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Assessing and Prioritizing Construction Contracting Risks with an Extended FMEA Decision-Making Model in Uncertain Environments

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ABSTRACT

This study aims to enhance risk assessment in construction contracting by addressing the limitations of traditional Failure Modes and Effects Analysis (FMEA), particularly its inability to effectively handle uncertainty and prioritize risks with equal Risk Priority Numbers (RPNs). To overcome these issues, a hybrid decision-making framework was developed by integrating fuzzy logic with the Step-wise Weight Assessment Ratio Analysis (SWARA) and Multi-Attributive Border Approximation Area Comparison (MABAC) methods. The proposed model enables more accurate weighting of risk criteria and prioritization of risks under uncertain conditions. A case study involving 18 identified construction contracting risks demonstrated the model's effectiveness, with key risks such as inadequate technical skills and poor contract conditions ranked highest due to their severe impact on cost and project outcomes. The hybrid approach improved the clarity and consistency of risk prioritization compared to traditional methods. This research contributes a flexible and practical tool for managing risks in complex construction environments. Future studies are encouraged to explore integration with real-time project monitoring systems and the application of this model across different infrastructure domains.

1. Introduction

The construction industry, due to its inherently complex and dynamic nature, consistently faces numerous challenges and is considered one of the most high-risk and demanding sectors worldwide [1]. These projects play a fundamental role in economic growth, infrastructure development, and the enhancement of social welfare. They encompass a wide range of activities, including the construction of residential buildings, commercial facilities, and critical infrastructure such as roads, bridges, and utility networks. Managing construction projects requires careful coordination of processes, resources, and stakeholders to ensure successful completion within specified budgets and timelines [2].

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Uncertain environments are a defining characteristic of the construction industry. These may include economic fluctuations, political changes, unexpected weather events, resource and material shortages, uncertainty in legal and technical requirements, and evolving stakeholder demands. Such factors significantly impact project planning and decision-making, thereby increasing overall risk levels. Consequently, risk management in these uncertain environments demands approaches that directly incorporate uncertainty into the decision-making process and prioritize risks based on their significance and impact. Effective risk management is vital for ensuring project success and requires a systematic approach to identifying, analyzing, and responding to potential risks throughout the project lifecycle. This is essential to minimize delays and cost overruns that could jeopardize project objectives [3,4]. Risks may stem from various sources such as design changes, regulatory compliance issues, labor shortages, and unforeseen conditions—each of which, if not addressed promptly, can lead to significant financial consequences and project delays [3,5].

The Failure Modes and Effects Analysis (FMEA) method is widely recognized and applied as a systematic approach for identifying and managing potential failures across various industries. It assists managers in implementing preventive measures before problems occur. However, the traditional FMEA model has limitations that affect its effectiveness. One of the most significant drawbacks is its reliance on the Risk Priority Number (RPN), calculated by multiplying three components: Severity (S), Occurrence (O), and Detection (D) of potential failure modes. This simplification can lead to risk oversight, as it assumes equal importance for S, O, and D—an assumption that often does not hold in practice. Furthermore, the traditional FMEA model is unable to distinguish between critical risks that share the same RPN score, making it unclear which should be prioritized for mitigation. These limitations reveal the inadequacy of the traditional FMEA model in complex and uncertain environments, such as those encountered in the construction industry.

In recent years, numerous methods have been developed to enhance the traditional FMEA technique, particularly to address its shortcomings in risk prioritization and evaluation accuracy. A major advancement has been the integration of fuzzy logic into FMEA, which allows for better handling of uncertainty in expert judgments. A study by Geramian *et al.*, [6] demonstrated that fuzzy inference systems improve risk assessment across various sectors, including the automotive industry. Similarly, Li *et al.*, [7] applied the fuzzy VIKOR method alongside FMEA to strengthen situational assessments by combining subjective and objective risk factors. This approach offers a more realistic alignment of risk analysis outcomes. Another notable development is the combination of soft set theory with FMEA and the COPRAS method, proposed by Wang *et al.*, [8], which effectively addresses vague and imprecise data and overcomes the prioritization limitations of traditional FMEA. Additionally, Zhou and Tang [9] improved risk assessments using an entropy-like metric, which allows for better aggregation of expert opinions when evaluating failure modes in complex systems.

Among these enhanced approaches, the Step-wise Weight Assessment Ratio Analysis (SWARA) method has emerged as a superior technique for weighting and prioritizing risks within the FMEA framework. SWARA uses a structured step-by-step evaluation process that results in more consistent and justified prioritization than traditional pairwise comparison methods. Unlike conventional FMEA, SWARA requires fewer comparisons, simplifying the risk assessment process and reducing bias in expert evaluations [10]. Its flexibility and effectiveness are further evidenced by its capacity to capture interdependencies among risk factors, offering a more comprehensive perspective on risk management. This makes SWARA particularly valuable in construction projects, distinguishing it from less integrated methods. Research by Duan *et al.*, [11] has shown that SWARA can be seamlessly combined with other multi-criteria decision-making (MCDM) tools, enhancing the overall reliability of risk evaluations in diverse contexts.

This study proposes integrating the SWARA method into risk management frameworks as an effective solution to the limitations of traditional FMEA (Table 1). SWARA performs exceptionally well in settings where expert judgment plays a key role, as its transparent step-by-step process determines the weight of each criterion while requiring fewer comparisons than approaches like AHP. This reduced complexity minimizes bias and enhances assessment accuracy—critical factors in high-risk environments such as construction. By using SWARA, construction professionals can better understand risk priorities, contributing directly to the development of more effective risk management strategies. Its flexibility in managing multidimensional criteria allows decision-makers to adapt assessments to evolving risks. Thus, incorporating SWARA into risk assessment frameworks not only addresses existing gaps but also provides a structured and reliable approach to managing uncertainty, ultimately leading to better outcomes in construction projects.

Table 1
Selected alternative and integrated approaches with the FMEA method for risk prioritization based on MCDM techniques

Author	Approaches	Case study	Specification- characteristics		
			Uncertainty	Full ranking	Weighting Criteria
Liu et *al.,*[12]	VIKOR and AHP	anesthesia process	✓	✓	
Liu et *al.,*[13]	VIKOR, AHP, DEMATEL	diesel engine's turbocharger	✓	✓	
Wang *et al.,* [14]	ANP, COPRAS	hospital service	✓	✓	✓
Bao *et al.,* [15]	AHP	Mining Industry	✓		✓
Baloch and Mohammadian [16]	DEA , VIKOR and AHP	car company	✓	✓	
Nazeri and Naderikia [17]	ANP, DEMATEL	railway of Iran	✓	✓	✓
Battirola Filho *et al.,* [18]	TOPSIS and AHP	maintenance	✓		✓
Chen [19]	ANP	Laptop manufacturers in Taiwan	✓	✓	
Melani *et al.,* [20]	ANP	Energy	✓		✓
Galehdar *et al.,* [21]	ANP , Fuzzy DEMATEL	automotive industry	✓	✓	
Kumar [22]	GRA	auto LPG Dispensing Station	✓	✓	
Yousef *et al.,* [23]	DEA	automotive parts industry	✓	✓	✓
Bian *et al.,* [24]	TOPSIS	rotor blades of an aircraft turbine	✓	✓	✓
Fattahi and Khalilzadeh [25]	MULTIMOORA, and AHP fuzzy	Kerman Steel Industries Factory	✓	✓	✓
Proposed approach	MOORA, Z-BWM	Automotive industry	✓	✓	✓

The current study presents an effective framework for assessing and prioritizing risks in construction projects under unpredictable conditions by utilizing a novel hybrid technique based on the SWARA and MABAC approaches. For precise criterion weighting, the method first applies the Step-wise Weight Assessment Ratio Analysis (SWARA) technique. SWARA enables rational and scientific weighting by overcoming the computational complexities associated with traditional methods like AHP and FMEA, thanks to its simplicity and responsiveness to expert judgment. Subsequently, the Multi-Attributive Border Approximation Area Comparison (MABAC) method is used to evaluate and prioritize the identified risks. Based on the concept of a "border approximation area," MABAC offers high accuracy and credibility in multi-criteria decision-making and effectively distinguishes between alternatives.

By combining these two methods, the proposed hybrid approach allows project managers to assess and prioritize risks more accurately in complex and uncertain environments. It addresses limitations of traditional techniques, such as the dependence on the Risk Priority Number (RPN) in conventional FMEA and the inability to handle uncertainty effectively. This novel framework reduces computational burden, enhances decision-making efficiency, and provides a practical and relevant tool for risk management in construction projects.

