**RESEARCH PAPER** 



# A New Risk Assessment Model for Construction Projects by Adopting a Best–Worst Method–Fuzzy Rule-Based System Coupled with a 3D Risk Matrix

Hayder Razzaq Abed<sup>1</sup> · Hatim A. Rashid<sup>1</sup>

Received: 25 January 2023 / Accepted: 25 March 2023 / Published online: 21 April 2023 © The Author(s), under exclusive licence to Shiraz University 2023

#### Abstract

Many organizations in developing countries have started to place a strong priority on risk management in their business. Therefore, this article proposes a novel model that incorporates organizational maturity as a new dimension in the risk evaluation of construction projects. The research methodology uses a hybrid best–worst method–fuzzy rule-based system (BWM-FRBS) combined with a 3D risk matrix to evaluate risks based on the probability and mathematical equations generated for the impact and the organizational maturity. After analyzing several research studies, the initial risk assessment structure was formed. A focus group session with 12 experts was carried out to confirm the final components of the model parameters. The component weights were calculated using the BWM technique. The impact and the organizational maturity equations and the probability of occurrence were then used as inputs to the FRBS model to determine the risk score. This model used a 3D risk matrix to construct fuzzy rules. Iraqi construction projects were used as a case study to confirm the validity of the integrated model. The authors concluded that this model is more effective and precise than conventional techniques for evaluating and prioritizing risk and can provide critical information for risk management.

Keywords Organizational maturity · Risk assessment · Mathematical equations · BWM-FRBS model · 3D risk matrix

### 1 Introduction

Construction projects are performed within dynamic and complex environments, making uncertainty and risk their defining characteristics. As a result, most construction projects fail to meet their stated objectives (Zegordi et al. 2014). The primary objective of risk management is to enhance the likelihood of project success. The way to achieve this goal is to methodically detect and evaluate potential risks, propose solutions to eliminate them, and take full advantage of favorable situations (Chapman 1996). Therefore, a successful process of risk management, beginning with risk assessment, cannot happen without this step, since taking the proper preventive and corrective measures in the

 Hayder Razzaq Abed alhussaniee@gmail.com; st.hayder.razzaq@ced.nahrainuniv.edu.iq next phase of risk management depends on completing this step (Alvand et al. 2021). Currently, the use of risk assessment techniques in the construction industry is growing. Researchers and practitioners in the construction sector have developed several approaches based on Monte Carlo simulation (MCS), risk matrix (RM), analytical hierarchy process (AHP), sensitivity analysis (SA), fault tree (FT), and event tree (ET) methods (Ahmadi et al. 2016).

In recent years, various models have been created to adequately evaluate the risks that projects can pose. In 2013, a fuzzy-inference system (FIS) was created to calculate the hazards associated with roof fall by predicting the roof fall rate (Razani et al. 2013). In Iran, Keramati et al. (2013a) utilized a fuzzy AHP to analyze customer relationship management risks depending on the expert opinions of project managers. In the same year, they utilized the fuzzy analytical network process (FANP) for expert-driven prioritization of risk factors (Keramati et al. 2013b). Ebrat and Ghodsi (2014) assessed construction project risks using an adaptive network-based fuzzy inference system (ANFIS) model. The findings demonstrate that the ANFIS model provides



<sup>&</sup>lt;sup>1</sup> Civil Engineering Department, College of Engineering, Al-Nahrain University, Baghdad, Iraq

more accurate risk assessments for building projects. Samadi et al. (2014) used the FANP to rank risk factors and the F-TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method for ranking responses. Valipour et al. (2016) proposed a new approach for fair risk allocation by utilizing fuzzy techniques and cybernetic ANP, focusing on detecting correlations between risk allocation criteria and obstacles. Using Dempster-Shafer theory, Hatefi et al. (2019) established an evidentiary system for project environmental risk evaluation that accounts for uncertainty. The model is used to calculate the potential impact of the Maroon oil pipelines on the Isfahan ecosystem. Also, a tunneling case study from the relevant literature is applied to the proposed model. In another study, Boral et. al. (2020) proposed a novel strategy by combining the fuzzy-AHP with the F-MAIRCA (Multi-Attribute Ideal-Real Comparative Analysis). This study estimated the relative weights of risk variables using the fuzzy-AHP approach and then proposed a modified F-MAIRCA to evaluate risk events. The findings of their study demonstrated that their improved F-MAIRCA approach is efficient and yields more feasible decisions. Li et al. (2020) developed an evaluation method for the underground gas hazard in coal mines using the fuzzy AHP and Bayesian network techniques. Based on the findings, the model can serve as a guide for decisions in the coal mining industry to mitigate the danger of gas explosions in the coal mines. Etemadinia et al. (2021) proposed a system dynamics and ISM approach for analyzing uncertainties during the design phase of construction projects. The findings demonstrate how managers may more precisely estimate project goals such as cost and completion time by considering the linked dynamics and structures of the entire project risk.

After this introduction, the remainder of the article is structured as follows: The second section highlights a review of the previous literature. Section 3 discusses research gaps and the study problem. In the fourth section, the research objectives are defined. Sections 5 and 6 describe the techniques used. The research method is clearly described in the seventh section. Section 8 describes the field work of this study, explaining the literature reviews and the meeting with experts as well as the case study that will be adopted. Section 9 includes the results obtained and the final form of the proposed model. Section 10 discusses the results and main contribution of this study, and the conclusions are given in section 11.

### 2 Literature Review

The meaning of the word "risk" is relatively unclear due to its many meanings and assessment techniques. Thus, risk could be uncertainty, possible loss, repercussions, the possibility of an undesirable occurrence, or the influence



of ambiguity on goals, depending on the situation. Often, it is a composite measure, such as Consequences or Damages + Uncertainty or Consequences + Probability (Aust and Pons 2021).

Over time, the ISO 31000 risk management (ISO 2009) principle interpretation has become the predominant standard. It defines risk as "the influence of uncertainty on the likelihood of attaining the organization's goals." In addition, this standard gives a precise method for determining risk and demonstrates that each risk is the result of combining two risk dimensions: the consequences of the risk and the likelihood of the risk occurring. These are then combined to form a risk metric. The combination can be accomplished in one of two approaches: (i) by multiplying the impact by the probability if both scales are numeric, or (ii) by utilizing a correlation matrix. The acceptable risk thresholds are then utilized to classify and prioritize the risks based on acceptability, practicability, reaction time, cost–benefit ratio, durability, enforceability, and compliance with the law.

One advantage of using the ISO 31000 "Impact  $\times$  Probability" model to determine risk is that it offers a standardized approach. Nevertheless, it has certain restrictions. When it comes to risk management in its broadest sense, the scales are virtually always subjective and highly varied from one organization to the other (Waldron 2016; Pons 2019). Even the same scale might result in different estimates from several analysts, further contributing to inconsistent results. These components do not provide enough detail for many situations.

In an effort to consider additional, conditional criteria, the available research demonstrates a variety of approaches to accomplishing this goal. Extending the risk measure to include three or more components is a popular strategy. The most popular ones were manageability (Aven et al. 2007; Azadeh-Fard et al. 2015), detectability (Youssef and Hyman 2010), and time (Osundahunsi 2012a, b). Vulnerability was mentioned most often (Kolesár et al. 2012; Cioaca et al. 2015). Other, more application-specific elements, such as knowledge (Paltrinieri et al. 2019), resilience (Chien et al. 2019), and experience (Gray et al. 2019), have also been incorporated into the risk equations. The definition of the effects and the probability comes first in many of these techniques; subsequent steps include adding the other components. Table 1 lists risk equations that use an additional variable as input.

