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A NOVEL FUZZY DELPHI DEMATEL-RANCOM APPROACH TO ASSESS ROOT CAUSES OF CONSTRUCTION ACCIDENTS

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Abstract. The construction industry remains one of the most hazardous sectors worldwide, consistently reporting high accident rates. This highlights the urgent need to systematically identify and address the root causes of such incidents. Although previous studies have explored causal relationships among accident factors, existing approaches are often complex and insufficient in prioritizing the root causes. To overcome these limitations, this study proposes an integrated framework combining the Fuzzy Delphi Method (FDM), Fuzzy Decision-Making Trial and Evaluation Laboratory (FDEMATEL), and the Ranking Comparison Method (RANCOM). Within this framework, FDM is enhanced with the Convert Fuzzy Data into Crisp Scores technique and the Pareto Principle to generate accurate crisp values and reduce experts' cognitive load by producing a concise list of significant causes. FDEMATEL quantifies interrelationships among these causes to derive the ranking vector, while RANCOM determines their relative importance. Notably, this study is the first to quantify criteria importance based on net influence values using the proposed FDEMATEL-RANCOM integration. A case study validates the framework and identifies six key causes: lack of safety policies, poor safety culture, inadequate supervision, ineffective enforcement, insufficient equipment expertise, and improper use of protective equipment. This study provides insights into improving occupational safety within the construction industry.

Keywords: Fuzzy Delphi Method, DEMATEL, RANCOM, construction accidents, Pareto principle, convert fuzzy data into crisp scores.

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1. Introduction

The construction industry is widely recognized as one of the most hazardous industries, consistently reporting high rates of accidents and fatalities. The frequency of these incidents remains a significant concern in both developed and developing countries, contributing to considerable human suffering and substantial economic losses. Furthermore, construction safety is an essential element of the United Nations Sustainable Development Goals (SDGs), specifically aligning with SDG 3: Good Health and Well-Being. Consequently, the literature has extensively examined construction accidents from various perspectives to develop intervention strategies. For instance, Ren et al. (2023) and Halabi et al. (2022) propose safety strategies tailored to specific accident types, such as collapse and fall accidents.

Furthermore, it is crucial to address the underlying causes of construction accidents in order to effectively reduce accident rates. The first dimension of the solution involves identifying the causes of construction accidents, such as those outlined in Mohandes et al. (2022) and Rafieyan et al. (2024). In these studies, the Fuzzy Delphi Method (FDM) has proven to be a reliable and effective tool for cause identification, as it provides consistent results and requires a moderate amount of data. However, most of the implementations of the FDM, such as that in Mohandes et al. (2022), rely on the centroid defuzzification approach. This method fails to distinguish between two fuzzy numbers with identical crisp values but differing shapes, thus neglecting potentially valuable information. Additionally, the Delphi method provides a foundation for subsequent analyses, such as weighting or ranking methods. Thus, the number of selected factors directly impacts the complexity of the problem and the cognitive workload of the experts. Threshold-based approaches, such as that of Mohandes et al. (2022) tends to yield a significant number of selected factors, particularly when a large number of variables are simultaneously considered. Consequently, this limitation adversely affects the accuracy of expert evaluations, as it increases the mental burden on the experts (Ball et al., 2023). Therefore, there is a need to introduce improvements to the Fuzzy Delphi Method to address these limitations and enhance its applicability in construction accident analysis.

The second dimension of the solution involves quantifying the relevance of the causes to prioritize safety strategies. Given the interdependencies between causes, methods such as Interpretive Structural Modeling (ISM) and Decision-Making Trial and Evaluation Laboratory (DEMATEL) are employed to categorize these causes based on their cause-effect relationships (Mohandes et al., 2022). However, these methods do not explicitly generate the relative importance of the criteria. To address this limitation, Rostamzadeh et al. (2023) introduced the DANP method, which combines DEMATEL and Analytic Network Process (ANP), to derive criteria weights based on the relationships among causes. Despite its advantages, the DANP method presents several critical disadvantages that hinder its practical application. First, it requires significant computational effort and domain knowledge for proper implementation. Second, the DANP algorithm does not explicitly prioritize driver factors within the system. As a result, the alternatives selected based on DANP-generated weights may not effectively address the root cause of the problem or introduce the necessary changes within the system.

Therefore, this study proposes an integrated framework combining a novel FDM, Fuzzy DEMATEL (FDEMATEL), and Ranking Comparison (RANCOM) technique to discover and assess relative importance of construction accident causes. In the framework, the FDM is integrated with Converting Fuzzy data into Crisp Scores (CFCS) method and Pareto Principle to refine the list of causes while producing better crisp values and minimizing experts' cognitive efforts. FDEMATEL quantifies the interrelationships among these causes and establishes their rankings, and RANCOM offers a simple approach to produce their relative weights. Notably, the FDEMATEL-RANCOM method presents a novel approach for generating criteria weights by prioritizing driver factors, thereby facilitating the selection of strategies that address the root causes within the system.

Accordingly, the study seeks to contribute to both the literature and practice in the field by achieving three primary objectives: (1) to improve the representation of crisp values in FDM by integrating the CFCS method, (2) to identify a minimal yet informative list of significant accident causes by combining Pareto Principle with FDM, (3) to propose a straightforward method for quantifying the relative importance of these causes based on their interrelationships using FDEMATEL-RANCOM approach. This framework aims to provide actionable insights to guide the development of strategies aimed at addressing the fundamental causes of accidents within the construction sector.

The study is organized as follows: "Introduction" outlines the motivation and objectives; "Literature review" reviews accidents in the construction industry and accident causes; "Proposed methods" details the analytical approach; "Empirical example" presents a case study and proposed measures; "Analysis results" highlights key findings; "Discussion" interprets findings and unique advantages of the proposed model; and "Conclusion and Remarks" summarizes the study, its limitations, and future research directions.

2. Literature review

This section reviews the literature on accidents in the construction industry and their causal factors.

2.1. Accidents in the construction industry

The construction industry plays a critical role in national economies but is widely recognized as one of the most hazardous sectors globally. In the United States, more than 1,000 fatal injuries occur annually in construction (Bureau of Labor Statistics, 2024). The situation is even more severe in Japan, where 31% of fatal accidents and 10% of non-fatal accidents occur within the construction sector (Safety Division, 2024). In developing countries such as Vietnam, these numbers range from 18 to 20% (Ministry of Labour, 2024). These statistics underscore the alarmingly high frequency of accidents and fatalities observed in the construction industry.

Construction accidents include falls, being struck by objects, cuts from sharp objects, electrocution, overturning accidents, explosions and chemical-related incidents (Zhu et al., 2022). Consequently, there have been various studies analyzing risks associated with specific accident types. For instance, Ren et al. (2023) proposed safety strategies for collapse accidents, while Halabi et al. (2022) analyzed causal factors and risk management strategies for fall accidents. Furthermore, studies have also focused on accidents based on structure type, such as high-rise buildings (Tripathi & Mittal, 2025), subway construction (Deng et al., 2024), and deep foundation pit projects (Shen et al., 2022). Additionally, there are also analyses of accidents related to specific construction methods, such as modular construction (Jeong et al., 2022).