The primary objective of this study is to develop and implement a hybrid decision-making framework for evaluating and ranking risks in construction projects under uncertainty. The proposed approach seeks to overcome the drawbacks of conventional risk management techniques and support improved decision-making by leveraging the strengths of both SWARA and MABAC. The simplicity and flexibility of SWARA facilitate accurate criterion weighting without requiring exact data or complex computations. Meanwhile, MABAC enhances the precision and credibility of risk prioritization by emphasizing the “border approximation area” concept, clearly distinguishing between risk levels. This integration not only improves performance in uncertain environments but also reduces reliance on RPN-based methods. Consequently, this study offers a significant contribution to the field of risk assessment and prioritization in construction projects, proposing a scientifically grounded model that can be applied in both future research and practical implementations.

This section also introduces fuzzy set theory and the study’s proposed hybrid approach for assessing and ranking multiple risk events in construction projects. It begins by outlining the fundamentals of fuzzy set theory, including the concepts of fuzzy sets and linguistic variables, to help managers navigate uncertainty and imprecise data. Following this, a new hybrid strategy is presented, incorporating the FMEA method under fuzzy conditions to address the shortcomings of conventional techniques.

2. Methodology

This section discusses the methodology used to apply an improved FMEA decision-making model under uncertain conditions for evaluating and prioritizing contractor risks in construction projects. The proposed approach integrates modern multi-criteria decision-making (MCDM) methods within a fuzzy environment, considering the inherent complexity and unpredictability of data and risk management processes in the construction industry. The method involves modeling uncertainty using fuzzy logic, accurately weighting criteria through fuzzy SWARA, and evaluating and prioritizing risks using fuzzy MOORA. Additionally, fuzzy MABAC is employed to rank the alternatives and analyze the factors influencing decision-making.

2.1. Fuzzy set theory

A Triangular Fuzzy Number (TFN) is a fuzzy number characterized by a triplet of real numbers in the format (l,m,u), where l represents the lower bound, m is the most likely or modal value, and u denotes the upper bound. The upper bound u indicates the highest possible value that the fuzzy number F can attain, while the lower bound l indicates the lowest possible value.

Definition 1. Equation (1) represents a fuzzy set A that is defined on a reference set X:

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

The membership function of set A is represented by $\mu_A(x): X \to [0,1]$ in equation (1). The value of $\mu_A(x)$ indicates the level of association between $x \in X$ and A. In other words, $\mu_A(x)$ shows the degree to which x belongs to the fuzzy set A.

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

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

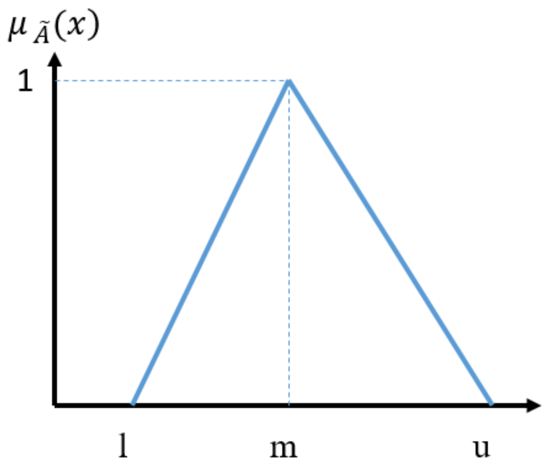

Fig. 1. Triangular Fuzzy Number

Definition 3. Triangular fuzzy numbers are computationally efficient due to their reliance on simple mathematical operations. This allows for easy execution of operations such as addition, subtraction, multiplication, and division on triangular fuzzy numbers like F1 and F2. The simplicity of these calculations makes triangular fuzzy numbers a popular choice in fuzzy logic and fuzzy mathematics for representing uncertain or imprecise values and performing computations on them:

$$F_1 = (l_1, m_1, u_1) \quad (3)$$

$$F_1 * F_2 = (l_1 * l_2, m_1 * m_2, u_1 * u_2) \quad (4)$$

$$\frac{F_1}{F_2} = \left(\frac{l_1}{u_2}, \frac{m_1}{m_2}, \frac{u_1}{l_2}\right) \quad (5)$$

$$F_1^{-1} = \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}\right) \quad (6)$$

$$K * F = (K * l, K * m, K * u) \quad (7)$$

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

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

2.2 Fuzzy SWARA

The literature offers a variety of MCDM methods to determine criteria weights, including the Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Decision-Making Trial and Evaluation Laboratory (DEMATEL), Simple Multi-Attribute Rating Technique (SMART), Weighted Sum Method (WSM), Best-Worst Method (BWM), and many others [26]. AHP is one of the most widely used techniques for determining criterion weights. However, an evaluation using the AHP approach can only be considered reliable if the consistency ratio falls within acceptable limits and the expert opinions are aligned.

To address these issues, Keršulienė *et al.*, [27] proposed the SWARA technique. The SWARA methodology overcomes the aforementioned limitations and offers a novel approach to determining criterion weights by assessing the differences in their importance. Additionally, the SWARA technique utilizes the implicit knowledge, experience, and insights of experts. It is also straightforward and easy for experts to understand and apply [28]. The primary feature of the SWARA method is its ability to estimate expert or stakeholder judgments regarding the relative significance of attributes during the weight determination process [27]. According to the intended purpose or objective, the most important criterion is assigned the highest rank, while the least important is given the lowest rank [29].

The growing popularity of the SWARA technique is evident from its recent applications in various domains such as supplier selection [30], logistics systems [31], construction equipment selection [31], and reverse logistics [32–34].

The procedure for determining the relative weights of criteria using fuzzy SWARA is described as follows:

Step 1: Factors are rated from most essential to least significant based on the decision-making process's goal. Table 2 displays the fuzzy scales.

Table 2
Fuzzy scales

Linguistic forms	Membership function
Identical Impact (II)	(1,1,1)
Slightly Impactful (SI)	(2/3,1, 3/2)
Moderately Impactful (MI)	(2/5,1/2,2/3)
Strongly Impactful (StI)	(2/7,1/3,2/5)
Dominantly Impactful (DI)	(2/9,1/4,2/7)

Step 2: The experts provide a score to factor j based on the previous criteria $(j - 1)$ for each criterion independently, beginning with the second factor [27]. This ratio is known as the $\tilde{s}_j$ value's comparative importance.

Step 3. Determine the coefficient $\tilde{k}_j$

$$\tilde{k}_j = \begin{matrix} \tilde{1}; j = 1 \\ \tilde{s}_j + \tilde{1}; j > 1 \end{matrix} \tag{9}$$

Step 4. Determine the recalculated fuzzy weights $\tilde{q}_j$

$$\tilde{q}_j = \begin{cases} \tilde{1}; j = 1 \\ \dfrac{\tilde{q}_j - \tilde{1}}{k_j}; j > 1 \end{cases} \tag{10}$$

Step 5: Calculating the respective weighting factors for the criterion under consideration

$$\widetilde{w}_j = \frac{\tilde{q}_j}{\sum_{k=1}^{n} \tilde{q}_k} \tag{11}$$

where n is the number of criteria and $\widetilde{w}_j$ is the comparative relative weights of the j criterion.

Step 6. Compute non-fuzzy value of $\widetilde{w}_j$, using equation, $x_{ij} = \frac{x_{ij}^u - x_{ij}^l + x_{ij}^m - x_{ij}^l}{3} + x_{ij}^l$

2.3 Fuzzy MOORA

The practice of concurrently maximizing two or more conflicting objectives under certain constraints is known as MOORA (Multi-Objective Optimization on the Basis of Ratio Analysis) [35]. The MOORA method was first introduced by Brauers and Zavadskas [36], and later extended to a fuzzy environment by Karande and Chakraborty [37]. Since then, the fuzzy MOORA approach has been applied in various fields of study. For example, it has been used to address MCDM problems [38], select supply chain strategies [35], evaluate employee candidates [39], choose the most suitable intelligent manufacturing systems [40], identify optimal sectors for industrial engineering students [41], and assist in supplier selection [42–44], as well as in selecting sustainable third-party reverse logistics providers [32].

This study proposes the fuzzy MOORA technique to evaluate and prioritize risks related to construction contracts under uncertain conditions, offering a novel contribution compared to prior studies. This method aims to enhance the decision-making process in scenarios where ambiguity and expert subjectivity significantly influence evaluations.

The steps of the fuzzy MOORA approach are as follows [45]:

Step 1: Form a committee of decision-makers (DM1, DM2, DM3, …, DMk). These decision-makers identify *m* alternatives and *n* evaluation criteria. The linguistic terms listed in Table 3 are then used to assess the alternatives. These linguistic characteristics are subsequently converted into fuzzy triangular numbers to derive the criteria weights [46].

