



## Research article

## Quantitative risk assessment of college campus considering risk interactions

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## ARTICLE INFO

## Keywords:

Risk assessment  
Campus risk  
Risk interaction  
DEMATEL  
Bayesian network

## ABSTRACT

Because of the more emerging risks and stronger risk interactions, the risk of college campuses as well as students and staff received more and more attention. Current works on campus risk mostly focus on single-category factors, and few of them considered risk interactions. Therefore, an integrated model for assessing comprehensive risks on the campus is proposed to put forward risk reduction strategies. First, a comprehensive risk identification of the college campus is conducted by integrating the modified egg model and the fault tree. Then, DEMATEL (Decision-Making Trial and Evaluation Laboratory) is applied to quantify the complex risk interactions and determine the influential causes for further modelling. Finally, the Bayesian network is established for cause diagnosis, consequence prediction, and risk reduction. The identified most sensitive cause is alcohol use. In the case of the four sensitive causes simultaneously occurring, the probability of high campus risk will increase from 21.9% of the original to 39.4%. Moreover, an efficiency analysis of different risk reduction strategies is performed to determine the most efficient risk reduction strategy. The results indicate that the proposed methodology may of great significance for the risk reduction of the college campus in the changing age.

## 1. Introduction

As a kind of huge social-technical system with enormous people, various hazards, multiple interactions, frequent mobility, and high social impact, the college campus is vulnerable to safety and security issues. In this era of rapid development, more and more emerging risks (cyber security, COVID-19, energy transition, etc.) may affect the campus and threaten students and employees. Three students from Beijing Jiaotong University die in a magnesium dust explosion on December 26, 2018, during sewage treatment experiments [1]. In the same year, a fire broke out in the dormitory of Boston University during the annual move-in weekend due to improper use of candles, causing 40 students displaced and one injured [2]. On July 5, 2019, a mechanical failure at the University of Nevada, Reno, injured eight people and caused a collapse of a residence hall [3]. Therefore, it is essential to assess as many campus risks as possible quantitatively and comprehensively.

Mostly, risk studies in college campuses cover building safety, laboratory safety, personal safety, etc. Separately, without holistic work on comprehensive risks. Darwis et al. employed SPSS to carry out a building project safety risk assessment at Hasanuddin University [4]. In order to efficiently evaluate multiple factors of campus building safety, Zhang et al. introduced an integrated technique based on fuzzy mathematics [5]. Rahman created a framework to quantify the safety of high-rise structures on the campus,

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and the outcome revealed that buildings housing the chemical department are at risk [6]. Li et al. presented a semi-quantitative approach using the Combined Ordinal Weighted Average (C-OWA) operator and the Matter-Element Extension Theory (MEET) to assess and evaluate the risk in chemical labs of universities [7]. Chi-square and correlation tests were used to prove that the infrastructure and operations of labs, libraries, and power plants within college campuses may be vulnerable and prone to major accidents [8]. To evaluate the health of employees and students at medical universities, Cheng et al. employed Monte Carlo simulation to analyse the importance of ventilation during the experiment [9]. Meanwhile, the uncertainty of risk assessments for such a complex system should be further analysed [10].

Recently, students' psychological and physical health in colleges and universities receive more focus, especially during the emerging pandemic. Currie et al. examined how the pandemic affected undergraduate instruction and noted that institutions confront difficulties in adjusting to the change of online teaching [11]. Dixon et al. gathered information from the early stages of the pandemic and demonstrated how COVID-19 may have a profound psychological effect on college students [12]. It is found that the incidence of COVID-19 was lower in contactless sports among high school athletes [13]. Also, some researchers indicated that lifestyle changes and health concerns would be triggered by the campus lockdown during the pandemic [14]. But most of the current health research of students focuses on the medical aspect, instead of a comprehensive aspect considering interactions.