Construction accidents have the most obvious and serious consequences for victims' physical health. Moreover, at the social level, these accidents significantly affect workers' families (Bilim, 2025). At the organizational level, the resulting losses have a substantial impact on profitability (Estudillo et al., 2024). In addition, construction safety is a critical component of the United Nations Sustainable Development Goals (SDGs), particularly SDG 3: Good Health and Well-Being. This goal emphasizes the importance of ensuring healthy lives and promoting well-being for individuals across all age groups. Therefore, ongoing research into construction safety remains of critical importance.

2.2. Studies on construction accident causes

This subsection reviews methods for identifying the causes of construction accidents and quantifying their relative importance.

2.2.1. Delphi method to identify significant accident causes

The Delphi method is widely employed to determine reliable accident causation factors. For instance, Abbasinia and Mohammadfam (2022) applied the technique to identify important criteria in construction accidents. To overcome uncertainty in experts' assessments, Mohandes et al. (2022) proposed the Fuzzy Delphi method (FDM), which combines the Delphi method with fuzzy numbers to construct a comprehensive list of accident causation factors at construction sites. Javaherikhah et al. (2025) used FDM to identify key construction site layout factors influencing the safety climate. Other applications of FDM in construction accident studies can be found in Shen et al. (2022) and Rafieyan et al. (2024). In most studies, FDM employs centroid defuzzification techniques due to their low computational complexity. However, this approach fails to differentiate between two fuzzy numbers that share the same crisp values but differ in shape. As a result, important insights may be neglected due to inadequate representation of the fuzzy numbers. There exists an opportunity to integrate a new defuzzification method into the Delphi technique in order to generate more meaningful crisp values.

The Delphi method usually serves as a foundation for subsequent analyses such as weighting or ranking methods. These methods often require experts to undertake cognitively demanding tasks, such as completing surveys with a large number of factors. This high cognitive load can result in inaccuracies in decision-making as noted by Ball et al. (2023). However, the Delphi literature has not proposed effective methods to reduce the number of selected factors for subsequent analysis without losing valuable insights. Recent studies, such as Mohandes et al. (2022) and Kumar et al. (2024), have introduced threshold-based approaches, utilizing the average performance of all factors to filter out insignificant ones. In practice, however, this approach still results in a significant number of selected factors when numerous factors are considered simultaneously. There is a need for a method that selects a minimal number of factors while yielding meaningful results.

2.2.2. Methods to prioritize accident causes

Given the interconnected nature of risk factors in construction, addressing isolated causes proves ineffective. The shift toward addressing multiple factors and their interdependencies has led to the integration of methods that consider these interrelationships. For example, Wu et al. (2023) integrated ISM with MICMAC (Matrice d'Impacts Croisés Multiplication Appliqués à un Classement) to analyze urban rail transit construction accident risks by examining the relationships among eighteen contributing factors. Yang et al. (2022) explored the relationships between factors causing tunnel construction accidents in China using DEMATEL. Mohandes et al. (2022) developed a Fuzzy DEMATEL (FDEMATEL) framework to identify and prioritize critical causes of construction site accidents, while Chen and Qiao (2023) integrated DEMATEL with ISM to pinpoint poor safety management and regulatory issues as root causes of building collapse accidents. Shi et al. (2025) applied the technique to evaluate risk factors of coal mine construction projects. These methods focus only on the overlapping interconnections among attributes and overlook their relative importance. This limitation leads to uncertainty when prioritizing measures to reduce accident rates. To address this gap, Rostamzadeh et al. (2023), Shen et al. (2022) and Javaherikhah et al. (2025) proposed a combined DEMATEL and Analytic Network Process (ANP) model to produce criteria weights based on their relationships. The DEMATEL-ANP (DANP) method is computationally demanding and less intuitive, requiring substantial computational effort. Furthermore, the criteria weights generated by the DANP algorithm do not offer a clear framework for prioritizing interventions or allocating resources to address root-cause issues, as the method does not explicitly derive weights based on criteria's potential to induce changes into the system. There is a clear need for a straightforward and intuitive method that captures the interconnections between criteria and establishes a clear hierarchical structure to effectively address the root causes of accidents in the construction sector.

In summary, a thorough literature review identifies several notable gaps: (1) FDMs require improved defuzzification techniques to distinguish between fuzzy numbers that have the same crisp values but different shapes. (2) Threshold-based approaches that rely on average performance values in FDMs are inadequate for minimizing the number of factors to alleviate the cognitive burden on experts. This limitation underscores the necessity for an alternative method that effectively reduces the number of factors and preserves essential insights. (3) Most importantly, literature lacks straightforward methodologies for quantifying criteria weights based on their driving roles within systems.

3. Proposed methods

The proposed model includes three main stages as summarized in Figure 1. First, the FDM is integrated with the CFCS method and the Pareto Principle to enhance the accuracy of crisp values and effectively select significant causes. Secondly, a novel FDEMATEL-RANCOM approach is proposed to prioritize causes based on their driving roles. Specifically, FDEMATEL is utilized to establish the ranking vector, while RANCOM is applied to generate results based on this vector. The analytical process is detailed as follows. To facilitate the presentation of the process, assume there are k experts denoted as $E = \{E_1, E_2, ..., E_k\}$ and n causes denoted as $C= \{C_1, C_2, ..., C_n\}$.

3.1. Obtain the validated causing factors

After identifying potential causes through a comprehensive literature review, this study applies the FDM to construct a refined framework of accident causes. In this method, the CFCS method (Opricovic & Tzeng, 2003) is

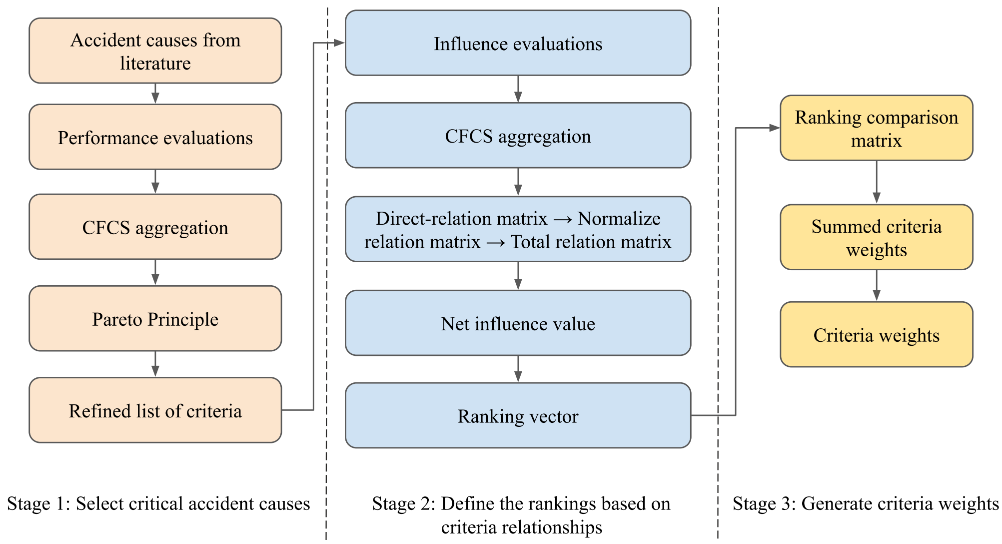

Figure 1. Proposed analytical model illustrating the three-stage integration of CFCS-FDM, FDEMATEL, and RANCOM