Table 3
Linguistic terms

Linguistic variables	Extremely Low (XL)	Slightly Low (SL)	Fairly Low (FL)	Neutral Level (NL)	Moderately High (MH)	Significantly High (SH)	Exceptionally High (EH)
TFNs	(0,0,1)	(0,1,3)	(1,3,5)	(3,5,7)	(5,7,9)	(7,9,10)	(9,10,10)

Step 2: Following the decision makers' evaluation of the options and criteria, Eqs. 12 and 13 are utilized, respectively, to create the decision matrix and reduce the decision makers' evaluations of the alternatives and criteria to a single value.

$$\tilde{x}_{ij} = \frac{1}{k}\left[\tilde{x}_{ij}^1 \oplus \tilde{x}_{ij}^2 \oplus \dots \oplus \tilde{x}_{ij}^k\right] \tag{12}$$

Here, $\tilde{x}_{ij}^k$ displays the decision maker k's evaluation rating of the ith $(i = 1, \dots, m)$ alternative under the jth $(j = 1, \dots, n)$ criterion.

$$\widetilde{w}_{ij} = \frac{1}{k}\left[\widetilde{w}_{ij}^{1} \oplus \widetilde{w}_{ij}^{2} \oplus \dots \oplus \widetilde{w}_{ij}^{k}\right] \quad (13)$$

Here, $\widetilde{w}_{ij}^{k}$ denotes the kth decision maker's evaluation outcome for the jth criterion.

Step 3: As shown in Eq. 14, a fuzzy decision matrix $\widetilde{D}$ and fuzzy weight vector are created once a single value has been determined for each criterion and option.

$$\widetilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \qquad \widetilde{W} = [\widetilde{w}_1, \widetilde{w}_2, \dots, \widetilde{w}_n] \quad (14)$$

In this matrix $\tilde{x}_{ij} = \left(x_{ij}^{l}, x_{ij}^{m}, x_{ij}^{u}\right)$ and $x_{ij}^{l}, x_{ij}^{m}, x_{ij}^{u}$ represent the triangle fuzzy number's lowest, middle, and higher values $\tilde{x}_{ij}$.

Step 4: The normalized fuzzy decision matrix $\tilde{R}$ is created in this phase.

$$\tilde{R} = \left[\tilde{r}_{ij}\right]_{m\times n} \quad (15)$$

Here $\tilde{r}_{ij} = \left(r_{ij}^{l}, r_{ij}^{m}, r_{ij}^{u}\right)$ and these values are obtained via Eq. 16, 17 and 18 respectively.

$$r_{ij}^{l} = \frac{x_{ij}^{l}}{\sqrt{\sum_{i=1}^{m}\left[\left(x_{ij}^{l}\right)^2 + \left(x_{ij}^{m}\right)^2 + \left(x_{ij}^{u}\right)^2\right]}} \quad (16)$$

$$r_{ij}^{m} = \frac{x_{ij}^{m}}{\sqrt{\sum_{i=1}^{m}\left[\left(x_{ij}^{l}\right)^2 + \left(x_{ij}^{m}\right)^2 + \left(x_{ij}^{u}\right)^2\right]}} \quad (17)$$

$$r_{ij}^{u} = \frac{x_{ij}^{u}}{\sqrt{\sum_{i=1}^{m}\left[\left(x_{ij}^{l}\right)^2 + \left(x_{ij}^{m}\right)^2 + \left(x_{ij}^{u}\right)^2\right]}} \quad (18)$$

Step 5: In this step, weighted normalized decision matrix $\tilde{V}$ is obtained by using Eq. 19.

$$\tilde{V} = \left[\tilde{v}_{ij}\right]_{m\times n} \quad (19)$$

Here, $\tilde{v}_{ij} = \tilde{r}_{ij}(.)\widetilde{w}_j$ and $\tilde{v}_{ij} = \left(v_{ij}^{l}, v_{ij}^{m}, v_{ij}^{u}\right)$.

Step 6: In this phase, each alternative's overall ratings for the cost and benefit criteria are determined. Eqs. 20, 21, and 22 are used to determine an alternative's overall ratings for lower, middle, and upper values for the benefit criteria.

$$s_i^{+l} = \sum_{j=1}^{n} v_{ij}^{l} \mid j \in J^{max} \quad (20)$$

$$s_i^{+m} = \sum_{j=1}^{n} v_{ij}^{m} \mid j \in J^{max} \quad (21)$$

$$s_i^{+u} = \sum_{j=1}^{n} v_{ij}^{u} \mid j \in J^{max} \quad (22)$$

For cost criterion, Eqs. 23, 24, and 25 are used to determine an alternative's overall ratings for lower, middle, and upper values, respectively.

$$s_i^{-l} = \sum_{j=1}^{n} v_{ij}^{l} \mid j \in J^{min} \tag{23}$$

$$s_i^{-m} = \sum_{j=1}^{n} v_{ij}^{m} \mid j \in J^{min} \tag{24}$$

$$s_i^{-u} = \sum_{j=1}^{n} v_{ij}^{u} \mid j \in J^{min} \tag{25}$$

Step 7: The overall performance index (Si) for each option is determined at this step. This is achieved by calculating the defuzzified values of the overall ratings for benefit and cost criteria for each option using the vertex technique [45,46], as shown in Eq. 26.

$$S_i(s_i^{+}, s_i^{-}) = \sqrt{\frac{1}{3}\left[\left(s_i^{+l} - s_i^{-l}\right)^2 + (s_i^{+m} - s_i^{-m})^2 + (s_i^{+u} - s_i^{-u})^2\right]} \tag{26}$$

Step 8: Ranking the choices according to their scores on the overall performance index is the last stage. The choice with the highest overall performance index will be the best one.

2.4 MABAC Method

The MABAC technique, developed by Pamučar and Ćirović [47], has been widely applied to solve a variety of real-world problems. The main advantages of the MABAC multi-criteria framework are as follows: the algorithm is suitable for addressing multi-criteria problems with many criteria and alternatives because its mathematical formulation is not affected by an increase in the number of alternatives or criteria. (*i*) The approach produces stable results when the type of criterion formulation changes—for example, when a criterion shifts from a benefit to a cost; (*ii*) the method yields consistent outcomes even when the units of measurement used to express the criterion values of alternatives vary. The mathematical formulation of the MABAC approach is based on determining the alternatives' distance from the border approximation area (Ʊ).

Algorithm: MABAC

Input: Initial decision matrix (I) and criteria weights. $w_j = (w_1, w_2, \dots, w_n)^T$

Output: Ranking of the alternatives

Step 1: Creating a normalized initial definition matrix (N).

$\gamma_{ij} = \frac{\xi_{ij} - \xi_i^-}{\xi_i^+ - \xi_i^-}$ if C_j is Benfit, $\quad \gamma_{ij} = \frac{\xi_{ij} - \xi_i^+}{\xi_i^- - \xi_i^+}$ if C_j is Cost.

Step 2: Calculation of the weighted initial definition matrix (V).

$\zeta_{ij} = w_j(\gamma_{ij} + 1)$.

Step 3: Calculation of the matrix of boundary approximate area (Ω).

$G = \begin{bmatrix} C_1 & C_2 & \dots & C_n \\ g_1 & g_2 & \dots & g_n \end{bmatrix}$, where $g_i = \left(\prod_{j=1}^{m} \zeta_{ij}\right)^{1/m}$.

Step 4: Determining the distance of alternatives from Ω.

$$Q = \begin{bmatrix} \zeta_{11} - g_1 & \zeta_{12} - g_2 & \dots & \zeta_{1n} - g_n \\ \zeta_{21} - g_1 & \zeta_{22} - g_2 & \dots & \zeta_{2n} - g_n \\ \dots & \dots & \dots & \dots \\ \zeta_{m1} - g_1 & \zeta_{m2} - g_2 & \dots & \zeta_{mn} - g_n \end{bmatrix} = \begin{bmatrix} \vartheta_{11} & \vartheta_{12} & \dots & \vartheta_{1n} \\ \vartheta_{21} & \vartheta_{22} & & \vartheta_{2n} \\ \dots & \dots & \dots & \dots \\ \vartheta_{m1} & \vartheta_{m2} & \dots & \vartheta_{mn} \end{bmatrix}.$$

Step 5: Selection of the optimal alternative from the set of considered alternatives.

$S_i = \sum_{j=1}^{n} \vartheta_{ij}$ $(j = 1,2, \dots, n,\ i = 1,2, \dots, m)$.

We separate all of the possibilities into two groups, which we refer to as the higher approximate area ($\Omega+$) and the lower approximate area ($\Omega-$), based on the alternatives' given distances from Ω (see Figure 2). All of the alternatives in the region about above are dominant alternatives since the ideal alternative is in Ω^+. However, because they are near the anti-ideal alternative, all of the alternatives in $\Omega^+$are non-dominant alternatives. The criterion values of the alternatives in $\Omega^+$are positive $\left(q_{ij}\ \right)$, whereas those in Ω^- are negative $\left(q_{ij}\ \right)$. The choice that meets the greatest number of criteria and falls inside Ω^+ is chosen.