# **3** Research Gaps and Problem Statement

Although standard methods such as a 2D risk matrix are easy to comprehend, they do not allow complicated causation to be depicted. This has produced a large body of literature about strategies that discuss the consequence, the

No.	Probability criteria	Impact criteria	Addition input	Application	Authors
1	Probability	Impact	Recovery time $\times$ expected cost	Construction projects	Al-Mhdawi et. al. (2022)
2	Likelihood	Consequence	Vulnerability	Construction projects	Asadi et al. (2018)
3	Probability	Impact	stakeholder attribute $(SA) \times Manageability$	Construction projects	Xia et al. (2017)
4	Probability	Impact (cost)	Impact (schedule)	Construction projects	Abd El-Karim et al. (2015)
5	Probability	Expected loss	Manageability	Industrial enterprise	Valitov et al. (2014)
6	Likelihood	Impact	Probability of detection	Supply chain	Griffis and Whipple (2012)

 Table 1
 List of models that use another factor as additional input

probability, and an extra contextual component. The majority of research has solely focused on creating one additional dimension. Based on the literature, there is no constant and straightforward approach on incorporating an additional dimension into risk assessment. This is particularly problematic in situations when there are multiple factors.

A survey of the literature mentioned in Sect. 2 reveals that significant efforts have been produced to address the shortcomings of traditional assessment approaches for risk factors. Despite the prevalence of risk identification and assessment methods in this field, there is still a need for novel studies to focus on four fundamental principles:

- Inaccurate determination of the impact level of an event on the projects' objectives. Expert assessment was often based on the impact of the event on the project cost or schedule, and some experts devoted less attention to the effects of this risk on the project environment and safety, and the project's reputation.
- Lack of attention to the maturity of the organizations in risk management as an essential dimension in assessing risks.
- Inattention to the precision and efficacy of the decisionmaking ranking processes.
- The majority of prior models cannot provide a reliable, all-inclusive strategy or methodology that integrates all essential elements of a risk assessment system.

# 4 Research Objective

Based on the gaps identified in section 3, the study aims to develop a novel model to assess, rank, and quantify risk factors by incorporating the organizational maturity as a third dimension in the risk evaluation of construction projects. Therefore, the objectives are as follows: (i) integrating three risk dimensions into a single index, where the first dimension is the probability of occurrence and the other two factors are the impact level and the organizational maturity; (ii) generating mathematical equations derived from a survey of relevant literature and expert judgments for the impact level and the organizational maturity by adopting the best–worst method (BWM); and (iii) inputting the probability of occurrence and the output of mathematical equations into the fuzzy rule-based system (FRBS)-3D risk matrix model, where the result will be the risk score.

### 5 Best-Worst Method (BWM)

A method of comparison similar to the AHP, the pairwise comparison method has been frequently used in multi-criteria decision-making (MCDM) situations (Jia et al. 2020). It generates preference matrices and provides an approach to establishing the weights of the parameters by showing the relative preferences between every pair of parameters. Because of the difficulty inherent in making comparisons and the limitations of human comprehension, using a pairwise comparison in practice suffers from the inconsistency of its comparison matrices. The BWM was developed by Rezaei; it is a vector-based approach in which the weights of parameters are derived differently depending on paired comparisons. In contrast to conventional comparison techniques, the BWM employs only integer values to describe preferences, decreases the time required for comparisons, and, most crucially, yields more consistent and trustworthy findings. The BWM stages are explained as follows (Rezaei 2015):

- From the set of parameters { P<sub>1</sub>, P<sub>2</sub>, P<sub>3</sub>, ..., P<sub>n</sub>} the best (most preferred, most important) and worst (the least preferred, least important) parameters are selected and designated by P<sub>B</sub> and P<sub>W</sub>, respectively, where P<sub>1</sub>, P<sub>2</sub>, P<sub>3</sub>, ..., P<sub>n</sub> are parameters to be compared. P<sub>B</sub> and P<sub>W</sub> are the best and worst parameters, respectively
- 2. The preference of the best parameter above all other parameters is obtained using a value ranging from 1 to 9, and the best vector for othering will be represented as  $A_B = (a_{B1}, a_{B2}, a_{B3}, ..., a_{Bn})$ , where  $A_B$ : best to others vector;  $(a_{B1}, a_{B2}, a_{B3}, ..., a_{Bn})$  or called  $a_{Bj}$  represents the preference of parameter  $P_B$  over parameters  $P_j$ , where  $P_j$  represents other parameters of study.



- 3. The preference of other parameters over the worst parameter is defined using the same range, and the other parameters compared to the worst vector may be represented as  $A_W = (a_{1w}, a_{2w}, ..., a_{nw})^T$ , where  $A_W$ : others to worst vector;  $(a_{1w}, a_{2w}, ..., a_{nw})^T$  or called  $a_{jW}$  denotes the preference of parameter  $P_j$  over the worst parameter  $P_w$ .
- 4. To determine the optimum weights, for the parameters, it is necessary to minimize the maximum absolute differences  $|W_B a_{Bj} W_j|$ ,  $|W_j a_{jW} W_W|$  for all j. This is expressed as follows:

$$\min \max_{j} = \left\{ \left| W_{B} - a_{Bj} W_{j} \right|, \left| W_{j} - a_{jW} W_{W} \right| \right\}$$
  
St.;  $\sum_{j} W_{j} = 1; W_{j} \ge 0$ , for all  $j$  (1)

Converting the problem to the following linear-programming formula can help find a solution:

$$\begin{split} \min \xi; S.t.; \left| W_B - a_{Bj} W_j \right| &\leq \xi, \text{ for all } j; \\ \left| W_j - a_{jW} W_W \right| &\leq \xi, \text{ for all } j; \\ \sum_j W_j &= 1; \\ W_j &\geq 0, \quad \text{for all } j; \end{split}$$
(2)

where  $W_B$  represents the optimal weight of the best parameter;  $W_W$  is the optimal weight of the worst parameter;  $W_j$  is the optimal weight of other parameters;  $\xi$  is the value of consistency. The linear Eq. (2) requires a novel solution. When this is done, the optimum weights  $(W_1^*, W_2^*, W_3^*, \dots, W_n^*)$ as well as optimal value of consistency of comparison  $\xi$ , designated  $\xi^*$ , are achieved. The consistency ratio indicates that the closer the value of  $\xi^*$  is to zero, the more reliable the comparison system offered by the decision-makers. Utilizing  $\xi^*$  and the relevant consistency index as illustrated in Table 2, we then compute the consistency ratio as follows:

Consistency Ratio = 
$$\frac{\xi^*}{\text{consistency index}}$$
 (3)

where  $a_{BW}$  represents the preference for the most desirable parameter over the least desirable parameter. The value of the consistency ratio will be compared with the threshold value as illustrated in Table 3.