used to consolidate data from experts as it produces better crisp numbers compared to the centroid method. The CFCS method generates crisp values from their left and right values based on the concept of fuzzy minimum and fuzzy maximum. The Pareto Principle selects the most significant causes based on their performance values to minimize experts' cognitive load during the subsequent assessment process. The Pareto Principle was developed by the Italian economist Vilfredo Pareto, who observed that 80% of Italy's land was owned by 20% of the population. This rule has since been generalized across various contexts. For example, it is often expressed that 80% of economic output is attributable to 20% of input. The principle has been applied in risk management (Charpentier & Flachaire, 2020), asset evaluation (Pavlik & Lukas, 2017), and quality management (Kwilinski & Kardas, 2024). Thus, this study argues that 20% of causes are responsible for the majority of construction accidents.

The FDM begins by inviting k experts to evaluate n causes using linguistic variables. Table 1 alters these variables into triangle fuzzy numbers (TFNs), denoted by (a, b, c). Here, a, b and c represent the lower bound, modal bound and upper bound of the TFNs, respectively. Thus, the assessment provided by the t^{th} expert regarding the importance level of the cause C_j is denoted as $G_j^t = \left(a_j^t, b_j^t, c_j^t\right)$, where t = 1, 2, ..., k, and j = 1, 2, ..., n.

The normalization process is then conducted through Eqns (1)–(3):

$$za_j^t = \left(a_j^t - \min a_j^t\right) / \alpha; \tag{1}$$

$$zb_j^t = \left(b_j^t - \min a_j^t\right) / \alpha; \tag{2}$$

$$zc_j^t = \left(c_j^t - \min a_j^t\right) /, \tag{3}$$

where $\alpha = \max a_j^t - \min a_j^t$.

The total normalized value z_j^t is computed through left (Winge & Albrechtsen, 2018) and right (Winge & Albrechtsen, 2018) normalized values using Eqns (4)–(6):

Table 1. Performance levels and TFNs

Linguistics variables	TFNs
Very important	(0.7, 0.9, 1.0)
Important	(0.5, 0.7, 0.9)
Moderately important	(0.3, 0.5, 0.7)
Slightly important	(0.1, 0.3, 0.5)
Unimportant	(0, 0, 0.3)

$$zl_j^t = zb_j^t / \left(1 + zb_j^t - za_j^t\right); \tag{4}$$

$$zr_j^t = zc_j^t / \left(1 + zc_j^t - zb_j^t\right); \tag{5}$$

$$z_j^t = \left[zl_j^t\left(1 - zl_j^t\right) + zr_j^t \times zr_j^t\right] / \left[1 - zl_j^t + zr_j^t\right]. \tag{6}$$

Crisp values are calculated using Eqn (7):

$$x_j^t = \min a_j^t + z_j^t. \tag{7}$$

The performance value of cause C_j is determined using Eqn (8):

$$x_j = \frac{x_j^1 + x_j^2 + \ldots + x_j^k}{k}. \tag{8}$$

The causes are sorted in descending order of performance values x_j to prioritize the largest values. The sorted values are denoted as $x'_1 \geq x'_2 \geq \ldots \geq x'_n$, where x'_1 is the largest value and x'_n is the smallest. According to the Pareto Principle, only the top 20% of causes are selected, so the causes with values x'_1, x'_2, ..., x'_v, where $v \leq n \times 0.2$, are retained as the most significant factors, denoted by S_1, S_2, ..., S_v, respectively.

3.2. Define criteria rankings based on their relationships

The DEMATEL technique, developed by the Geneva Research Centre of the Battelle Memorial Institute, is designed to quantify the interrelationships among various attributes. To address uncertainty in expert assessments, FDEMATEL approach is employed (Appasamy, 2026; Ferrazzi et al., 2025). In the FDEMATEL analysis, k experts provide their evaluations of the influence levels between and factors using linguistic variables. These linguistic variables are then converted into triangular numbers, as shown in Table 2. Thus, assessment provided by the t^{th} expert regarding the influence level of the cause S_i on cause S_j is denoted as $U_{ij}^t = \left(m_{ij}^t, o_{ij}^t, p_{ij}^t\right)$, where t = 1, 2, ..., k, and i, j = 1, 2, ..., v.

Table 2. Influence levels and TFNs

Linguistics variables	TFNs
Very strong influence (VI)	(0.75, 1.0, 1.0)
Strong influence (SI)	(0.5, 0.75, 1.0)
Moderate influence (MI)	(0.25, 0.5, 0.75)
Little influence (LI)	(0, 0.25, 0.5)
No influence (NI)	(0, 0, 0.25)

The CFCS method is utilized to calculate the influence degree between accident causes S_i and S_j, denoted by y_{ij}, using Eqns (1)–(8). Thus, the direct-relation matrix is established as $\boldsymbol{Y} = [y_{ij}]$.

The normalized direct relation matrix $\boldsymbol{Z}$ is obtained through Eqns (9) and (10):

$$\boldsymbol{Z} = \gamma \times \boldsymbol{Y}, \tag{9}$$

where $\gamma = \min_{i,j}\left[\frac{1}{\max_{1\le i\le v}\sum_{j=1}^{v} y_{ij}}, \frac{1}{\max_{1\le j\le v}\sum_{i=1}^{v} y_{ij}}\right]$.

The total relation matrix $\boldsymbol{D}$ is formed using Eqn (10):

$$\boldsymbol{D} = [d_{ij}] = \boldsymbol{Z}(\boldsymbol{I} - \boldsymbol{Z})^{-1}, \tag{10}$$

where $\boldsymbol{I}$ denotes the identity matrix.

Given-influence degrees and received-influence degrees of each criteria are derived using Eqns (11) and (12), respectively:

$$A = \sum_{j=1}^{v} d_{ij}; \tag{11}$$

$$B = \sum_{i=1}^{v} d_{ij}. \tag{12}$$

In DEMATEL method, $A + B$ values represent the total interaction degree and $A - B$ signifies the net influence degree. While the former shows the significance of the causes, the latter reflects their driving roles. Attributes with positive values of net influence degree are called drivers and those with negative values are receivers. The higher values of net influence degree represent the causes' potential to induce sustainable changes into the systems as these causes exert high levels of influence on other causes and receive comparably less influence. However, it remains challenging to apply this valuable insight to ranking problems, as quantifying attribute weights based on their net influence is difficult. This is due to the fact that their net influence values include both positive and negative values. Thus, this study introduces a new way by converting the values into a ranking vector.

The cause rankings are determined based on their net influence degrees to prioritize the root causes. The cause exhibiting the highest net influence degrees is assigned the highest rank. Accordingly, the initial ranking vector is defined as $R = (r_1, r_2, ..., r_v)$, where r_i denotes the rank assigned to cause S_i, for $i \in \{1, 2, ..., v\}$. A smaller numerical value of r_i indicates a higher rank.