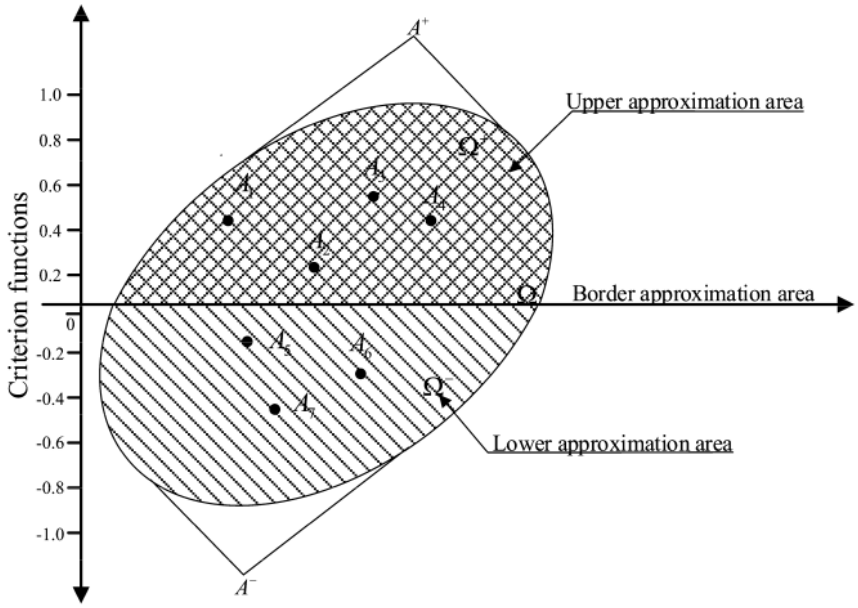

Fig. 2. Approximate MABAC technique areas.

3. Case study

The construction industry, due to its inherent complexity and the multitude of risks involved, requires precise and scientific approaches to risk management. In this study, an enhanced decision-making model based on Failure Mode and Effects Analysis (FMEA) under fuzzy conditions is proposed for evaluating and prioritizing contracting risks in construction projects. The model integrates fuzzy SWARA (for weighting the criteria), fuzzy MOORA (for assessing and ranking the risks), and fuzzy MABAC (for final analysis).

Initially, a highly experienced expert (project manager) provided the preliminary inputs. However, to enhance the accuracy and reliability of the results, a group decision-making approach was adopted. This approach involved the collaboration of three key experts: a senior contracting manager, a civil engineer specializing in risk management, and a university professor in the field of construction project management. By combining diverse perspectives and areas of expertise, this multidisciplinary team was able to effectively identify and prioritize failures within the contracting processes.

The group approach significantly improved the precision of risk identification and prioritization by considering various dimensions of each risk. For every identified failure, three key parameters were evaluated: Severity, Occurrence, and Detection. These parameters were meticulously assessed by the expert team, and based on their evaluations, the risks were prioritized. Subsequently, corrective and preventive action plans were developed for each risk to mitigate potential negative impacts.

For instance, to reduce the risk of execution errors due to inadequate supervision, the use of automated monitoring systems and surveillance cameras at the project site was recommended. Additionally, to address the risk of a shortage of skilled labor, it was suggested that specialized training programs be organized for contractor personnel. This group-based and hybrid decision-making approach not only enhanced the accuracy of risk identification and prioritization but also enabled project managers to design effective strategies for minimizing the adverse effects of risks (Tables 4 and 5).

Table 4
Risks identified in contracting in construction projects

Risk	Cause	Effect	Corrective Actions
1. Human Resource Performance	Lack of necessary skills, Poor recruitment practices	Decreased project efficiency and outcomes, Difficulty in hiring qualified personnel	- Provide training and development programs, Implement better recruitment strategies.
2. Difficulty in attracting skilled personnel	Challenges in attracting qualified candidates	Inability to fill critical roles	- Improve employer branding and outreach efforts.
3. Insufficient skills of workers	Failure to meet industry standards	Poor project quality and outcomes	- Regularly update training programs to industry standards.
4. Lack of effective project management tools	Inadequate management of project progress	Delays and overspending	- Utilize project management software (e.g., MS Project, Primavera).
5. Inefficient team collaboration	Poor communication among team members	Misalignment of project goals	- Foster team-building activities and regular meetings.
6. Lack of Proper Support from Stakeholders	Ineffective management of expectations and relationships with stakeholders.	Delays in project execution and increased risks.	- Establish a systematic approach to stakeholder engagement.
7. Implementation of Ineffective Approval Processes	Delays in obtaining approvals from relevant authorities.	Extended project timelines and increased costs.	- Streamline the approval process by identifying bottlenecks.
8. Poor Coordination Between Project Schedules	Conflicts between overlapping project timelines.	Inefficiencies and potential resource clashes.	- Regularly review and adjust project schedules to ensure alignment.
9. Lack of Effective Quality Control (QC)	Insufficient checks and balances in project execution.	Compromised project quality and client dissatisfaction.	- Implement rigorous QC processes and regular audits.
10. Inadequate Communication with Stakeholders	Failure to effectively convey project updates and requirements.	Misinformation and potential client misunderstandings.	- Enhance communication protocols and feedback mechanisms.
11. Conditions and limits of non-exceptional contracts	Contractual ties with stakeholders overlooked.	Increased liability and project disputes.	- Ensure strict adherence to contractual obligations.
12. Coordination issues with various stakeholders	Delays in obtaining feedback from involved parties.	Project timelines are extended.	- Regular check-ins and updates with stakeholders.
13. Changes in laws and regulations	New regulations impacting project requirements.	Project compliance issues may arise.	- Keep updated with governmental regulations and adjust project plans accordingly.

Table 4
Continued

Risk	Cause	Effect	Corrective Actions
14. Inadequate guidance and guidelines	Poorly defined roles and responsibilities among team members.	Confusion and overlap in tasks.	- Clearly define roles and responsibilities in project documentation.
15. Increased project costs	Unexpected expenses not budgeted.	Budget overruns affecting project viability.	- Implement rigorous budget monitoring and management.
16. Risks from external factors	External disruptions, affecting project progress.	Delays and possible cost increases.	- Develop contingency plans, for external disruptions.
17. Lack of utilization of modern technologies	Inadequate application of tools and management practices.	Increased project duration and reduced efficiency.	- Invest in modern tools, such as BIM (Building Information Modeling) or drones, rain the team on using new technologies effectively.
18. Local contractual problems	Inability to comply with local project regulations.	Legal issues leading to project delays.	- Ensure legal compliance by consulting with local experts.

Table 5
Expert-Based Fuzzy Assessment of Failure Modes Across Five Risk Criteria in Construction Projects

	Severity (S)	Occurrence (O)	Detection (D)	Expected Cost (C)	Time (T)	RPN	Rank
R1	8	6	4	7	5	6720.0	5
R2	7	5	3	6	4	2520.0	6
R3	9	7	3	8	5	7560.0	4
R4	6	4	5	5	3	1800.0	9
R5	8	6	4	7	5	6720.0	5
R6	7	5	3	6	4	2520.0	6
R7	9	7	4	7	6	10584.0	1
R8	6	4	5	5	3	1800.0	9
R9	8	6	4	7	5	6720.0	5
R10	5	4	3	6	5	1800.0	9
R11	9	7	4	8	5	10080.0	2
R12	6	3	4	5	4	1440.0	10
R13	8	6	4	7	5	6720.0	5
R14	8	4	3	4	3	1152.0	11
R15	9	7	3	8	6	9072.0	3
R16	7	3	6	5	3	1890.0	8
R17	8	6	4	7	5	6720.0	5
R18	7	5	3	4	5	2100.0	7

4. Analyzing the results

The following section examines and evaluates the outcomes resulting from the implementation of the proposed risk assessment approach in construction projects. In the initial phase of this approach, the expert team—comprising specialists in risk management—identified various potential failure modes and determined the values of five related factors for each risk (Table 5).

To address the uncertainty associated with these factors, fuzzy number theory was employed. This theory not only accounts for the numerical ambiguity inherent in fuzzy variables but also considers their reliability. Based on the expert team's assessments, Table 6 presents the fuzzy values corresponding to the five failure mode factors, namely: Severity, Time, Cost, Detection, and Occurrence.

The results of applying the proposed method to assess and rank risks in construction projects are analyzed in this section. Initially, the fuzzy SWARA approach was used to weight the criteria. Subsequently, the fuzzy MOORA approach was applied to assess and rank the hazards. Finally, the fuzzy MABAC approach was used to verify the findings and ensure the accuracy of the ranking.