#### 6 Fuzzy Rule-Based System (FRBS)

Fuzzy logic is commonly employed in environments characterized by impression, ambiguity, lack of full knowledge, contradictory information, partial truth, and the potential of occurring, i.e. an environment described by uncertain and defective evidence (Nauck et al. 1999). A fuzzy rule-based system (FRBS) is able to combine the knowledge of experts with data presented numerically to create fuzzy rules for analyzing the performance of a system. Knowledge may be expressed in a variety of ways. The greatest way to describe human knowledge is via expressions derived from reality. Typically, the knowledge base represents familiarity with an issue that can be solved using fuzzy linguistic principles such as IF-THEN and the effective use of a fuzzy system through an inference engine which can aid in the production of FRBS output with specified input (Ghosha et al. 2020). There are four basic components of a typical fuzzy inference process (Gallab et al. 2018):

- Fuzzification
- Fuzzy rule
- Fuzzy inference engine

Table 2Consistency index (CI)(Rezaei 2015)		a <sub>BW</sub>	1	2	3	4	5	6	7	8	9
	<u>CI (max ξ)</u>	0	0.440	1	1.630	2.30	3	3.730	4.470	5.23	
Table 3 Illustrates the threshold           for different combinations	Scale $(a_{\rm BW})$	Para	meters								
(Lieng et al. 2020)		3	4		5	6		7	8		9
	3	0.20	87 0	.2087	0.2087	0.2	087	0.2087	0.2087		0.2087
	4	0.15	81 0	.2352	0.2738	0.2	928	0.3102	0.3154		0.3273
	5	0.21	11 0	.2848	0.3019	0.3	309	0.3479	0.3611		0.3741
	6	0.21	64 0	.2922	0.3565	0.3	924	0.4061	0.4168		0.4225
	7	0.20	90 0	.3313	0.3734	0.3	931	0.4035	0.4108		0.4298
	8	0.22	67 0	.3409	0.4029	0.4	230	0.4379	0.4543		0.4599
	9	0.21	22 0	.3653	0.4055	0.4	225	0.4445	0.4587		0.4747



#### Defuzzification process

**Fig. 1** Structure of FRBS (Hatefi et al. 2019)

Figure 1 illustrates the structure of FRBS. The fuzzification method is done to create values of membership for a variable utilizing the membership functions (MF) depending on the fundamental notions of the theory of fuzzy set. With the aid of the membership functions, their value for a fuzzy variable may be generated using the fuzzification process. The membership functions will take on a trapezoidal or triangular form depending on the issue. Fuzzification involves a transformation from the crisp numbers of inputs to their related fuzzy ones (Rastiveis et al. 2013). Nonetheless, a rule-based system often assumes that all input variables have independent connections. As can be seen from the figure, the main contrast between crisp and fuzzy systems is how the input space is partitioned according to the rules.

Mamdani, Tsukamoto, and Takagi-Sugeno fuzzy algorithms are three rule-based system algorithms that are regularly employed. The antecedent section of every algorithm is identical. In contrast, they vary in the consequent section. Mamdani presented the most frequently used inference engine approach. On the other hand, the complexity of Mamdani's approach increases linearly with the size of the set of variables in the premise. As the set of rules increases, building rules may become highly laborious, and it often becomes difficult to grasp the links between the antecedents and consequences (Cavallaro 2015). The Tsukamoto approach defines the consequence of each rule using a fuzzy set with a monotonic membership function. The output is derived via a weighted average procedure. Fuzzy inputs lead to a clear result in the Takagi-Sugeno-type approach (linearly combining the information). It is efficient, robust, and well suited to deal with optimization and adaptive processes. Therefore, it is particularly appropriate to control problems, notably for nonlinear dynamic systems. However, the Mamdani approach is more accommodating to human input (Rastiveis et al. 2013; Asadi et al. 2018). The current study uses the Mamdani algorithm in the proposed model for project risk assessment.

Fuzzy values are produced through the inference process. By defuzzification, the results of a fuzzy risk assessment will be "defuzzed." Different methods of defuzzification have been used, including centroid of area, smallest of maximum, and mean of maximum. The appropriate defuzzification method must be selected depending on application (Abed 2022). This research applies the centroid of area (COA) approach to defuzzification.

### 7 Methodology

This article presents an integrated risk assessment framework that can assist construction project managers in assessing and prioritizing project risk factors more efficiently and systematically than the existing risk assessment methods, which provide ambiguous visions of risk factor priority. Consequently, the developed model may help construction project managers to put suitable response plans for assessed risks.

The proposed integrated model is broken down into the following six primary stages:

1. Stage 1: Preparing the initial structure of the risk assessment algorithm:

Extensive systematic literature studies are carried out for a large number of papers concentrating on risk assessment to characterize an initial set of evaluation parameters.

2. Stage 2: Focus group session.

Twelve experts of academia and industry engineers collaborate to verify and reach a consensus on a set of evaluation dimensions. Three evaluation dimensions with nine sub-dimensions have been considered the most important factors for evaluating risks as follows:





- Probability of occurrence.
- Impact level (including financial loss, schedule loss, quality loss, health and safety loss, reputation damage).
- Organizational maturity (including risk detection, risk control, resilience, risk communication).
- 3. Stage 3: Constructing mathematical equations of impact level and organizational maturity.

The BWM under LINGO software, version 20, is used to determine the preferable weights of the sub-dimensions of both impact level and organizational maturity in order to make the final mathematical equations for the dimensions.

- 4. Stage 4: Building a fuzzy-rule based system model The outputs from the previous stage will be combined with the outputs from the risk occurrence probability. These outputs will be inputs to the fuzzy rule-based system (FRBS) model designed based on the Mamdani algorithm in MATLAB software package to compute final risks scores.
- 5. Stage 5: 3D risk matrix.

A 3D risk matrix will be used to construct the FRBS model rules in the MATLAB environment.

6. Stage 6: Validation and sensitivity analysis:

A comparison and sensitivity analysis reveal the validity of the proposed model's outcomes.

Figure 2 illustrates the steps of this model.

The integration of these techniques was as follows:

After defining the main and sub-dimensions of the proposed model from stages 1 and 2, the technique (BWM), with the help of 12 construction experts, will then be used to find the weights of the sub-dimensions and build mathematical equations for both the impact level and the organizational maturity. After that, the outputs of these two equations and the third dimension (which is the probability of the risk occurrence) will be inputs to the FRBS model. The 3D risk matrix is used to generate the rules for the FRBS technique in the MATLAB program. Thus the result will be the risk score.

# 8 Field Work

This step consists of three main sections, which are as follows:

### 8.1 Preparing the Initial Structure of the Risk Assessment Algorithm

In the traditional scenario, risk is determined by the probability and impact of a potentially unfavorable occurrence.



During a comprehensive examination of the prior literature, the authors discovered that no research had addressed "organizational maturity" as an extra factor in the risk assessment equation for building projects. Therefore, they propose adding this dimension to the structure of the prototype to become three primary dimensions: "probability of occurrence," "impact level," and "organizational maturity." In addition, they propose subdividing the dimensions of "impact level" and "organizational maturity" into subdimensions to cover all aspects and ensure that the model is comprehensive and precise in its outcomes. The proposed sub-dimensions are collected from different articles and categorized under these main dimensions as shown in Table 4.

# 8.2 Focus Group Session

The focus group considers a qualitative data collection method. It is defined as "a group of persons with certain features whose talks are centered on a specific problem or subject" (Anderson 1991). A focus group interview allows the largely homogeneous group to respond to the interviewer's questions, and will be chosen when data-gathering opportunities are scarce. Compared to individual interviews, focus groups are preferable (Vanderstoep and Johnston 2008). Consequently, as Patton (2002) underlined, focus groups are used to gather high-quality data in the social environment. They must be adequately defined and understood to perform focus group discussions effectively. Typically, focus groups need between 6 and 12 participants each session (Harthi 2015). This technique was used to develop the components of the impact level and organizational maturity.