3.3. Compute the relative importance of causal factors based on their rankings

The RANCOM is a straightforward and user-friendly weighting method, particularly suitable for practitioners with limited expertise in multi-criteria decision analysis (Więckowski et al., 2023). RANCOM is widely adopted in various domains such as waste management (Uzun et al., 2026) and innovation management (Korucuk, 2026). The method offers advantages over traditional subjective weighting approaches such as the Step-Wise Weight Assessment Ratio Analysis (SWARA) (Görçün et al., 2025), the Best–Worst Method (BWM) (Redwan & Shabur, 2025), and the Analytic Hierarchy Process (AHP) (Nadeem et al., 2025) by providing a simple mechanism for determining criteria weights. The RANCOM simply requires the ranking of criteria, whereas the other methods involve either pairwise or stepwise comparisons, adding extra steps and increasing cognitive burden. Moreover, AHP may lead to inconsistency problems, while SWARA and BWM can become complex when experts have differing opinions about the most and least important criteria. On the other hand, objective methods such as Criteria Importance Through Intercriteria Correlation (CRITIC) (Mahboob et al., 2025) and entropy-based techniques (Bezdan et al., 2025) rely on performance data for various alternatives to determine the criteria weights, which neglect their real-world importance – an aspect that can only be captured through expert judgment. Therefore, RANCOM is adopted in this study. Table 3 presents a comparison of the methods.

The original RANCOM proposes four techniques for generating the ranking vector: direct ranking, scoring, sorting algorithms, and the tournament method. However, these techniques do not explicitly account for the interrelationships among evaluation criteria. This limitation becomes particularly critical when such interrelationships play a significant role, potentially leading to inaccuracies in the ranking vector. Consequently, the final estimation of criteria weights may lack reliability and fail to accurately reflect the underlying relationship structure. To address this limitation, the present study introduces the DEMATEL-RANCOM approach by using the net influence value ($A - B$) derived from the FDEMATEL method to establish the ranking vector. This integration enables a more accurate representation of the causal relationships among criteria and the prioritization of driving factors within the ranking vector. Thus, this approach can improve the accuracy of the final weights generated by the RANCOM and allow the resulting weights to offer valuable insights into the selection of targeted interventions aimed at addressing the root causes.

Table 3. Comparison of MCDM weighting methods

Methods	Consider real-world importance	Computational effort	Suffer from inconsistency	Expert cognitive load
Entropy Weight	No	Low	No	Low
CRITIC	No	Medium	No	Low
SWARA	Yes	Medium	Yes	Medium
BWM	Yes	High	Yes	Medium
AHP	Yes	High	Yes	High
RANCOM	Yes	Low	No	Low

Given the ranking vector for list of cause $C = \{C_1, C_2, \ldots, C_v\}$ is $R = (r_1, r_2, \ldots, r_v)$, the matrix of ranking comparison $\boldsymbol{F} = [\omega_{ij}]$ ($i = 1, 2, \ldots, v$, $j = 1, 2, \ldots, v$) is formed by using pairwise comparison of the cause rankings as shown in Eqn (13):

$$\boldsymbol{F} = \begin{bmatrix} \omega_{11} & \omega_{12} & \cdots & \omega_{1v} \\ \omega_{21} & \omega_{22} & \cdots & \omega_{2v} \\ \vdots & \vdots & \ddots & \vdots \\ \omega_{v1} & \omega_{v2} & \cdots & \omega_{vv} \end{bmatrix}, \tag{13}$$

where $[\omega_{ij}]$ is the ranking coefficient between C_i and C_j and determined by rule in Eqn (14):

$$\omega_{ij} = \begin{cases} 1, & \text{if} \quad r_i < r_j \\ 0.5, & \text{if} \quad r_i = r_j \\ 0, & \text{if} \quad r_i > r_j \end{cases}. \tag{14}$$

The summed cause weights H_i is then computed using Eqn (15):

$$H_i = \sum_{j=1}^{v} \omega_{ij}. \tag{15}$$

Finally, the relative importance of each cause is determined by Eqn (16):

$$w_i = \frac{S_i}{\sum_{i=1}^{v} S_i}. \tag{16}$$

4. Empirical example

Company P is a construction firm specializing in the development and execution of infrastructure projects, including residential buildings and other structural works. While Company P has a formal safety management system in place, its senior management has identified a persistent challenge: a recurring pattern of on-site incidents and near-misses that existing safety protocols have failed to prevent. Historically, the organization recorded an average annual rate of 1 fatality, 16 major injuries (resulting in at least one day of lost time), and over 100 minor injuries. The management team expressed concern that their current safety reviews were often reactive, focusing on immediate and observable failures. There is a growing consensus within the company that these incidents were merely symptoms of deeper, systemic issues that were not being adequately identified or addressed. This highlights the critical need for a systematic analysis of the factors contributing to these incidents. Identifying the root causes is essential for developing targeted interventions that address both the frequency and severity of accidents. Such measures will not only mitigate risks but also enhance overall safety standards, thereby ensuring the protection and well-being of workers within the organization.

Following the implementation of the proposed model, Company P successfully identified and remediated several systemic root causes, resulting in a substantial improvement in organizational safety performance. Most notably, annual fatalities were eliminated entirely, falling to zero. The frequency of major injuries was reduced by 75%, decreasing from 16 to 4 cases annually, while minor injuries declined significantly from over 100 to approximately 32 recorded incidents. These results demonstrate the effectiveness of shifting toward a root-cause-oriented intervention strategy. The following subsections detail the specific application of this methodology within the organizational framework. Examples demonstrating the application of this framework are provided in Appendix.

4.1. Initial accident causes

This study proposes 30 causes for accidents in the construction industry based on the literature. These causes are classified into four aspects: worker factors, leadership and management, policy and procedures, and working environment as shown in Table 4. The expert panel includes 5 male experts: 1 project manager, 1 contractor, 1 construction engineer and 2 construction workers, as described in Table 5. The experts are selected based on their expertise, experience with construction accident cases, and alignment with the objectives of the study.

4.2. Refine accident causes

Each expert' assessments are converted into crisp values using Eqns (1)–(7). To demonstrate the calculation process, we will take the evaluation for criteria C_1 from expert E_1 as an example. First, the assessments are altered into TFNs as shown in Table 6.

