise resource planning project. *Eur. J. Oper. Res.* 230:604–614
- Zadeh LA (1965) Fuzzy sets. *Inf. Control* 8:338–353
- Zafropoulos EP, Dialynas EN (2005) Reliability prediction and failure mode effects and criticality analysis (FMECA) of electronic devices using fuzzy logic. *Int J Qual Reliab Manag* 22:183–200
- Zammori F, Gabrielli R (2012) ANP/RPN: a multi criteria evaluation of the risk priority number. *Qual Reliab Eng Int* 28:85–104
- Zhang Z, Chu X (2011) Risk prioritization in failure mode and effects analysis under uncertainty. *Expert Syst. Appl.* 38:206–214
- Zimmermann H-J (1990) *Fuzzy set theory—and its applications*. Kluwer, Alphen aan den Rijn