In this study, the authors used strict rules to choose the focus group experts to ensure that the meeting results were accurate:

- 1. The experts must have at least 10 years of construction project experience.
- 2. Academic experts are required to have at least two articles in risk management.

Based on these criteria, 12 experts were selected for the focus group meeting. This group comprises project managers and academics (Ph.D. in civil engineering) who have extensive knowledge of construction projects and more than 15 years of experience working in various public and private organizations. Initially, a presentation was provided on the initial structure of the proposed risk assessment model and the primary and sub-dimensions derived from prior studies. The experts were asked about additional dimensions and modes if deemed essential. According to the findings of this section, other sub-dimensions were added, and the

#### Fig. 2 Research methodology



No.	Main dimensions	Sub-dimensions	Author
1	Impact level	Financial loss	Abd El-Karim et al. (2015); Asadi et al. (2018); Farahani et al. (2021)
		Schedule loss	Osundahunsi (2012a, b); Abd El-Karim et al. (2015); Asadi et al. (2018); Farahani et al. (2021)
		Quality loss	Asadi et al. (2018); Farahani et al. (2021)
2	Organizational maturity	Detection	Alvand et al. (2021)
		Resilience	Asadi et al. (2018); Chien et al. (2019)
		Risk control	Zhang et al. (2016)



dimensions' states were confirmed, organized, and ranked from 1 to 5 based on the experts' consensus.

## 8.3 Application of the Model in Iraqi Construction Projects

In this section, to validate the proposed model, ten critical risk factors were gathered from sources (Sami Ur Rehman et. al. 2020; Kassem et al 2020; Al-Juboori et al. 2021; Jahan et al. 2022), in addition to historical data. These risks were evaluated by decision-makers (DMs) using both the conventional methods and the proposed model. The DM team comprises five specialists working on the projects: three from the supervision team (owner, employer representatives), and others from the contractor team (project manager and worker supervisor). Table 5 presents the list of risk factors.

### 9 Results

#### 9.1 Focus Group Results

This study's expert panel comprised 12 individuals from prominent building organizations. Nearly 80% of the experts possessed a postgraduate degree. The initial structure of the model, which consists of main and sub-dimensions, was submitted to the experts so that they could verify the model and recommend any additional dimensions or states. The experts proposed adding three sub-dimensions for "impact level" and "organizational maturity," and confirmed the structure of mathematical equations; in addition, the characteristics of model criteria were developed.

Tables 6 and 7 illustrate the final findings of the focus group session to establish and validate the structure and components of the qualitative risk assessment model for construction projects. The risk assessment model comprises three primary dimensions: the probability of occurrence, impact level, and organizational maturity. The impact level includes five components, namely financial loss ( $F_{loss}$ ),

Table 5         List of risk factors	Risk code	Risk description
	<i>R</i> 1	Lack of expertise and qualifications of the contractor or subcontractors
	<i>R</i> 2	Owner intervention, as in the selection of suppliers or subcontractors
	R3	Delay in the client paying the financial dues to the contractors
	<i>R</i> 4	Inaccurate and insufficient information from the site investigation and survey
	<i>R</i> 5	Multiple change orders from the client
	R6	Fluctuation in foreign exchange rates
	<i>R</i> 7	Financial and economic crisis/financial instability
	<i>R</i> 8	Inconsistency in contract documents/ambiguous contract terms and conditions
	<i>R</i> 9	Inaccuracy in estimating time and budget
	<i>R</i> 10	Lack of skilled workers in the region where the project is being carried out/ insufficient number of site workers

Index	Financial loss	Schedule loss	Quality loss	Health and safety loss	Reputation damage
1	Very low financial loss	Very low impact on schedule	Very low impact on quality	Very low (minor Injuries or harms that may require first aid)	Very low (no damage to project reputation)
2	Low financial loss	Low impact on schedule	Low impact on quality	Low (injuries or harms that requiring first aid)	Low damage to project reputation
3	Moderate financial loss	Moderate impact on schedule	Moderate impact on quality	Moderate (injuries or harms that required hospitalization)	Moderate damage to pro- ject reputation
4	High financial loss	High impact on schedule	High impact on quality	High (injuries or harms that required long-term hospitalization)	High damage to project reputation
5	Extreme financial loss	Extreme impact on schedule	Extreme impact on quality	Extreme (death of a per- son in site)	Extreme damage to project reputation



Index	Risk detection	Risk control	Resilience	Risk communication
1	Extreme (100% capability of risk detection)	Extreme capability in control- ling risk	Extreme resilience to overcome risks	Extreme risk communication
2	High (75% probability of detect- ing risk)	High capability in controlling risk	High resilience to overcome risks	High risk communication
3	Moderate (50% probability of detecting risk)	Moderate capability in control- ling risk	Moderate resilience to overcome risks	Moderate risk communication
4	Low (25% probability of detect- ing risk)	Low capability in controlling risk	Low resilience to overcome risks	Low risk communication
5	Very low (not capable of detect- ing risk)	Very low capability in control- ling risk	Very low resilience to overcome risks	Very low risk communication

 Table 7
 Index numbers of the sub-dimensions of organizational maturity

scheduling loss ( $S_{loss}$ ), quality loss ( $Q_{loss}$ ), health and safety loss ( $H\&S_{loss}$ ), and reputation damage ( $R_{damage}$ ), as illustrated in Eq. 4. Additionally, the organizational maturity included four elements—risk detection ( $R_{detection}$ ), risk control ( $R_{control}$ ), resilience (Re), and risk communication ( $R_{communication}$ )—as illustrated in Eq. 5.

$$\{\text{Impact level} = C_1 \times F_{\text{loss}} + C_2 \times S_{\text{loss}} + C_3 \times Q_{\text{loss}} + C_4 \times H\&S_{\text{loss}} + C_5 \times R_{\text{damage}} \}$$
(4)

{Organization Maturity = 
$$X_1 \times R_{detection} + X_2 \times R_{control}$$
  
+ $X_3 \times \text{Re.} + X_4 \times R_{communication}$ } (5)

where  $(C_1, ..., C_5; X_1, ..., X_4)$  represent the normalized weight of sub-dimensions. All identified components were classified on a scale of 1 to 5, where the probability of occurrence is classified from 1 = very low to 5 = very high. Impact level and organizational maturity are classified in Tables 6 and 7.

#### 9.2 BWM Results

After the expert panel has confirmed the risk assessment model in construction projects and the focus group research has been completed, the BWM will determine the weight of each component in the impact level and organizational maturity equations. Below is a numerical example showing the calculation of sub-dimensional weights for an impact level. The example was applied to one of the 12 experts. The same procedure is used for other dimensions with other expert opinions.

 Twelve BWM questionnaires were sent to the same experts (individually). In this phase, the authors solicit experts' opinions about the best/worst parameters. The best parameter is the one each responder recognizes as the most significant sub-dimension in each major dimension equation. In contrast, the worst parameter is the one selected by each expert/decision-maker as the

 Table 8
 Sub-dimensions of impact level

Sub- dimen- sions	Financial loss	Schedule loss	Quality loss	Health and safety loss	Reputation damage
Best cri- Quality loss terion					
Worst cri- terion	Reputation	n damage			

Table 9 Preferences of expert 2

Best-to- others	Financial loss	Schedule loss	Quality loss	Health and safety loss	Reputation damage
Quality loss	3	4	1	3	5

 Table 10 Preferences of other parameters against worst factor of expert2

Others-to-worst	Reputa- tion damage
Financial loss	2
Schedule loss	2
Quality loss	5
Health and safety loss	3
Reputation damage	1

least essential sub-dimension in each central dimension equation. A brief questionnaire collects this data. The 12 responders are required to provide their preferences. Table 8 below shows, for example, the preferences of expert 2 for sub-dimensions of impact level.