Second, normalization process is applied using Eqns (1)–(3) as follows:

$$za_1^1 = (0.5 - 0)/(1 - 0) = 0.5;$$
$$zb_1^1 = (0.7 - 0)/(1 - 0) = 0.7;$$
$$zc_1^1 = (0.9 - 0)/(1 - 0) = 0.9.$$

Table 4. Accidents causes in the construction industry

Aspects	Causes and codes	References
Worker factors (Q_1)	Lack of experience (C_1)	Aksorn and Hadikusumo (2007), Bourahla et al. (2024), Mohandes et al. (2022), Sankar et al. (2024), Tam et al. (2004)
	Poor attitude (C_2)	
	Bad communication skills (C_3)	
	Improper use of protection equipment (C_4)	
	Weak physical health (C_5)	
	Unsteady mental well-being (C_6)	
	Insufficient expertise with working equipment (C_7)	
Leadership and management (Q_2)	Inadequate supervision (C_8)	
	Poor team cooperation (C_9)	
	Lack of resources (C_{10})	
	Project managers' low safety awareness (C_{11})	
	Poor safety culture (C_{12})	
	Unqualified management team (C_{13})	
	Inexperienced management team in safety matters (C_{14})	
	Managers' lack of safety knowledge (C_{15})	
Policy and procedures (Q_3)	Training deficiency (C_{16})	Aksorn and Hadikusumo (2007), Bourahla et al. (2024), Feng (2023) Mohandes et al. (2022), Tam et al. (2004)
	Lack of safety policy and procedures (C_{17})	
	Ineffective enforcements (C_{18})	
	Inadequate safety inspections (C_{19})	
	Weak maintenance strategy (C_{20})	
	Unsystematic hiring system (C_{21})	
	Weak safety control system (C_{22})	
Working environment (Q_4)	High pressure (C_{23})	Bourahla et al. (2024), Feng (2023), Mohandes et al. (2022)
	Machinery risk (C_{24})	
	Electrical risk (C_{25})	
	Environmental hazards (C_{26})	
	Weather variability (C_{27})	
	Noise pollution (C_{28})	
	Unstable ground condition (C_{29})	
	Inadequate safety alert system (C_{30})	

Table 5. Expert information

Code	Occupational positions	Gender	Age	Years of experience
E_1	Construction worker	Male	45	21
E_2	Project manager	Male	42	18
E_3	Construction engineer	Male	48	22
E_4	Contractor	Male	41	15
E_5	Construction engineer	Male	39	15

The total normalized value is computed through Eqns (4)–(6):

$zl_1^1 = 0.7/\left(1+0.7-0.5\right) = 0.583;$

$zr_1^1 = 0.9/\left(1+0.9-0.7\right) = 0.75;$

$z_1^1 = \left[0.583\times\left(1-0.583\right)+0.75\times0.75\right]/\left[1-0.583+0.75\right] = 0.69.$

Finally, the crisp value is computed using Eqn (7):

$$x_1^1 = 0+0.69\left(1-0\right) = 0.69.$$

The performance values of the criteria are determined by aggregating data provided by experts using Eqn (8). The causes are then ranked based on their significance values. There 30 causes in total, so $v = 0.2\times30 = 6$. Thus, 6 most critical accident causes are selected, namely C_4, C_7, C_8, C_{12}, C_{17}, C_{18}. Table 7 shows the results and the new codes.

4.3. Relationships among causes and their ranking vector

There are 6 causes in total, so each expert gives assessments on 30 pairwise comparison questions as shown in Table 8.

Table 6. The first experts' assessments

Criteria	TFNs		
	a	b	c
C_1	0.5	0.7	0.9
C_2	0.7	0.9	1
C_3	0.3	0.5	0.7
C_4	0.7	0.9	1
C_5	0.5	0.7	0.9
C_6	0.7	0.9	1
C_7	0.7	0.9	1
C_8	0.7	0.9	1
C_9	0.1	0.3	0.5
C_{10}	0.5	0.7	0.9
C_{11}	0.1	0.3	0.5
C_{12}	0.5	0.7	0.9
C_{13}	0	0	0.3
C_{14}	0.3	0.5	0.7
C_{15}	0.7	0.9	1
C_{16}	0.5	0.7	0.9
C_{17}	0.7	0.9	1
C_{18}	0.5	0.7	0.9
C_{19}	0.3	0.5	0.7
C_{20}	0	0	0.3
C_{21}	0	0	0.3
C_{22}	0.1	0.3	0.5
C_{23}	0.5	0.7	0.9
C_{24}	0	0	0.3
C_{25}	0.5	0.7	0.9
C_{26}	0	0	0.3
C_{27}	0	0	0.3
C_{28}	0	0	0.3
C_{29}	0	0	0.3
C_{30}	0	0	0.3

Table 7. Cause selection

Criteria	Significance value	Rank	Decision	New Codes
C_1	0.522	15	Deleted	
C_2	0.446	20	Deleted	
C_3	0.613	8	Deleted	
C_4	0.838	2	Selected	S_1
C_5	0.468	19	Deleted	
C_6	0.726	7	Deleted	
C_7	0.838	2	Selected	S_2
C_8	0.875	1	Selected	S_3
C_9	0.613	8	Deleted	
C_{10}	0.560	12	Deleted	
C_{11}	0.392	24	Deleted	
C_{12}	0.801	4	Selected	S_4
C_{13}	0.505	16	Deleted	
C_{14}	0.485	18	Deleted	
C_{15}	0.505	16	Deleted	
C_{16}	0.560	12	Deleted	
C_{17}	0.801	5	Selected	S_5
C_{18}	0.801	5	Selected	S_6
C_{19}	0.559	14	Deleted	
C_{20}	0.393	23	Deleted	
C_{21}	0.226	28	Deleted	
C_{22}	0.150	29	Deleted	
C_{23}	0.561	10	Deleted	
C_{24}	0.432	21	Deleted	
C_{25}	0.561	10	Deleted	
C_{26}	0.317	25	Deleted	
C_{27}	0.302	27	Deleted	
C_{28}	0.432	21	Deleted	
C_{29}	0.317	25	Deleted	
C_{30}	0.135	30	Deleted	

Table 8. Experts' influence assessments

Expert	Assessments				
	Causes	S_1	S_2	…	S_6
E_1	S_1	(0, 0, 0)	NI	…	NI
	S_2	VI	(0, 0, 0)	…	NI
		⋮	⋱		⋮
	S_6	SI	SI	…	(0, 0, 0)
E_2	S_1	(0, 0, 0)	NI	…	LI
	S_2	VI	(0, 0, 0)	…	LI
		⋮	⋱		⋮
	S_6	SI	SI	…	(0, 0, 0)
⋮		⋮	⋱		⋮
E_5	S_1	(0, 0, 0)	NI	…	NI
	S_2	VI	(0, 0, 0)	…	LI
		⋮	⋱		⋮
	S_6	SI	NI	…	(0, 0, 0)

Table 9. Experts' assessment TFNs

Expert	TFNs				
	Causes	S_1	S_2	...	S_6
E_1	S_1	(0, 0, 0)	(0, 0, 0.25)	...	(0, 0, 0.25)
	S_2	(0.75, 1, 1)	(0, 0, 0)	...	(0, 0, 0.25)
	⋮		⋱		⋮
	S_6	(0.5, 0.75, 1)	(0.5, 0.75, 1)	...	(0, 0, 0)
E_2	S_1	(0, 0, 0)	(0, 0, 0.25)	...	(0, 0.25, 0.5)
	S_2	(0.75, 1, 1)	(0, 0, 0)	...	(0, 0.25, 0.5)
	⋮		⋱		⋮
	S_6	(0.5, 0.75, 1)	(0.5, 0.75, 1)	...	(0, 0, 0)
⋮	⋮		⋱		⋮
E_5	S_1	(0, 0, 0)	(0, 0, 0.25)	...	(0, 0, 0.25)
	S_2	(0.75, 1, 1)	(0, 0, 0)	...	(0, 0.25, 0.5)
	⋮		⋱		⋮
	S_6	(0.5, 0.75, 1)	(0, 0, 0.25)	...	(0, 0, 0)