Table 6
The decision matrix represented as Fuzzy-Numbers

Symbol	S			O			D			C			T		
	TM1	TM2	TM3	TM1	TM2	TM3	TM1	TM2	TM3	TM1	TM2	TM3	TM1	TM2	TM3
F1	MH	NL	SH	NL	NL	MH	FL	FL	NL	MH	NL	MH	NL	FL	NL
F2	MH	NL	SH	NL	NL	NL	FL	SL	FL	NL	NL	MH	FL	FL	NL
F3	SH	MH	EH	MH	NL	MH	FL	SL	FL	MH	MH	SH	NL	NL	MH
F4	NL	NL	MH	FL	FL	NL	FL	FL	NL	NL	FL	NL	SL	SL	FL
F5	MH	MH	SH	NL	NL	MH	FL	SL	NL	MH	NL	SH	NL	FL	NL
F6	MH	NL	MH	NL	FL	NL	SL	SL	FL	NL	NL	MH	FL	SL	NL
F7	SH	MH	MH	MH	NL	NL	FL	FL	SL	MH	MH	NL	NL	FL	NL
F8	NL	NL	FL	FL	NL	NL	NL	FL	NL	NL	SL	NL	SL	FL	NL
F9	MH	NL	NL	NL	NL	NL	FL	SL	NL	MH	NL	MH	NL	FL	FL
F10	NL	MH	MH	FL	NL	NL	SL	FL	SL	NL	NL	NL	NL	NL	FL
F11	SH	MH	SH	MH	NL	MH	FL	FL	FL	MH	MH	MH	NL	FL	NL
F12	NL	NL	NL	SL	SL	FL	FL	NL	NL	NL	NL	NL	FL	SL	SL
F13	MH	MH	NL	NL	NL	NL	FL	NL	NL	MH	NL	MH	NL	NL	NL
F14	MH	NL	MH	FL	NL	NL	SL	SL	SL	FL	NL	NL	SL	SL	FL
F15	SH	MH	MH	MH	MH	NL	SL	SL	FL	SH	MH	NL	NL	NL	FL
F16	MH	MH	NL	FL	FL	FL	NL	NL	NL	NL	FL	NL	SL	SL	SL
F17	MH	NL	NL	NL	FL	NL	FL	FL	NL	MH	SH	NL	NL	FL	NL
F18	MH	MH	MH	NL	NL	NL	SL	SL	SL	FL	NL	NL	NL	FL	FL

The Fuzzy-SWARA methodology is used in the second step of the suggested method to estimate the weights of the five components. As shown in Tables 7 and 8, the FMEA team uses linguistic descriptors to assess each factor's relative significance in relation to the preceding one in order to accomplish this goal.

Table 7
The values determined by the experts for the risk factors are presented in the form of Fuzzy Numbers

TM1		TM2		TM3	
Risk Factor	Relative Important	Risk Factor	Relative Important	Risk Factor	Relative Important
S		S		S	
C	SI	T	SI	T	MI
T	MI	C	MI	C	MI
O	MI	D	StI	O	StI
D	StI	O	StI	D	MI

Table 8
The Risk Factor Weights

Team		The relative significance of the average value $\tilde{s}_j$			Coefficient $\tilde{k}_j = \tilde{s}_j + \tilde{1}$			Recalculated weight $\tilde{q}_j = \frac{\tilde{x}_{j-1}}{\tilde{k}_j}$			Weight $\tilde{w}_j = \frac{\tilde{q}_j}{\sum_{k=1}^{n} \tilde{q}_k}$		
TM1	S				1.000	1.000	1.000	1.000	1.000	1.000	0.389	0.450	0.530
	C	0.667	1.000	1.500	1.667	2.000	2.500	0.400	0.500	0.600	0.155	0.225	0.318
	T	0.400	0.500	0.667	1.400	1.500	1.667	0.240	0.333	0.429	0.093	0.150	0.207
	O	0.400	0.500	0.667	1.400	1.500	1.667	0.144	0.222	0.306	0.056	0.100	0.162
	D	0.286	0.333	0.400	1.286	1.333	1.400	0.103	0.167	0.238	0.040	0.075	0.126
							sum	1.887	2.222	2.573			
TM2	S				1.000	1.000	1.000	1.000	1.000	1.000	0.382	0.440	0.517
	C	0.667	1.000	1.500	1.667	2.000	2.500	0.400	0.500	0.600	0.153	0.220	0.310
	T	0.400	0.500	0.667	1.400	1.500	1.667	0.240	0.333	0.429	0.092	0.147	0.207
	O	0.286	0.333	0.400	1.286	1.333	1.400	0.171	0.250	0.333	0.065	0.110	0.172
	D	0.286	0.333	0.400	1.286	1.333	1.400	0.122	0.188	0.259	0.047	0.083	0.134
							sum	1.934	2.271	2.621			
TM3	S				1.000	1.000	1.000	1.000	1.000	1.000	0.344	0.375	0.422
	T	0.400	0.500	0.667	1.400	1.500	1.667	0.600	0.667	0.714	0.207	0.250	0.301
	C	0.400	0.500	0.667	1.400	1.500	1.667	0.360	0.444	0.510	0.124	0.167	0.247
	O	0.286	0.333	0.400	1.286	1.333	1.400	0.257	0.333	0.397	0.089	0.125	0.167
	D	0.400	0.500	0.667	1.400	1.500	1.667	0.154	0.222	0.283	0.053	0.083	0.120
							sum	2.371	2.667	2.905			

Table 9
Risk factor final weights

Risk Factors	Final Weight		
S	0.371	0.422	0.490
O	0.064	0.103	0.155
D	0.053	0.089	0.139
C	0.124	0.179	0.257
T	0.117	0.176	0.241

The intensity and cost criterion have the largest weights among the criteria, respectively, as shown by Table 9, which displays the weights of the elements as triangular fuzzy numbers. This implies that risks that directly affect expenses and serious outcomes are more significant, and the weights are as follows:
$\tilde{w}_S = (0.371, 0.422, 0.490)$,
$\tilde{w}_O = (0.064, 0.103, 0.155)$,
$\tilde{w}_D = (0.053, 0.089, 0.139)$,
$\tilde{w}_C = (0.124, 0.179, 0.257)$,
$\tilde{w}_T = (0.117, 0.176, 0.241)$.

The third step of the proposed approach uses the enlarged Fuzzy-MOORA technique to rank the risk scenarios according to the results of the first and second phases. First, fuzzy numbers are used to construct the Fuzzy-MOORA decision matrix. The assessed alternatives (risk scenarios) are represented in the rows, and the evaluation criteria (the five components) are represented in the columns. This choice matrix is converted into a triangular fuzzy number decision matrix using the changes indicated in Table 3, with the results shown in Table 10.

Table 10
Aggregated fuzzy weights of risk variables and fuzzy group assessment matrix

S									O									D								
T1			T2			T3			T1			T2			T3			T1			T2			T3		
l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u
5	7	9	3	5	7	7	9	10	3	5	7	3	5	7	5	7	9	1	3	5	1	3	5	3	5	7
5	7	9	3	5	7	7	9	10	3	5	7	3	5	7	3	5	7	1	3	5	0	1	3	1	3	5
7	9	10	5	7	9	9	10	10	5	7	9	3	5	7	5	7	9	1	3	5	0	1	3	1	3	5
3	5	7	3	5	7	5	7	9	1	3	5	1	3	5	3	5	7	1	3	5	1	3	5	3	5	7
5	7	9	5	7	9	7	9	10	3	5	7	3	5	7	5	7	9	1	3	5	0	1	3	3	5	7
5	7	9	3	5	7	5	7	9	3	5	7	1	3	5	3	5	7	0	1	3	0	1	3	1	3	5
7	9	10	5	7	9	5	7	9	5	7	9	3	5	7	3	5	7	1	3	5	1	3	5	0	1	3
3	5	7	3	5	7	1	3	5	1	3	5	3	5	7	3	5	7	3	5	7	1	3	5	3	5	7
5	7	9	3	5	7	3	5	7	3	5	7	3	5	7	3	5	7	1	3	5	0	1	3	3	5	7
3	5	7	5	7	9	5	7	9	1	3	5	3	5	7	3	5	7	0	1	3	1	3	5	0	1	3
7	9	10	5	7	9	7	9	10	5	7	9	1	3	5	5	7	9	1	3	5	1	3	5	1	3	5
3	5	7	3	5	7	3	5	7	0	1	3	0	1	3	1	3	5	1	3	5	3	5	7	3	5	7
5	7	9	5	7	9	3	5	7	3	5	7	3	5	7	3	5	7	1	3	5	3	5	7	3	5	7
5	7	9	3	5	7	5	7	9	1	3	5	3	5	7	3	5	7	0	1	3	0	1	3	0	1	3
7	9	10	5	7	9	5	7	9	5	7	9	5	7	9	1	3	5	0	1	3	0	1	3	1	3	5
5	7	9	5	7	9	3	5	7	1	3	5	1	3	5	1	3	5	3	5	7	3	5	7	3	5	7
5	7	9	3	5	7	3	5	7	3	5	7	1	3	5	3	5	7	1	3	5	1	3	5	3	5	7
5	7	9	5	7	9	5	7	9	3	5	7	3	5	7	3	5	7	0	1	3	0	1	3	0	1	3