2. Practitioners are required to compare their chosen best parameter to the remaining parameters and indicate their choice using a number between 1 and 9. A score of 1



indicates that both parameters are of equal significance. A score of 9 indicates that the most important parameter is far favored over the other one. This will produce best-to-others vectors. Table 9 shows the selections of expert 2.

- 3. Respondents are requested to prioritize all other factors above the least significant parameter. Once again, values of 1 to 9 will be used. This yields vectors of others-toworst (OW). Table 10 shows the preferences of expert 2 for other parameters against the worst factor.
- 4. Based on Tables 9 and 10, the best-to-others linear model and others-to-worst linear model can be generated according to Eqs. 1 and 2:

 $\operatorname{Min} \xi$ 

$$\begin{split} \left| W_{\text{Q,loss}} - 3W_{\text{F,loss}} \right| &\leq \xi \\ \left| W_{\text{Q,loss}} - 4W_{\text{S,loss}} \right| &\leq \xi \\ \left| W_{\text{Q,loss}} - 1W_{\text{Q,loss}} \right| &\leq \xi \\ \left| W_{\text{Q,loss}} - 3W_{\text{H\&S,loss}} \right| &\leq \xi \\ \left| W_{\text{Q,loss}} - 5W_{\text{Re,damage}} \right| &\leq \xi \\ \left| W_{\text{F,loss}} - 2W_{\text{R,damage}} \right| &\leq \xi \end{split}$$

$$W_{\text{S.loss}} - 2W_{\text{R.damage}} \le \xi$$

 $\left| W_{\text{H\&S.loss}} - 3W_{\text{R.damage}} \right| \le \xi$ 

 $W_{\text{F.loss}} + W_{\text{S.loss}} + W_{\text{Q.loss}} + W_{\text{H\&S.loss}} + W_{\text{R.damage}} = 1$ 

$$\begin{split} W_{\text{F.loss}} &\geq 0; W_{\text{S.loss}} \geq 0; W_{\text{Q.loss}} \geq 0; \\ W_{\text{H\&S.loss}} &\geq 0; W_{\text{R.damage}} \geq 0 \end{split}$$

- 5. The unique solution can be obtained using LINGO software, version 20, 64x. Figure 3 illustrates the programming steps in LINGO software and results for the opinion of expert 2.
- 6. Finally, we find the consistency ratio by using  $\xi$ calculated from LINGO software and value ( $\xi_{max}$ ) from Table 2, then compare the value with the threshold value from Table 3:

$$C.R. = \frac{0.0622}{2.3} = 0.027 < 0.3019 \cdots$$
(ok)

The same procedure will be used for all experts' opinions. Two invalid questionnaires were omitted from the research due to inconsistency ratio. The final weight of the sub-dimensions was then determined by calculating the arithmetic mean of the weights derived from 10 experts' opinions. Table 11 presents a list of parameter weights (the bold numbers represent the final weights of parameters).

Thus, the final Eqs. 6 and 7 of the impact level and organizational maturity were calculated as follows:

🖉 Lingo Model - Lingo1	Solution Repo	rt - Lingo1		• ×
MIN= g;		113		^
<pre>@ABS(WQloss-3*WFloss)&lt;=g;</pre>	ros:	0		
<pre>@ABS(WQloss-4*WSloss)&lt;=g;</pre>				
<pre>@ABS(WQloss-1*WQloss)&lt;=g;</pre>	omponents a	dded:		
<pre>@ABS(WQloss-3*WHSloss)&lt;=g;</pre>	:	32		
<pre>@ABS(WQloss-5*WRdamage)&lt;=g;</pre>		32		
<pre>@ABS(WFloss-2*WRdamage)&lt;=g;</pre>		8		
<pre>@ABS(WSloss-2*WRdamage)&lt;=g;</pre>				
<pre>@ABS(WHSloss-3*WRdamage)&lt;=g;</pre>				
WFloss+WSloss+WQloss+WHSloss+WRdamage=1;				
WFloss>=0;		Variable	Value	Red
WSloss>=0;		G	0.6225681E-01	
WQloss>=0;		WOLOSS	0.4513619	
WHSloss>=0;		WFLOSS	0.1712062	
WRdamage>=0;		WSLOSS	0.1284047	
END		WHSLOSS	0.1712062	
		WRDAMAGE	0.7782101E-01	
				- *
	<			>

Fig. 3 Results of weights and consistency indicator



**Table 11** Relative weightsbased on experts' opinions

{

Experts	$F_{\rm loss}$	$S_{\rm loss}$	$Q_{ m loss}$	$H\&S_{loss}$	R <sub>damage</sub>	R <sub>detection</sub>	R <sub>control</sub>	Re.	R <sub>comm.</sub>
1	0.178	0.053	0.482	0.178	0.107	0.06	0.58	0.226	0.136
2	0.171	0.128	0.451	0.171	0.077	0.477	0.182	0.273	0.068
3	0.44	0.196	0.1288	0.061	0.17	0.533	0.072	0.113	0.282
4	0.37	0.205	0.205	0.137	0.082	0.21	0.577	0.126	0.087
5	0.34	0.184	0.184	0.184	0.105	0.143	0.607	0.1786	0.0714
6	0.4	0.07	0.226	0.113	0.191	0.561	0.211	0.07	0.158
7	0.077	0.192	0.346	0.192	0.192	0.073	0.183	0.122	0.622
8	0.16	0.426	0.24	0.12	0.053	0.176	0.588	0.06	0.176
9	0.225	0.394	0.225	0.112	0.042	0.553	0.219	0.164	0.064
10	0.166	0.426	0.249	0.06	0.1	0.2155	0.5629	0.0599	0.1617
Weights	0.253	0.228	0.274	0.133	0.112	0.248	0.363	0.19	0.199

$$\{\text{Impact level} = 0.253F_{\text{loss}} + 0.228S_{\text{loss}} + 0.274Q_{\text{loss}} + 0.133H\&S_{\text{loss}} + 0.112R_{\text{damage}}\}$$
(6)

Organization Maturity = 
$$0.248R_{detection} + 0.363R_{control} + 0.19Re + 0.199R_{communication}$$
}  
(7)

9.3 Fuzzy Rule-Based System Results

The risk assessment model is established using a fuzzy platform based on the Mamdani approach and implemented in MATLAB software. The model consists of three inputs: the probability of occurrence, the impact level, the organizational maturity, and one output (i.e., risk score). According to several research studies on applied building and risk management, the Gaussian membership function is the most appropriate geometry for situations like the one under inquiry (Iliadis et al. 2010). The shape of the proposed



Tab	le 12	Linguistic	variables	of input a	and outp	out of FRBS model	
-----	-------	------------	-----------	------------	----------	-------------------	--

Variables	Linguistic term	Fuzzy rating
Probability of occurrence	Extreme (EX)	
	High (H)	
	Moderate (M)	$\land$ $\land$ $\land$ $\land$
	Low (L)	
	Very low (VL)	
Impact level	Extreme (EX)	
	High (H)	
	Moderate (M)	$  \land \land \land \land  $
	Low (L)	
	Very low (VL)	
Organizational maturity	Very low(VL)	
	Low (L)	
	Moderate (M)	$  \land \land \land \land \rangle$
	High (H)	
	Extreme (EX)	
Risk score	Extreme (EX)	
	High (H)	
	Moderate (M)	
	Low (L)	

Gaussian MFs has been employed in several models for risk assessment and was chosen based on prior research. The Gaussian shape is used as a membership function for all input and output variables in the proposed model. Figure 4 illustrates the structure of FRBS in MATLAB.