Therefore, it seems that there is still a need for analysing the interactions of various risks, including safety and security issues, health issues, and natural hazards. Quantifying the comprehensive risk of college campuses and proposing risk reduction strategies can effectively facilitate safety and security. Therefore, an integrated model for assessing comprehensive risks on the college campus is proposed in this work. The methodology is elaborated in Section 2. The systematic risk identification based on the modified egg model

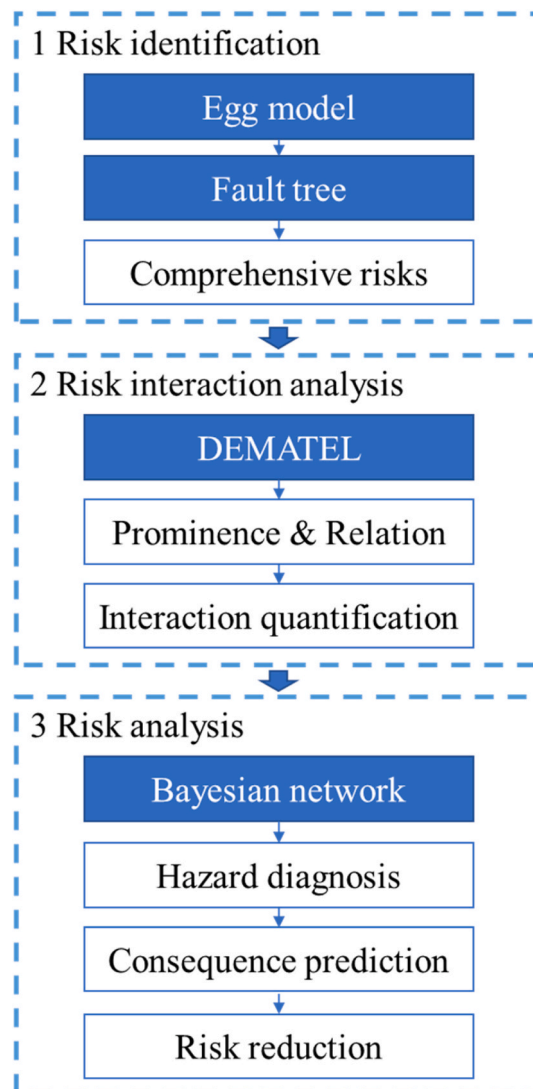


Fig. 1. Flow chart of the integrated model.

and FTA is presented in Section 3. The DEMATEL (Decision-Making Trial and Evaluation Laboratory) is applied to quantify the risk interactions and determine the influential causes in Section 4. Then, the Bayesian network is established to quantitatively analyse comprehensive risks and propose risk reduction strategies in Section 5. Finally, the conclusion is remarked in Section 6.

## 2. Methodology

### 2.1. The proposed integrated model

To quantitatively assess the comprehensive risk of college campuses, an integrated model is proposed in this work as shown in Fig. 1. There are generally three steps for the risk assessment of college campuses. First, the modified egg model is proposed to comprehensively illustrate the campus system and determine the risk categories to elicit fault trees to systematically identify causes of campus accidents. Second, DEMATEL is applied to quantify the complex risk interactions and determine the influential causes for further modelling. Finally, the Bayesian network is utilized to model the evolution of campus risks to diagnose sensitive causes, predict potential consequences, and optimize risk reduction strategies. Therefore, the proposed model is a novel and feasible approach for a comprehensive and quantitative risk assessment of college campuses considering risk interactions. With the proposed model, various risks and their complex interactions on the college campus can be systematically extracted, illustrated, and assessed. And the following risk reduction strategies consider risk interactions and emerging risks, which may of great significance for college campuses in the changing age.

### 2.2. The egg model

The egg model (The Egg Aggregation Model, TEAM) is proposed to illustrate the human dynamics behind behavior-based systems considering all aspects of safety science in an organization [15]. This model provides a clear overview for illustrating the safety culture in an organization with different factors that interact with each other. The egg model consists of an egg shell and four components as shown in Fig. 2. The factors that can be most easily observed are represented by the yolk, which is the most nutritious part of an egg. Protein is translucent and harder to observe, so it represents perceptual and psychological factors, sometimes categorized as “psycho-social factors for safety”. The belief and value are implicit but an essential part of the whole system, so they can be the air in an egg. The technological domain of observable factors, the organizational domain of safety perceptions, and the human domain of personal behaviors. Moreover, the eggshell indicates the peripheral barrier of the system.