Table 10. Total normalized values

	Causes	S_1	S_2	...	S_6
E_1	S_1	0.000	0.033	...	0.033
	S_2	0.967	0.000	...	0.033
	⋮		⋱		⋮
	S_6	0.733	0.733	...	0.000
E_2	S_1	0.000	0.033	...	0.267
	S_2	0.967	0.000	...	0.267
	⋮		⋱		⋮
	S_6	0.733	0.733	...	0.000
⋮	⋮		⋱		⋮
E_5	S_1	0.000	0.033	...	0.033
	S_2	0.967	0.000	...	0.267
	⋮		⋱		⋮
	S_6	0.733	0.033	...	0.000

These assessments are then converted into TFNs as shown in Table 9.

Subsequently, normalized values are obtained through Eqns (1)–(3). Total normalized values are computed using Eqns (4)–(6), as shown in Table 10.

Crisp values are computed using Eqn (7). The aggregated direct relation matrix $\boldsymbol{Y}$ is obtained as shown in Table 11 through Eqn (8).

Total relation matrix $\boldsymbol{D}$ is computed through Eqns (9)–(0), as displayed in Table 12.

The net influence degrees ($A - B$) values are then obtain through Eqns (11) and (12). Based on net influence degrees, criteria rankings are then determined. The results are displayed in Table 13. Thus, the ranking vector established as R = (6, 5, 3, 2, 1, 4).

Table 11. Direct relation matrix

	S_1	S_2	S_3	S_4	S_5	S_6
S_1	0	0.033	0.033	0.267	0.033	0.080
S_2	0.920	0	0.033	0.313	0.033	0.127
S_3	0.780	0.267	0	0.920	0.220	0.547
S_4	0.780	0.547	0.780	0	0.780	0.780
S_5	0.547	0.500	0.547	0.547	0	0.687
S_6	0.733	0.500	0.593	0.687	0.407	0

Table 12. Total relation matrix

	S_1	S_2	S_3	S_4	S_5	S_6
S_1	0.060	0.042	0.048	0.107	0.041	0.061
S_2	0.330	0.050	0.067	0.153	0.058	0.095
S_3	0.473	0.216	0.172	0.424	0.196	0.311
S_4	0.554	0.319	0.388	0.285	0.341	0.408
S_5	0.434	0.273	0.299	0.354	0.134	0.342
S_6	0.473	0.270	0.306	0.381	0.232	0.185

Table 13. Total interaction degree and net influence degree

	A	B	A–B	Ranking
S_1	0.360	2.325	–1.965	6
S_2	0.753	1.170	–0.417	5
S_3	1.793	1.280	0.513	3
S_4	2.295	1.704	0.591	2
S_5	1.836	1.003	0.833	1
S_6	1.848	1.402	0.445	4

4.4. The relative importance of causes

Based on criteria rankings, the ranking matrix $\boldsymbol{F}$ is determined through Eqn (14) as shown in Table 14. For example, criteria C_1 is ranked sixth and criteria C_2 is ranked fifth, so $\omega_{12} = 0$ and $\omega_{21} = 1$.

Summed cause weights are acquired through Eqn (15). Finally, the relative importance of causes is determined using Eqn (16). Table 15 shows the results. In Table 15, C_5 and C_4 and C_3 have the highest relative weights, so these causes are the most important.

Table 14. Ranking comparison matrix

S_1	S_2	S_3	S_4	S_5	S_6	S_1
S_1	0.5	0	0	0	0	0
S_2	1	0.5	0	0	0	0
S_3	1	1	0.5	0	0	1
S_4	1	1	1	0.5	0	1
S_5	1	1	1	1	0.5	1
S_6	1	1	0	0	0	0.5

Table 15. Summed cause weights

Criteria	Summed cause weights	Relative weights
S_1	0.5	0.028
S_2	1.5	0.083
S_3	3.5	0.194
S_4	4.5	0.250
S_5	5.5	0.306
S_6	2.5	0.139

5. Discussion

This section examines the contributions of the study and highlights the distinct advantages of the proposed methodologies in comparison to existing approaches.

5.1. Theoretical contributions and practical implications

Construction sites experience frequent accidents that result in serious injuries, fatalities, and project disruptions. To address this critical issue, researchers have developed a comprehensive framework for identifying and ranking the most important causes of construction accidents, enabling safety managers to focus their limited resources on the highest-impact interventions. Our framework incorporates several advanced analytical methods to improve decision-making accuracy and efficiency. The CFCS technique transforms uncertain, fuzzy expert judgments into precise numerical values, making the results more reliable. Additionally, this study combines the Fuzzy Delphi Method with the Pareto Principle to systematically reduce the number of accident causes requiring analysis. This approach identifies the critical 20% of causes responsible for 80% of accidents, streamlining the evaluation process from 30 potential causes down to just 6 key factors. This reduction dramatically decreases the required expert comparisons from 870 to 30, significantly reducing the cognitive burden on safety professionals while improving consistency. The study's primary innovation lies in developing a hybrid FDEMATEL-RANCOM weighting approach that addresses existing gaps in construction safety research. This method goes beyond traditional weighting techniques by considering how different accident causes influence each other within complex construction environments. The DEMATEL component maps these interdependencies, while RANCOM provides a computationally efficient way to determine the relative importance of each cause based on its role as a system driver.

From a practical standpoint, the study identifies 6 significant accident causes in the construction industry, namely "Improper use of protection equipment" (S_1), "Insufficient expertise with working equipment" (S_2), "Inadequate supervision" (S_3), "Poor safety culture" (S_4), "Lack of safety policies and procedures" (S_5), and "Ineffective enforcements" (S_6). These three factors represent the critical 20% of causes that, according to the Pareto Principle analysis, are responsible for approximately 80% of construction accidents, making them the highest-priority targets for safety interventions and resource allocation. Moreover, the most significant root causes of construction accidents are "Lack of safety policies and procedures" (S_5), "Poor safety culture" (S_4), and "Inadequate supervision" (S_3). The findings align with Mohandes et al. (2022) and Zahoor et al. (2017).

"Lack of safety policies and procedures" (S_5) refers to the absence of appropriate guidelines to ensure awareness of hazards, appropriate response measures, and systematic safety checks. As the most influential factor in the accident causation system, this deficiency creates a cascading effect that undermines all other safety efforts. Implementing structured and detailed safety frameworks, including site-specific hazard assessments, mandatory safety training programs, and regular audits, would significantly reduce ambiguity and ensure compliance with safety policies. Furthermore, safety performance can be improved by standardizing safety protocols and regularly updating them in line with emerging risks and technological advancements. Given its dominant influence on other safety factors, addressing policy gaps should be the primary focus of organizational safety investments.