#### 9.3.1 Fuzzy Input and Output

The variables regarded as input, the probability of occurrence, impact level, and organizational maturity, and output, risk score, were represented using linguistic variables as shown in the following Table 12. Figures 5 and 6 illustrate MFs of input and output.

#### 9.3.2 Fuzzy Rule Encoding by 3D Risk Matrix

There are three input variables in this research. Each is represented using five linguistic terms. Therefore, this will generate  $5 \times 5 \times 5 = 125$  rules. In previous studies, fuzzy rules have been derived from expert opinions. In this study, the authors use a novel method for rule generation utilizing the three-dimensional (3D) risk matrix developed by Amirshenava and Osanloo (2018). The three-dimensional risk cube, which is color-coded like a traffic light, may be a valuable modern method for generating fuzzy rules. The researchers adapted the risk cube's traffic light scale to the scale of the present study (preserving the cube's color gradation). The risk cube has five layers in each direction corresponding to the probability of occurrence, impact level,



and organizational maturity scales. The cube's traffic light consists of four zones (colors), namely very high, high, moderate, and low, which correspond to the risk score, and each zone corresponds to a different level of risk. Table 13 illustrates the gradation of the cube's traffic light according to the study's scale. Figure 7 shows the details of the cube's traffic light.

#### 9.3.3 Final Assessment of the Risk Score

In the last step, the total risk score was computed by combining three inputs based on the membership function presented in Table 12. The risk score provided by the model may be advantageous to various projects by identifying those with a high prospect of failure and offering a good scenario. It is recognized that risk appraisal is a dynamic activity, yet fuzzy set theory has proven effective in addressing these issues. The 3D risk matrix is a perfect approach employed in the current study to define the complex relationship between input and output parameters. Figures 8 and 9 illustrate the control surface of the risk score in the MATLAB environment and its graphical representation, respectively.

## 9.4 Validity Test and Sensitivity Analysis of the Proposed Model

Validation is the process of determining the quality and accuracy of the results produced from a particular model

### Fig. 5 MFs of inputs







Table 13	Risk levels	of the 3D	risk matrix
----------	-------------	-----------	-------------

Matrix Zone	Risk Level
	Extreme (EX)
	High (H)
	Moderate (M)
	Low (L)

and the extent to which they represent reality (Thacker et al. 2004). To this end, methods of comparison and sensitivity analysis were used in two major portions. First, to validate the efficacy of the proposed model, the authors validated the architecture of the model with the help of an expert in the fuzzy technique. In addition, they compared the proposed model to the conventional approaches. Second, the sensitivity analysis of the dimensions was demonstrated to investigate the most influential risk score components.

#### 9.4.1 Validity of the Model

In this study, the proposed model was validated in three steps.

 The model's architecture was assessed by two experts with a Ph.D. in risk management with more than 10 years of experience. They have conducted much research in risk management utilizing fuzzy techniques. The experts confirmed that the model architecture was validated.



Fig. 8 Control surface of FRBS model

- 2. A comparison is utilized to ascertain the feasibility of the proposed model in evaluating project risk. Consequently, the conventional probability impact (PI) and traditional failure mode and effect analysis (FMEA) were used for comparisons. Five DMs with more than 10 years of experience evaluated ten risk factors using the three approaches. The findings of models are listed in Table 14.
- 3. The authors presented the findings from Table 14 to the experts in the focus group to get their feedback on the reliability of the proposed model. The experts agreed that the model's results were consistent with the actual reality of construction projects. They attribute this to the fact that the proposed model accounted for the weighted



Fig. 7 3D risk matrix heat map. For example, the first rule will be extracted by the first layer (EX): If probability is VL (green), impact is VL(green) and organizational maturity is EX, then the risk score is L (green)





relevance of variables (sub-dimensions) in the equations for impact level and organizational maturity, which conventional models overlooked. In other words, we can say that the present model addresses the shortcomings of earlier models. It is noted that the PI method ranked risks in four classes, while the FMEA method ranked risks in six. In comparison, these factors have different levels of risk score in the proposed model. Therefore, they will be more accurate in assessing and ranking risk factors.

#### 9.4.2 Sensitivity Analysis

rules of FRBS model

Sensitivity analysis is an approach for determining the most significant input factors influencing outputs (Shams et al. 2015). The sensitivity analysis was performed to identify the most influential risk score components. The cosine amplitude can be used to do this (Ji and Liang 2015). The following Eq. (8) represents this procedure:

$$R_{ij} = \frac{\sum_{l=1}^{n} \left( x_{il} \times x_{jl} \right)}{\left( \sum_{l=1}^{n} x_{il}^2 \sum_{l=1}^{n} x_{jl}^2 \right)^{\frac{1}{2}}}$$
(8)

where  $x_i$  and  $x_j$  denote input variables and output variables, respectively, while *n* represents the total data used.  $R_{ii}$  represents the strength relationship between input and output variables. The strength of the relationships are shown in Table 15. According to this table, the influential elements of the risk score are organizational maturity, impact, and probability, respectively.

### 10 Discussion

The purpose of this section is to discuss the study outcomes and the main contributions that will add to the body of knowledge. After systematic review for many studies, the authors inferred that utilizing innovative algorithms and techniques helps minimize uncertainty in assessment procedures. Additionally, new and essential factors which impact the risk levels of building projects should be investigated. Consequently, this research recommended the development of a new method to risk assessment in building projects. They found that most previous models



5	5	6	
)	J	υ	

Risk factors	(PI) appros	ach			FMEA					Proposed	model			
	Prob. (P)	Impact (I)	Risk score (PI)	Ranking	Occur- rence (0)	Severity (S)	Detec- tion (D)	RPN (OSD)	Ranking	Prob. (P)	Impact (I)	Organizational maturity (O)	Risk score (RS)	Ranking
R1	3	4	12	3	3	4	3	36	3	3	3.348	3.562	0.445	5
R2	4	3	12	3	4	3	5	60	5	4	3.074	4.058	0.639	10
R3	4	3	12	3	4	3	4	48	4	4	3.207	3.248	0.421	4
R4	3	4	12	3	3	4	4	48	4	3	3.481	3.801	0.493	8
R5	4	4	16	4	4	4	4	64	9	4	3.207	3.447	0.486	٢
R6	4	3	12	3	4	3	3	36	3	4	3.103	3.164	0.394	б
R7	2	3	9	1	2	3	3	18	1	2	3.095	3.752	0.356	1
R8	4	3	12	3	4	3	ю	36	3	4	3.12	3.354	0.449	9
R9	2	4	8	2	2	4	3	24	2	2	4.112	3.19	0.382	2
R10	б	4	12	3	3	4	3	36	3	3	3.726	3.553	0.52	6

Table 15	Explains	the strength re	lationship b	etween input and output
Input var	iable	Probability	Impact	Organizational maturity

R <sub>ij</sub>	0.9768	0.979	0.99

focus on the impact of risk on project cost and time while paying less attention to the project environment and safety and the project's reputation.