Table 10
Continued

C									T								
T1			T2			T3			T1			T2			T3		
l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u
5	7	9	3	5	7	5	7	9	3	5	7	1	3	5	3	5	7
3	5	7	3	5	7	5	7	9	1	3	5	1	3	5	3	5	7
5	7	9	5	7	9	7	9	10	3	5	7	3	5	7	5	7	9
3	5	7	1	3	5	3	5	7	0	1	3	0	1	3	1	3	5
5	7	9	3	5	7	7	9	10	3	5	7	1	3	5	3	5	7
3	5	7	3	5	7	5	7	9	1	3	5	0	1	3	3	5	7
5	7	9	5	7	9	3	5	7	3	5	7	1	3	5	3	5	7
3	5	7	0	1	3	3	5	7	0	1	3	1	3	5	3	5	7
5	7	9	3	5	7	5	7	9	3	5	7	1	3	5	1	3	5
3	5	7	3	5	7	3	5	7	3	5	7	3	5	7	1	3	5
5	7	9	5	7	9	5	7	9	3	5	7	1	3	5	3	5	7
3	5	7	3	5	7	3	5	7	1	3	5	0	1	3	0	1	3
5	7	9	3	5	7	5	7	9	3	5	7	3	5	7	3	5	7
1	3	5	3	5	7	3	5	7	0	1	3	0	1	3	1	3	5
7	9	10	5	7	9	3	5	7	3	5	7	3	5	7	1	3	5
3	5	7	1	3	5	3	5	7	0	1	3	0	1	3	0	1	3
5	7	9	7	9	10	3	5	7	3	5	7	1	3	5	3	5	7
1	3	5	3	5	7	3	5	7	3	5	7	1	3	5	1	3	5

The results of the suggested fuzzy-MOORA approach, as shown in Table 11, are shown by taking into account both the reliability of the risks and the uncertainty related to risk variables.

Table 11
The fuzzy-MOORA triple approaches are used to prioritize risks

Risks	$\tilde{y}_i$			$\bar{y}_i$	Rank
	l	m	u		
R1	0.766	1.340	2.493	1.533	5
R2	0.647	1.593	2.190	1.477	7
R3	1.423	2.124	3.037	2.195	1
R4	0.326	0.798	1.631	0.919	14
R5	0.934	1.650	2.654	1.746	3
R6	0.498	1.282	1.959	1.246	11
R7	0.877	1.561	2.569	1.669	4
R8	0.228	0.694	1.525	0.815	17
R9	0.486	1.216	2.091	1.264	10
R10	0.515	1.338	2.033	1.296	9
R11	1.074	1.807	2.786	1.889	2
R12	0.280	0.721	1.520	0.840	16
R13	0.699	1.409	2.504	1.537	6
R14	0.415	1.106	1.668	1.063	13
R15	0.920	1.608	2.579	1.702	3
R16	0.466	0.953	1.804	1.074	12
R17	0.558	1.337	2.214	1.370	8
R18	0.584	1.467	2.060	1.370	8

Using the fuzzy MOORA method, the risks were evaluated and ranked based on weighted criteria. The results show that the risks of insufficient technical skills among contractor staff (R3) and unfavorable contractual conditions and relationships (R11) are ranked first and second, respectively. This conclusion is due to the high weights of the severity and cost criteria (obtained from fuzzy SWARA) and the direct impact of these two risks on those criteria. The risk of insufficient technical skills received a high score due to increased errors and corrective costs, while the risk related to poor contractual conditions scored highly due to the potential for legal disputes and additional indirect expenses.

Table 12
Fuzzy Integrated Weight and Score Matrix

	W1			W2			W3			W4			W5		
	5.00	6.33	8.67	3.67	5.67	7.67	1.67	3.67	5.67	4.33	6.33	8.33	2.33	4.33	6.33
	5.00			7.00			8.67			3.00			5.00		
R1	7.00	8.67	9.67	4.33	6.33	8.33	0.67	2.33	4.33	5.67	7.67	9.33	3.67	5.67	7.67
R2	3.67	5.67	7.67	1.67	3.67	5.67	1.67	3.67	5.67	2.33	4.33	6.33	0.33	1.67	3.67
R3	5.67	7.67	9.33	3.67	5.67	7.67	1.33	3.00	5.00	5.00	7.00	8.67	2.33	4.33	6.33
R4	4.33	6.33	8.33	2.33	4.33	6.33	0.33	1.67	3.67	3.67	5.67	7.67	1.33	3.00	5.00
R5	5.67	7.67	9.33	3.67	5.67	7.67	0.67	2.33	4.33	4.33	6.33	8.33	2.33	4.33	6.33
R6	2.33	4.33	6.33	2.33	4.33	6.33	2.33	4.33	6.33	2.00	3.67	5.67	1.33	3.00	5.00
R7	3.67	6.33	7.67	3.00	5.00	7.00	1.33	3.00	5.00	4.33	6.33	8.33	1.67	3.67	5.67
R8	4.33	6.33	8.33	2.33	4.33	6.33	0.33	1.67	3.67	3.00	5.00	7.00	2.33	4.33	6.33
R9	6.33	8.33	9.67	3.67	5.67	7.67	1.00	3.00	5.00	5.00	7.00	9.00	2.33	4.33	6.33
R10	3.00	5.00	7.00	0.33	1.67	3.67	2.33	4.33	6.33	3.00	5.00	7.00	0.33	1.67	3.67
R11	4.33	6.33	8.33	3.00	5.00	7.00	2.33	4.33	6.33	4.33	6.33	8.33	3.00	5.00	7.00
R12	4.33	6.33	8.33	2.33	4.33	6.33	0.00	1.00	3.00	2.33	4.33	6.33	0.33	1.67	3.67
R13	5.67	7.67	9.33	3.67	5.67	7.67	0.33	1.67	3.67	5.00	7.00	8.67	2.33	4.33	6.33
R14	4.33	6.33	8.33	1.00	3.00	5.00	3.00	5.00	7.00	2.33	4.33	6.33	0.00	1.00	3.00
R15	3.67	6.33	7.67	2.33	4.33	6.33	1.67	3.67	5.67	5.00	7.00	8.67	2.33	4.33	6.33
R16	5.00	7.00	9.00	3.00	5.00	7.00	0.00	1.00	3.00	2.33	4.33	6.33	1.67	3.67	5.67
R17	5.00	6.33	8.67	3.67	5.67	7.67	1.67	3.67	5.67	4.33	6.33	8.33	2.33	4.33	6.33
R18	5.00	7.00	8.67	3.00	5.00	7.00	0.67	2.33	4.33	3.67	5.67	7.67	1.67	3.67	5.67

Table 12 presents the combined results of the criterion weights (obtained from fuzzy SWARA) and the fuzzy scores of the risks (derived from fuzzy MOORA). This matrix served as the input for validating the results using the fuzzy MABAC method.

Table 13
Data Normalization Matrix in Fuzzy MABAC

	W1			W2			W3		
	0.371	0.422	0.490	0.371	0.422	0.490	0.371	0.422	0.490
	X1			X2			X3		
R1	0.364	0.545	0.864	0.417	0.667	0.917	0.238	0.524	0.810
R2	0.364	0.636	0.864	0.333	0.583	0.833	0.095	0.333	0.619
R3	0.636	0.864	1.000	0.500	0.750	1.000	0.095	0.333	0.619
R4	0.182	0.455	0.727	0.167	0.417	0.667	0.238	0.524	0.810
R5	0.455	0.727	0.955	0.417	0.667	0.917	0.190	0.429	0.714
R6	0.273	0.545	0.818	0.250	0.500	0.750	0.048	0.238	0.524
R7	0.455	0.727	0.955	0.417	0.667	0.917	0.095	0.333	0.619
R8	0.000	0.273	0.545	0.250	0.500	0.750	0.333	0.619	0.905
R9	0.182	0.545	0.727	0.333	0.583	0.833	0.190	0.429	0.714
R10	0.273	0.545	0.818	0.250	0.500	0.750	0.048	0.238	0.524
R11	0.545	0.818	1.000	0.417	0.667	0.917	0.143	0.429	0.714
R12	0.091	0.364	0.636	0.000	0.167	0.417	0.333	0.619	0.905
R13	0.273	0.545	0.818	0.333	0.583	0.833	0.333	0.619	0.905
R14	0.273	0.545	0.818	0.250	0.500	0.750	0.000	0.143	0.429
R15	0.455	0.727	0.955	0.417	0.667	0.917	0.048	0.238	0.524
R16	0.273	0.545	0.818	0.083	0.333	0.583	0.429	0.714	1.000
R17	0.182	0.545	0.727	0.250	0.500	0.750	0.238	0.524	0.810
R18	0.364	0.636	0.909	0.333	0.583	0.833	0.000	0.143	0.429