"Poor safety culture" (S_4) fundamentally influences individual and collective attitudes toward workplace safety, shaping behaviors and decision-making at all organizational levels. As one of the three critical root causes identified through the framework's systematic reduction process, poor safety culture acts as a foundational driver that amplifies the impact of other accident-causing factors throughout the construction environment. A strong safety culture requires a top-down commitment, wherein leadership demonstrates consistent and visible support for safety initiatives. Additionally, encouraging open communication about safety concerns, along with fostering accountability through incentives for positive safety behaviors and disciplinary measures for negligence, can progressively shift organizational culture towards one that prioritizes safety as a core value.

"Inadequate supervision" (S_3) further exacerbates the likelihood and severity of construction accidents, emphasizing the critical need for competent and continuous oversight on construction sites. This factor's inclusion among the vital few causes demonstrates its role as a key system driver that influences multiple downstream safety outcomes simultaneously. Effective supervision entails more than mere presence; it involves active monitoring, timely intervention, and ongoing mentoring of workers in safety practices. Enhancing supervision can be achieved through targeted training programs aimed at equipping supervisors with advanced safety management skills and the authority to enforce compliance. Additionally, deploying digital monitoring systems such as real-time hazard detection and reporting tools could supplement human oversight, ensuring swift identification and rectification of unsafe behaviors and conditions, thereby substantially reducing the incidence of accidents.

By focusing organizational resources and attention on these three critical factors, which collectively represent the essential 20% responsible for the majority of construction accidents, safety managers can achieve maximum impact with their limited resources, creating systemic improvements that address root causes rather than merely treating symptoms. This integrated approach offers practical advantages for construction safety management. By identifying root causes that trigger cascading effects throughout the safety system, the framework helps organizations target interventions that will produce the greatest overall improvement. The method's computational simplicity ensures that safety managers can implement it without requiring extensive technical expertise or sophisticated software, making evidence-based safety decisions more accessible across the construction industry.

5.2. Model comparison

To validate the advantages of the proposed DEMATEL-RANCOM approach, this subsection compares the approach with three alternative weighting methods that take into account both relationships and the relevance of the criteria. The first alternative is the DEMATEL weighting method, as outlined in Yuan et al. (2022). In this approach, criteria weights are determined by dividing their total interaction degrees ($A + B$ values) by the total interaction degree of the whole system. The second alternative is similar, but criteria weights are based on the given influence values (A values) (Amirghodsi et al., 2020). The third is the DANP method, as detailed in Rostamzadeh et al. (2023) and Javaherikhah et al. (2025).

The first alternative prioritizes attributes based on their relevance within the system rather than emphasizing driver factors. While this approach may yield similar results to the proposed model when the driver factors are also the most significant, it may fail to identify the most important causal factors when these factors are not heavily influenced by other elements. In the second weighting method, the criteria weights are established based on the given influence values, which reflects the influencing degrees of the criteria but not necessarily their role as driver factors. This is because criteria with high given influence degrees may not always be the drivers of the system. Therefore, an exclusive investment on these factors may induce changes within the system; however, such changes are typically unsustainable, as these factors are not the root causes but are highly dependent on other factors. In Table 13, the cause "Poor safety culture" (S_4) has the highest given influence values, but it is also the second most influenced factor. As a result, improvements in S_4 do not produce sustainable impacts in the system. Therefore, criteria weights based on the given influence values may be less effective than those derived from net influence values in addressing the underlying causes and inducing sustainable changes. The DANP method does not sufficiently emphasize the significance of driver factors; instead, it prioritizes those factors effectively represent the overall performance of the system.

The numerical comparison between these methods is presented in Figure 2. The results indicate substantial differences in the ranking vector and criteria weights, thereby confirming the unique advantages of the proposed approach in identifying and prioritizing driver factors. For instance, while the proposed method identifies "Lack of safety policies and procedures" (S_5) as the most significant driver of the system and allocates it the highest weight, the DEMATEL based on total interaction degrees and based on given influence values methods prioritize "Poor safety culture" (S_4). The DANP method emphasizes "Insufficient expertise with working equipment" (S_2). Unlike alternative methods that overlook root causes, the proposed model identifies and prioritizes factors with lasting influence to address the fundamental causes of accidents.

6. Conclusions and remarks

This study introduces a framework for tackling the fundamental causes of construction accidents, marking it as the first study to develop a weighting methodology that prioritizes underlying driver factors in safety decision-making. The framework represents a significant advancement in construction safety research by offering an innovative approach to evaluate and select safety strategies that address root causes rather than superficial symptoms.

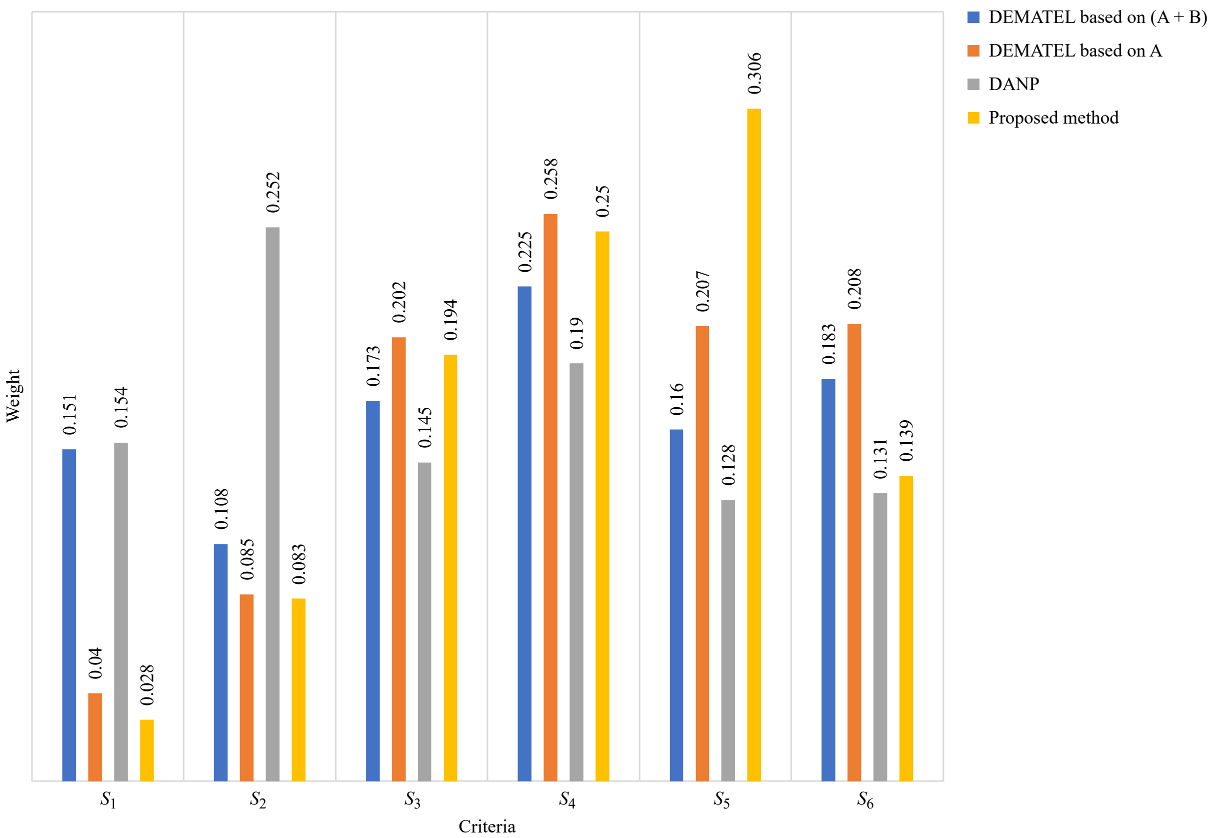

Figure 2. Comparative analysis of criteria weights across different MCDM methods

Comparative analysis with existing methodologies demonstrates the superior effectiveness of this new approach in enhancing safety performance within construction environments.