Based on extensive review of previous studies and the consensus of the focus group experts, the most critical dimensions in the new model were identified. Consequently, the two equations, the impact level and the organizational maturity were built. The researchers' next plan was to adopt a new hybrid approach to risk assessment using (BWM-FRBS) coupled with the 3D risk matrix. The BWM aimed to find the weights of the dimensions developed in this study. The outputs of these equations and the probability of the event occurring will be the inputs for the FRBS model. The role of the 3D risk matrix was to build the model's rules used in MATLAB software. The authors validated the proposed model through compared it with two of the most prevalent conventional risk assessment methods, namely the PI approach and the FMEA. With the assistance of five decision-makers, these three models were used to evaluate ten of the most significant risks affecting building projects in Iraq. Using the PI approach, the authors observed that this method gives equal ranking to risk (R1, R2, R3, R4, R6, R8, and R10). In the FMEA, the order of risk factors was computed by multiplying the parameters (O, S, D) without regard to their relative importance. This approach has a similar ranking (R1, R6, R8, and R10). These two methods may impose some restrictions on real-world applications. In contrast, the new technique based on BWM-FRBS eliminated these deficiencies and provided logical classifications based on the experts' opinions. Based on the aforementioned, the main contributions of the proposed model can be described as follows:

- 1. Provides a suitable approach to uncertainties associated with critical risk assessments of project failure where fuzzy logic can effectively deal with these uncertainties.
- 2. BWM is considered to calculate the weights of the parameters; it is not a complex calculation, and the experts utilize their expertise, knowledge, and information.
- 3. The proposed model successfully detects, evaluates, and prioritizes the most significant risks of construction projects and, consequently, delivers precise and useful information on risk management in building projects.
- 4. The three-dimensional risk matrix is adopted as a new approach combined with the fuzzy logic approach.

 Table 14
 Comparison of proposed model with other models

5. In general, the current study findings enhance our knowledge in assessing the dangers that might affect building projects.

# **11 Conclusion**

Adopting a suitable scientific approach to risk assessment can help prevent many consequences which can lead to schedule delays, budget overruns, and failure to fulfill safety and quality requirements. Because of the significance of risk evaluation and prioritizing in construction projects, the study aims to present a novel approach based on BWM-FRBS for assessing construction project risks. The research methodology involves a six-stage procedure: (i) preparing the initial structure of risk assessment which introduces new dimensions; (ii) focus group session; (iii) constructing mathematical equations using the BWM; (iv) building a fuzzy-rule-based system model; (v) using a 3D risk matrix to construct the FRBS model's rules; (vi) validation and sensitivity analysis. The most important findings in the practical part are summarized as follows:

- 1. A new dimension represented in the organizational maturity was added in the risk assessment model.
- 2. New mathematical equations were built for impact level of risk and organizational maturity. The relative importance (weights) of the sub-dimensions for both the impact level and the organizational maturity is calculated by adopting the BWM.
- The organizational maturity mathematical equation involves four components: risk detection, risk control, resilience, and risk communication. In addition, five criteria—financial loss, schedule loss, quality loss, health and safety loss, and reputation damage—are employed in the impact level equation.
- 4. The outputs derived from the previous equations with the output of the probability of occurrence resulting from experts' opinions were combined as inputs to the developed FRBS model to determine the risk score.
- 5. A 3D risk matrix was adopted in this model to generate 125 fuzzy rules utilized in MATLAB software.
- 6. A case study was employed to explain the possible applicability of the proposed paradigm by evaluating ten risk factors with the help of five decision-makers employed at an Iraqi construction organization.
- The proposed model effectively identifies, assesses, and ranks the most severe risks associated with building projects. As a result, it provides accurate and helpful information on risk management in construction projects.

Acknowledgements This work is part of a Ph.D. thesis on Risk Management, Al-Nahrain University, Iraq. I want to extend my thanks to my supervisor for the support he provided, as well as to the experts who contributed to enriching my research with valuable information.

Funding For this work, the authors did not receive funding.

#### Declarations

**Conflict of interest** The authors state that they have no conflicting interests to declare.

# References

- Abd El-Karim MSBA, Mosa El Nawawy OA, Abdel-Alim AM (2015) Identification and assessment of risk factors affecting construction projects. HBRC J 13(2):202–216
- Abed KA (2022) Three dimensional fuzzy reliability for system performance evaluation. Al-Nahrain J Eng Sci 25(2):81–90. https:// doi.org/10.29194/NJES.25020081
- Ahmadi M, Behzadian K, Ardeshir A, Kapelan Z (2016) Comprehensive risk management using fuzzy FMEA and MCDA techniques in highway construction projects. J Civil Eng Manag 23(2):300–310
- Al-Juboori OA, Rashid HA, Mahjoob AMR (2021) investigating the critical success factors for water supply projects: case of Iraq. Civil Environ Eng 17(2):438–449. https://doi.org/10.2478/ cee-2021-0046
- Al-Mhdawi MKS, Brito MP, Onggo BS, & Rashid HA (2022) Analyzing the impact of the COVID-19 pandemic risks on construction projects in developing countries: case of Iraq. In: construction research congress. pp 1013–1023
- Alvand A, Mirhosseini SM, Ehsanifar M, Zeighami E, Mohammadi A (2021) Identification and assessment of risk in construction projects using the integrated FMEA-SWARA-WASPAS model under fuzzy environment: a case study of a construction project in Iran. Int J Const Manag. https://doi.org/10.1080/15623599.2021. 1877875
- Amirshenava S, Osanloo M (2018) Mine closure risk management: an integration of 3D risk model and MCDM techniques. J Clean Prod 184:389–401
- Asadi P, Zeidi JR, Mojibi T, YazdaniChamzini A, Tamošaitienė J (2018) Project risk evaluation by using a new fuzzy model based on Elena guideline. J Civ Eng Manag 24(4):284–300
- Aust J, Pons D (2021) Methodology for evaluating risk of visual inspection tasks of aircraft engine blades. Aerospace 8(4):117
- Aven T, Vinnem JE, Wiencke HS (2007) A decision framework for risk management, with application to the offshore oil and gas industry. Reliab Eng Syst Saf 92(4):433–448
- Azadeh-Fard N, Schuh A, Rashedi E, Camelio JA (2015) Risk assessment of occupational injuries using accident severity grade. Saf Sci 76:160–167
- Boral S, Howard I, Chaturvedi SK, McKee K, Naikan V (2020) An integrated approach for fuzzy failure modes and effects analysis using fuzzy AHP and fuzzy MAIRCA. Eng Fail Anal 108:104195
- Cavallaro F (2015) A takagi-sugeno fuzzy inference system for developing a sustainability index of biomass. Sustainability 7(9):12359–12371
- Chapman C, Ward S (1996) Project risk management: processes, techniques and insights. John Wiley, Chichester, UK, p 344