Table 13
Continued

	W4			W5		
	0.371	0.422	0.490	0.371	0.422	0.490
	X4			X5		
R1	0.318	0.591	0.864	0.304	0.565	0.826
R2	0.227	0.500	0.773	0.217	0.478	0.739
R3	0.500	0.773	1.000	0.478	0.739	1.000
R4	0.045	0.318	0.591	0.043	0.217	0.478
R5	0.409	0.682	0.909	0.304	0.565	0.826
R6	0.227	0.500	0.773	0.174	0.391	0.652
R7	0.318	0.591	0.864	0.304	0.565	0.826
R8	0.000	0.227	0.500	0.174	0.391	0.652
R9	0.318	0.591	0.864	0.217	0.478	0.739
R10	0.136	0.409	0.682	0.304	0.565	0.826
R11	0.409	0.682	0.955	0.304	0.565	0.826
R12	0.136	0.409	0.682	0.043	0.217	0.478
R13	0.318	0.591	0.864	0.391	0.652	0.913
R14	0.045	0.318	0.591	0.043	0.217	0.478
R15	0.409	0.682	0.909	0.304	0.565	0.826
R16	0.045	0.318	0.591	0.000	0.130	0.391
R17	0.409	0.682	0.909	0.304	0.565	0.826
R18	0.045	0.318	0.591	0.217	0.478	0.739

Table 13 contains normalized data values that are used to prepare the data for more accurate calculations in the MABAC phase.

Table 14
Data Normalization Matrix in Fuzzy MABAC

	X1			X2			X3		
R1	0.507	0.652	0.912	0.526	0.703	0.938	0.460	0.643	0.886
R2	0.507	0.690	0.912	0.495	0.668	0.898	0.407	0.562	0.793
R3	0.608	0.786	0.979	0.557	0.738	0.979	0.407	0.562	0.793
R4	0.439	0.614	0.846	0.433	0.598	0.816	0.460	0.643	0.886
R5	0.540	0.729	0.957	0.526	0.703	0.938	0.442	0.603	0.839
R6	0.473	0.652	0.890	0.464	0.633	0.857	0.389	0.522	0.746
R7	0.540	0.729	0.957	0.526	0.703	0.938	0.407	0.562	0.793
R8	0.371	0.537	0.757	0.464	0.633	0.857	0.495	0.683	0.933
R9	0.439	0.652	0.846	0.495	0.668	0.898	0.442	0.603	0.839
R10	0.473	0.652	0.890	0.464	0.633	0.857	0.389	0.522	0.746
R11	0.574	0.767	0.979	0.526	0.703	0.938	0.425	0.603	0.839
R12	0.405	0.575	0.801	0.371	0.492	0.694	0.495	0.683	0.933
R13	0.473	0.652	0.890	0.495	0.668	0.898	0.495	0.683	0.933
R14	0.473	0.652	0.890	0.464	0.633	0.857	0.371	0.482	0.699
R15	0.540	0.729	0.957	0.526	0.703	0.938	0.389	0.522	0.746
R16	0.473	0.652	0.890	0.402	0.562	0.775	0.531	0.723	0.979
R17	0.439	0.652	0.846	0.464	0.633	0.857	0.460	0.643	0.886
R18	0.507	0.690	0.935	0.495	0.668	0.898	0.371	0.482	0.699

Table 14
Continued

	X4			X5		
R1	0.490	0.671	0.912	0.485	0.660	0.894
R2	0.456	0.633	0.868	0.452	0.624	0.851
R3	0.557	0.748	0.979	0.549	0.734	0.979
R4	0.388	0.556	0.779	0.388	0.513	0.724
R5	0.523	0.709	0.935	0.485	0.660	0.894
R6	0.456	0.633	0.868	0.436	0.587	0.809
R7	0.490	0.671	0.912	0.485	0.660	0.894
R8	0.371	0.518	0.734	0.436	0.587	0.809
R9	0.490	0.671	0.912	0.452	0.624	0.851
R10	0.422	0.594	0.823	0.485	0.660	0.894
R11	0.523	0.709	0.957	0.485	0.660	0.894
R12	0.422	0.594	0.823	0.388	0.513	0.724
R13	0.490	0.671	0.912	0.517	0.697	0.937
R14	0.388	0.556	0.779	0.388	0.513	0.724
R15	0.523	0.709	0.935	0.485	0.660	0.894
R16	0.388	0.556	0.779	0.371	0.477	0.681
R17	0.523	0.709	0.935	0.485	0.660	0.894
R18	0.388	0.556	0.779	0.452	0.624	0.851

Table 14 shows the normalized values after multiplying by the criteria weights (resulting from SWARA fuzzy). This step helps us to consider the importance of each criterion in the calculations.

Table15

Distance matrix of alternatives from the Border Approximation Area (BAA)

	X1			X2			X3		
R1	-0.388	-0.015	0.428	-0.350	0.054	0.457	-0.367	0.051	0.453
R2	-0.388	0.023	0.428	-0.381	0.018	0.417	-0.421	-0.029	0.360
R3	-0.286	0.119	0.495	-0.319	0.089	0.498	-0.421	-0.029	0.360
R4	-0.455	-0.054	0.361	-0.443	-0.052	0.335	-0.367	0.051	0.453
R5	-0.354	0.061	0.473	-0.350	0.054	0.457	-0.385	0.011	0.406
R6	-0.422	-0.015	0.406	-0.412	-0.017	0.376	-0.438	-0.069	0.313
R7	-0.354	0.061	0.473	-0.350	0.054	0.457	-0.421	-0.029	0.360
R8	-0.523	-0.130	0.272	-0.412	-0.017	0.376	-0.332	0.091	0.500
R9	-0.455	-0.015	0.361	-0.381	0.018	0.417	-0.385	0.011	0.406
R10	-0.422	-0.015	0.406	-0.412	-0.017	0.376	-0.438	-0.069	0.313
R11	-0.320	0.100	0.495	-0.350	0.054	0.457	-0.403	0.011	0.406
R12	-0.489	-0.092	0.317	-0.505	-0.157	0.213	-0.332	0.091	0.500
R13	-0.422	-0.015	0.406	-0.381	0.018	0.417	-0.332	0.091	0.500
R14	-0.422	-0.015	0.406	-0.412	-0.017	0.376	-0.456	-0.110	0.266
R15	-0.354	0.061	0.473	-0.350	0.054	0.457	-0.438	-0.069	0.313
R16	-0.422	-0.015	0.406	-0.474	-0.087	0.294	-0.297	0.131	0.546
R17	-0.455	-0.015	0.361	-0.412	-0.017	0.376	-0.367	0.051	0.453
R18	-0.388	0.023	0.450	-0.381	0.018	0.417	-0.456	-0.110	0.266

Table 15

Continued

	X4			X5		
R1	-0.375	0.038	0.456	-0.356	0.047	0.440
R2	-0.409	-0.001	0.411	-0.388	0.010	0.397
R3	-0.308	0.114	0.522	-0.291	0.120	0.525
R4	-0.476	-0.077	0.322	-0.453	-0.100	0.270
R5	-0.341	0.076	0.478	-0.356	0.047	0.440
R6	-0.409	-0.001	0.411	-0.404	-0.026	0.355
R7	-0.375	0.038	0.456	-0.356	0.047	0.440
R8	-0.493	-0.116	0.277	-0.404	-0.026	0.355
R9	-0.375	0.038	0.456	-0.388	0.010	0.397
R10	-0.443	-0.039	0.366	-0.356	0.047	0.440
R11	-0.341	0.076	0.500	-0.356	0.047	0.440
R12	-0.443	-0.039	0.366	-0.453	-0.100	0.270
R13	-0.375	0.038	0.456	-0.323	0.084	0.482
R14	-0.476	-0.077	0.322	-0.453	-0.100	0.270
R15	-0.341	0.076	0.478	-0.356	0.047	0.440
R16	-0.476	-0.077	0.322	-0.469	-0.136	0.227
R17	-0.341	0.076	0.478	-0.356	0.047	0.440
R18	-0.476	-0.077	0.322	-0.388	0.010	0.397

Table 15 shows the distance of each risk (option) from the approximate border area (BAA). These distances determine the position of each risk relative to the border between positive and negative areas.