Despite its contributions, the study has several limitations that require future research attention. The primary limitation of this study is the relatively small size of the expert panel. Future studies should employ larger and more diverse groups – incorporating safety auditors, government regulators, and academic researchers – to enhance the robustness and objectivity of the evaluations. RANCOM uses only ranking positions without considering the actual magnitude of net influence degrees between factors. Future research should refine RANCOM to incorporate actual influence values, providing more precise weighting that better represents each factor's impact on construction safety. The current RANCOM approach also fails to handle uncertainty in expert judgments and real-world construction environments. Integrating fuzzy set theory could address this limitation by enabling more flexible and accurate management of imprecise information. The DEMATEL method presents additional improvement opportunities, particularly regarding indirect relationships between accident-causing factors. While it captures direct interactions effectively, it does not explicitly model the complex indirect influences within construction safety systems. Future research could incorporate the ISM technique to provide deeper insights into hierarchical and indirect relationships among safety factors. This integration would offer a more comprehensive understanding of how various causes interact within the broader safety ecosystem, improving the framework's accuracy and practical applicability for construction safety management. Furthermore, while the current study utilizes a case study from a specific construction firm to validate the model, future research should focus on applying this framework across diverse geographical regions and various project types. Such cross-validation would help verify the stability of the identified root causes across different regulatory and cultural environments.

Author contributions

James J. H. Liou: Conceptualization, Methodology, Formal analysis, Writing – review & editing, Supervision. Tuong T. Vo: Conceptualization, Methodology, Data collection, Formal analysis, Visualization, Writing – original draft.

Disclosure statement

The authors declare that they have no financial or personal interests that could be perceived as influencing the research presented in this paper.

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APPENDIX

This framework is designed to be implemented using standard office software such as Microsoft Excel, ensuring it is accessible to practitioners without advanced MCDM expertise.

Stage 1: Refine the causes

Experts' evaluations are collected and entered into Excel.

Expert 1	a	b	c
C_1	0.5	0.7	0.9
C_2	0.7	0.9	1
C_3	0.3	0.5	0.7
C_4	0.7	0.9	1
C_5	0.5	0.7	0.9
C_6	0.7	0.9	1
C_7	0.7	0.9	1
C_8	0.7	0.9	1
C_9	0.1	0.3	0.5
C_{10}	0.5	0.7	0.9
C_{11}	0.1	0.3	0.5
C_{12}	0.5	0.7	0.9
C_{13}	0	0	0.3
C_{14}	0.3	0.5	0.7
C_{15}	0.7	0.9	1

Left and right values are computed through Eqns (4) and (5).

Criteria	Left value	Right value
C_1	0.583	0.75
C_2	0.75	0.909
C_3	0.417	0.583
C_4	0.75	0.909
C_5	0.583	0.75
C_6	0.75	0.909
C_7	0.75	0.909
C_8	0.75	0.909
C_9	0.25	0.417
C_{10}	0.583	0.75
C_{11}	0.25	0.417
C_{12}	0.583	0.75
C_{13}	0	0.231
C_{14}	0.417	0.583
C_{15}	0.75	0.909

Criteria performance is sorted, and decisions are made accordingly.

Criteria	Value	Rank	Decision
C_8	0.875	1	Selected
C_4	0.838	2	Selected
C_7	0.838	2	Selected
C_{12}	0.801	4	Selected
C_{17}	0.801	5	Selected
C_{18}	0.801	5	Selected
C_6	0.726	7	Deleted
C_3	0.613	8	Deleted
C_9	0.613	8	Deleted
C_{23}	0.561	10	Deleted
C_{25}	0.561	10	Deleted
C_{10}	0.56	12	Deleted
C_{16}	0.56	12	Deleted
C_{19}	0.559	14	Deleted
C_1	0.522	15	Deleted

Stage 2: Relationships among causes

Experts' assessments are recorded into worksheet.

Expert 1						
Lower bound	S_1	S_2	S_3	S_4	S_5	S_6
S_1	0	0	0	0.5	0	0
S_2	0.75	0	0	0	0	0
S_3	0.75	0	0	0.75	0	0.25
S_4	0.75	0.25	0.5	0	0.75	0.5
S_5	0.25	0	0.5	0.25	0	0.25
S_6	0.5	0.5	0.5	0.5	0.25	0
Middle bound	S_1	S_2	S_3	S_4	S_5	S_6
S_1	0	0	0	0.75	0	0
S_2	1	0	0	0	0	0
S_3	1	0.25	0	1	0	0.5
S_4	1	0.5	0.75	0	1	0.75
S_5	0.5	0.25	0.75	0.5	0	0.5
S_6	0.75	0.75	0.75	0.75	0.5	0
Upper bound	S_1	S_2	S_3	S_4	S_5	S_6
S_1	0	0.25	0.25	1	0.25	0.25
S_2	1	0	0.25	0.25	0.25	0.25
S_3	1	0.5	0	1	0.25	0.75
S_4	1	0.75	1	0	1	1
S_5	0.75	0.5	1	0.75	0	0.75
S_6	1	1	1	1	0.75	0

Relationships and ranking vector are determined.

	S_1	S_2	S_3	S_4	S_5	S_6	Net influence	Ranking
S_1	0.060	0.042	0.048	0.107	0.041	0.061	–1.965	6
S_2	0.330	0.050	0.067	0.153	0.058	0.095	–0.417	5
S_3	0.473	0.216	0.172	0.424	0.196	0.311	0.513	3
S_4	0.554	0.319	0.388	0.285	0.341	0.408	0.591	2
S_5	0.434	0.273	0.299	0.354	0.134	0.342	0.833	1
S_6	0.473	0.270	0.306	0.381	0.232	0.185	0.445	4

Stage 3: Compute weights

Ranking comparison matrix is constructed based on the ranking vector, and the relative weights are derived.

	S_1	S_2	S_3	S_4	S_5	S_6	Summed ranking score	Weights
S_1	0.5	0	0	0	0	0	0.5	0.028
S_2	1	0.5	0	0	0	0	1.5	0.083
S_3	1	1	0.5	0	0	1	3.5	0.194
S_4	1	1	1	0.5	0	1	4.5	0.250
S_5	1	1	1	1	0.5	1	5.5	0.306
S_6	1	1	0	0	0	0.5	2.5	0.139