- Chien LK, Wu JP, Tseng WC (2019) The study of risk assessment of soil liquefaction on land development and utilization by GIS in Taiwan. Geograp Inform Syst Sci, 59
- Cioaca C, Constantinescu CG, Boscoianu M, Lile R (2015) Extreme risk assessment methodology (ERAM) in aviation systems. Environ Eng Manag J (EEMJ), 14(6)
- Ebrat M, Ghodsi R (2014) Construction project risk assessment by using adaptive-network-based fuzzy inference system: an empirical study. KSCE J Civil Eng 18(5):1213–1227. https://doi.org/10. 1007/s12205-014-0139-5
- Etemadinia H, Tavakolan M (2021) Using a hybrid system dynamics and interpretive structural modeling for risk analysis of design phase of the construction projects. Int J Constr Manag 21(1):93–112
- Farahani AF, Khalili-Damghani K, Didehkhani H, Sarfaraz AH, Hajirezaie M (2021) A framework for project risk assessment in dynamic networks: a case study of oil and gas megaproject construction. IEEE Access 9:88767–88781
- Ghosh S, Thang DV, Satapathy SC, Mohanty SN (2020) Fuzzy rule based cluster analysis to segment consumers' preferences to eco and non-eco-friendly products. Int J Knowledge Based Intell Eng Syst 24(4):343–351
- Gray G, Bron D, Davenport ED, d'Arcy J, Guettler N, Manen O, Nicol ED (2019) Assessing aeromedical risk: a three-dimensional risk matrix approach. Heart 105(suppl1):s9–s16
- Griffis SE, Whipple JM (2012) A comprehensive risk assessment and evaluation model: proposing a risk priority continuum. Transp J 51(4):428–451
- Harthi BAA (2015) Risk management in fast-track projects: a study of UAE construction projects. Doctoral dissertation, University of Wolverhampton
- Hatefi SM, Basiri ME, Tamošaitienė J (2019) An evidential model for environmental risk assessment in projects using dempster–shafer theory of evidence. Sustainability 11(22):6329
- Iliadis L, Skopianos S, Tachos S, Spartalis S (2010, October) A fuzzy inference system using Gaussian distribution curves for forest fire risk estimation. In: IFIP international conference on artificial intelligence applications and innovations, pp 376–386. Springer, Berlin, Heidelberg
- International Organization for Standardization (ISO) (2009). Risk management: principles and guidelines ISO; 31000: Montreal, QC, Canada
- Jahan S, Khan KIA, Thaheem MJ, Ullah F, Alqurashi M, Alsulami BT (2022) Modeling profitability-influencing risk factors for construction projects: a system dynamics approach. Buildings 12(6):701
- Ji X, Liang SY (2015) Model-based sensitivity analysis of machininginduced residual stress under minimum quantity lubrication. Proc Inst Mech Eng Part B J Eng Manuf 231(9):1528–1541
- Jia F, Wang X (2020) Rough-number-based multiple-criteria group decision-making method by combining the BWM and prospect theory. Math Problems Eng, 2020
- Kassem MA, Khoiry MA, Hamzah N (2020) Theoretical review on critical risk factors in oil and gas construction projects in Yemen. Eng Constr Architect Manag 28:934–968
- Keramati A, NazariShirkouhi S, Moshki H, Afshari-Mofrad M, Maleki-Berneti E (2013a) A novel methodology for evaluating the risk of CRM projects in fuzzy environment. Neural Comput Appl 23(1):29–53
- Keramati A, Samadi H, Nazari-Shirkouhi S (2013b) Managing risk in information technology outsourcing: an approach for analysing and prioritising using fuzzy analytical network process. Int J Business Inform Syst 12(2):210–242

- Kolesár J, Petruf M (2012) Safety management system protection against acts of unlawfull interference of civil airport. J Logistics Manag 1(2):6–12
- Li M, Wang H, Wang D, Shao Z, He S (2020) Risk assessment of gas explosion in coal mines based on fuzzy AHP and bayesian network. Process Saf Environ Prot 135:207–218
- Liang F, Brunelli M, Rezaei J (2020) Consistency issues in the best worst method: measurements and thresholds. Omega 96:102175
- Nauck D, Kruse R (1999) Neuro-fuzzy systems for function approximation. Fuzzy Sets Syst 101(2):261–271
- Osundahunsi A (2012a) Effective project risk management using the concept of risk velocity, agility, and resiliency. Project Management Institute. (https://www.pmi.org/learning/library/effective-risk-management-velocity-agility-resiliency-6386)
- Osundahunsi A (2012b) Effective project risk management using the concept of risk velocity, agility, and resiliency. Project Management Institute
- Paltrinieri N, Comfort L, Reniers G (2019) Learning about risk: machine learning for risk assessment. Saf Sci 118:475–486
- Patton MQ (2002) Qualitative evaluation and research methods, 3rd edn. Sage, Thousand Oaks, CA
- Pons DJ (2019) Alignment of the safety assessment method with New Zealand legislative responsibilities. Safety 5(3):59
- Rastiveis H, Samadzadegan F, Reinartz P (2013) A fuzzy decision making system for building damage map creation using high resolution satellite imagery. Nat Hazard 13(2):455–472
- Razani M, Yazdani-Chamzini A, Yakhchali SH (2013) A novel fuzzy inference system for predicting roof fall rate in underground coal mines. Saf Sci 55:26–33. https://doi.org/10.1016/j.ssci.2012.11. 008
- Sami Ur Rehman M, Thaheem MJ, Nasir AR, Khan KIA (2020) Project schedule risk management through building information modelling. Int J Const Manag 22(8):1489–1499
- Rezaei J (2015) Best-worst multi-criteria decision-making method. Omega 53:49–57
- Samadi H, Nazari-Shirkouhi S, Keramati A (2014) Identifying and analyzing risks and responses for risk management in information technology outsourcing projects under fuzzy environment. Int J Inf Technol Decis Mak 13(06):1283–1323
- Shams S, Monjezi M, Majd VJ, Armaghani DJ (2015) Application of fuzzy inference system for prediction of rock fragmentation induced by blasting. Arab J Geosci 8(12):10819–10832
- Thacker BH, Doebling SW, Hemez FM, Anderson MC, Pepin JE, Rodriguez EA (2004) Concepts of model verification and validation. Los Alamos National Lab, New Mexico
- Valipour A, Yahaya N, Md Noor N, Mardani A, Antuchevičienė J (2016) A new hybrid fuzzy cybernetic analytic network process model to identify shared risks in PPP projects. Int J Strateg Prop Manag 20(4):409–426
- Valitov SM, Sirazetdinova AZ (2014) Project risks' management model on an industrial entreprise. Asian Soc Sci 10(21):242
- Vanderstoep SW, Johnson DD (2008) Research methods for everyday life: blending qualitative and quantitative approaches, vol 32. John Wiley & Sons, Hoboken, New Jersey, U.S.
- Waldron K (2016) Risk analysis and ordinal risk rating scales-a closer look. J Valid Technol, 22(5)
- Xia N, Zhong R, Wu C, Wang X, Wang S (2017) Assessment of stakeholder-related risks in construction projects: Integrated analyses of risk attributes and stakeholder influences. J Constr Eng Manag 143(8):04017030
- Youssef NF, Hyman WA (2010) Risk analysis: beyond probability and severity. Med Dev Diag Indus, 32(8)
- Zegordi S, Nazari A, Rezaee NE (2014) Project risk assessment by a hybrid approach using fuzzy-anp and fuzzy-topsis. Sharif J Ind Eng Manag 29(1):3–14



Zhang D, Han J, Song J, Yuan L (2016, October) A risk assessment approach based on fuzzy 3D risk matrix for network device. In: 2016 2nd IEEE international conference on computer and communications (ICCC) (pp 1106–1110). IEEE Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.