Table 16
Final ranking of risks based on fuzzy MABAC

Alternative	Si			Defuzzification of Si	Defuzzification of Si	Ranking
A1	-1.8366	0.1740	2.2338	0.1904	0.1904	5
A2	-1.9867	0.0219	2.0127	0.0159	0.0159	10
A3	-1.6252	0.4131	2.4000	0.3960	0.3960	1
A4	-2.1952	-0.2315	1.7408	-0.2286	-0.2286	16
A5	-1.7867	0.2489	2.2539	0.2387	0.2387	3
A6	-2.0852	-0.1285	1.8604	-0.1178	-0.1178	12
A7	-1.8559	0.1704	2.1851	0.1665	0.1665	6
A8	-2.1648	-0.1979	1.7799	-0.1943	-0.1943	15
A9	-1.9851	0.0620	2.0370	0.0380	0.0380	9
A10	-2.0706	-0.0935	1.9010	-0.0877	-0.0877	11
A11	-1.7706	0.2872	2.2984	0.2717	0.2717	2
A12	-2.2217	-0.2968	1.6651	-0.2845	-0.2845	17
A13	-1.8336	0.2157	2.2599	0.2140	0.2140	4
A14	-2.2189	-0.3187	1.6396	-0.2993	-0.2993	18
A15	-1.8398	0.1685	2.1607	0.1631	0.1631	7
A16	-2.1378	-0.1847	1.7952	-0.1757	-0.1757	14
A17	-1.9323	0.1421	2.1077	0.1058	0.1058	8
A18	-2.0896	-0.1352	1.8526	-0.1240	-0.1240	13

Table 16 presents the final results of risk prioritization using the fuzzy MABAC method. In this table, eighteen risks (A1 to A18) are ranked based on their distance from the Border Approximation Area (BAA). The values of S_i indicate the position of each risk relative to the BAA. Risks with positiveS_i values fall within the positive region and are considered higher in priority, whereas risks with negative S_i values fall within the negative region and require greater attention. According to this table, Risk A3 (lack of technical skills among contractor staff) with $S_i = 0.396$ is ranked first and is recognized as the most critical risk. Additionally, Risk A11 (inappropriate contractual conditions and relationships) with $S_i = 0.2717$ holds the second rank and requires careful management. On the other hand, risks such as A4, A5, and A6, with negative S_i values, are located in the negative region, indicating the need for more focused attention. These results demonstrate that the fuzzy MABAC method is an effective complementary tool for validating the outcomes obtained through the fuzzy MOORA method, enhancing both the accuracy and reliability of the risk prioritization process.

The fuzzy MABAC approach's final risk rankings are then contrasted with those of other traditional approaches, such as the fuzzy MOORA method and the conventional FMEA approach, in Table 17.

Table 17
Prioritized outcomes of the recommended strategy and traditional techniques are compared

Risks	Conventional FMEA		Fuzzy MOORA		Fuzzy MABAC	
	RPN	Rank	$\bar{y}_i$	Rank	S_i	Rank
R1	6720.0	5	1.533	5	0.1904	5
R2	2520.0	6	1.477	7	0.0159	10
R3	7560.0	4	2.195	1	0.3960	1
R4	1800.0	9	0.919	14	-0.2286	16
R5	6720.0	5	1.746	3	0.2387	3
R6	2520.0	6	1.246	11	-0.1178	12
R7	10584.0	1	1.669	4	0.1665	6
R8	1800.0	9	0.815	17	-0.1943	15
R9	6720.0	5	1.264	10	0.0380	9
R10	1800.0	9	1.296	9	-0.0877	11

Table 17
Continued

Risks	Conventional FMEA		Fuzzy MOORA		Fuzzy MABAC	
	RPN	Rank	$\bar{y}_i$	Rank	S_i	Rank
R11	10080.0	2	1.889	2	0.2717	2
R12	1440.0	10	0.840	16	-0.2845	17
R13	6720.0	5	1.537	6	0.2140	4
R14	1152.0	11	1.063	13	-0.2993	18
R15	9072.0	3	1.702	3	0.1631	7
R16	1890.0	8	1.074	12	-0.1757	14
R17	6720.0	5	1.370	8	0.1058	8
R18	2100.0	7	1.370	8	-0.1240	13

The ultimate outcomes of risk ranking using three distinct approaches—traditional FMEA, fuzzy MOORA, and fuzzy MABAC—are shown in Table 17. A comparison of these findings reveals serious flaws in the standard FMEA method's dependence on the Risk Priority Number (RPN). For example, risks R1, R5, R9, R13, and R17 all have the same RPN value of 6720, which places them at the same rank. Overall, the RPN-based ranking separates the risks into only 11 different groups, indicating a lack of clarity in the prioritization process. This could cause uncertainty for decision-makers when managing risks and planning preventive or remedial measures. The shortcomings of RPN ranking may be attributed to its disregard for uncertainty in these values and its inability to allocate distinct weights to the risk factors—Severity (S), Occurrence (O), Detection (D), Controllability (C), and Time (T)—based on organizational circumstances and expert judgment.

The fuzzy MOORA approach has effectively improved upon conventional FMEA outcomes by applying fuzzy logic and more accurate criterion weighting. For instance, using fuzzy MOORA, risk R3, which was classified fourth in the standard FMEA, rose to the top rank. This enhancement demonstrates how well fuzzy MOORA works as an adjunct to conventional FMEA, leading to more precise outcomes. However, despite providing better differentiation in risk prioritization, fuzzy MOORA still has issues with decision dependability. This paper proposes an improved strategy to address this problem by employing the fuzzy MABAC method, which assigns clearly defined priority levels to all identified hazards. The suggested approach attempts to overcome major drawbacks of the conventional RPN, such as faulty decision-making, by incorporating uncertainty and reliability concepts into risk assessment.

Ultimately, the fuzzy MABAC approach serves as a validation tool that offers a final risk score in addition to confirming more accurate findings. Due to its substantial influence on project severity and expense, risk R3 (lack of technical skills among contractor workers) ranks first in fuzzy MABAC with an Si value of 0.3960. Because it directly affects cost and schedule, risk R11 (inadequate contractual conditions and relationships) comes in second with an Si value of 0.2717. With an Si value of 0.2387, risk R5 (poor financial management) ranks third due to its significant impact on project costs. This ranking demonstrates how fuzzy MABAC improves the accuracy and stability of the findings. Additionally, this approach enables more precise identification of key risks and more efficient allocation of management resources.

For instance, professional development projects and training programs can be implemented to enhance the technical proficiency of contractor employees in order to reduce R3. Performance reviews and ongoing monitoring can also help lower this risk. Risk R11, related to insufficient contractual arrangements, can be mitigated by creating more precise and comprehensive contracts, clearly defining roles, and establishing efficient dispute resolution procedures. For R5, financial resource management can be improved by implementing a more reliable financial management system and leveraging advanced tools for cost forecasting and budget control. Cost-cutting measures and routine financial assessments are also crucial.

5. Conclusion

These days, risk management is crucial for construction projects, particularly since a failure to recognize and manage risks can result in delays, higher expenses, or even the project's total shutdown. One of the most widely used risk analysis techniques across various industries is the classic FMEA method, which aids in project risk identification and prioritization. However, its shortcomings—such as failing to account for the weight of criteria, disregarding data uncertainty, and issues with the RPN index—make it clear that it needs to be improved and further developed.

This paper introduces a hybrid decision-making strategy that combines the fuzzy MABAC, fuzzy MOORA, and fuzzy SWARA methodologies. By allowing for the inclusion of uncertainty and reliability in both the weighting of criteria and risk prioritization, this method successfully overcomes many of the classic FMEA's drawbacks. In other words, this approach offers a more accurate and trustworthy risk ranking by utilizing fuzzy computations and result validation. As a result, project managers are better able to recognize and control such hazards.

Risks R3 (lack of technical skills among contractor staff), R11 (poor contractual terms and relationships), and R5 (poor financial management) were ranked first, second, and third, respectively, according to the fuzzy MABAC method's results. This ranking reflects the significant influence these hazards have on important factors such as severity, occurrence, cost, and time, underscoring their critical importance. Specialized training programs for R3, more precise and transparent contract drafting for R11, and a stronger financial management system for R5 are among the suggested remedial measures.

Furthermore, by combining the fuzzy MOORA and fuzzy MABAC approaches, the decision-making process has become more stable and reliable, in addition to producing better results than traditional FMEA. This illustrates how well the proposed method works for detecting and ranking hazards as well as organizing preventive and remedial actions.

In conclusion, using this technique can help project managers precisely identify and handle the most important risks, as well as allocate managerial resources efficiently. However, this study has certain limitations. The two most prominent are the presence of ambiguity in expert evaluations and the disregard for causal linkages between hazards. Future research could address these problems using evidence-based methods and more sophisticated theories, such as causal networks (e.g., DEMATEL). All things considered, the strategy suggested in this study provides a strong tool for risk management in construction projects, ultimately enhancing performance and mitigating the adverse effects of risk.

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Conflicts of Interest

The authors declare no conflicts of interest.

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