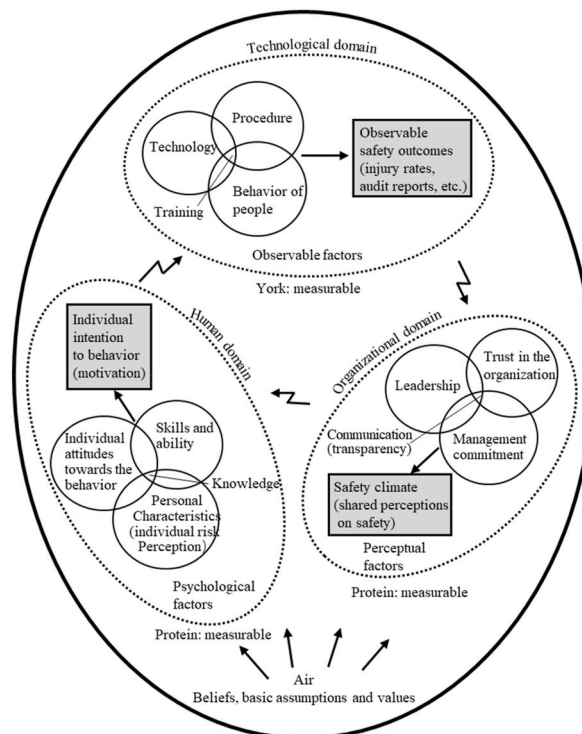


Fig. 2. The egg-aggregated model of safety culture.

### 2.3. FTA

Fault tree analysis (FTA) is an important and widely-used method for hazard identification and causation illustration [16]. The undesired event is determined as the top event to further find out all the direct factors and causes that affect the top event. This graphical technique could explicitly show the hazards and causal topology of accidents and thus can naturally connect accidents with the failures of system components [17,18]. To depict the causation path between events graphically, some symbols are introduced in FTA as shown in Fig. 3. By identifying the critical points in the system and completing system optimization, FTA accomplishes the prediction and diagnosis of causes and is frequently used in the safety management of various area [19,20].

### 2.4. DEMATEL

DEMATEL (Decision-Making Trial and Evaluation Laboratory) is a kind of multi-criteria decision-making approach first proposed by Gabus and Fontela [21]. DEMATEL is suitable for tackling interacted relationships of multiple factors in a complex system. Based on the calculation of the “Prominence” and “Relation” of each factor, the correlations and dependencies can be quantified [22,23]. It is widely used for many decision-making issues in different area [24–26]. Generally, there are 4 steps for a DEMATEL approach.

First, consulting  $m$  experts to determine the average direct relation matrix  $A$  of  $n$  factors based on Eq. (1) where  $a_{ij}^k$  is the influence of factor  $i$  on factor  $j$  determined by the  $k$ th expert. The individual influence scale can be “very high influence (4)”, “high (3)”, “moderate influence (2)”, “low influence (1)”, and “no influence (0)”.

$$a_{ij} = \frac{1}{m} \sum_{k=1}^m a_{ij}^k, i, j = 1, 2, \dots, n; k = 1, 2, \dots, m \tag{1}$$

Second, obtaining the normalized direct relation matrix  $M$  based on Eq. (2).

$$M = A \times \min \left( \frac{1}{\max \sum_{i=1}^n a_{ij}}, \frac{1}{\max \sum_{j=1}^n a_{ij}} \right) \tag{2}$$

Third, obtaining the total relation matrix  $T$  based on Eq. (3) where  $I$  is the identity matrix.

$$T = M + M^2 + M^3 + \dots + M^\infty = M(I - M)^{-1} \tag{3}$$

Finally, calculating the  $R$  and  $C$  based on Eq. (4) and (5) to plot the influential relation map ( $R + C; R-C$ ).  $R + C$  is called the “Prominence” and  $R-C$  is called the “Relation”. A positive prominence refers to a cause and a negative to an effect. And the  $R + C$  presents the total relation strength of a factor (the higher  $R + C$ , the more influencing the factor).

$$R_i = \sum_{j=1}^n t_{ij} \tag{4}$$

$$C_i = \sum_{j=1}^n t_{ji} \tag{5}$$

### 2.5. Bayesian network

Bayesian network (BN) is a probabilistic graphical model that uses the directed acyclic graph to represent random variables and causal interactions between variables [27]. The components of BN are parent nodes (variables A and B), child node (variables C), and the arc from a parent to a child (which means causation) as shown in Fig. 4. Along with the arc, the conditional probability table is used to quantify the conditional reliance between linked nodes.

Variables typically have binary or multivariate mutually incompatible states. The benefit of BN is that Bayes’ theory may be used to execute probabilistic updates as new information is discovered. The joint probability  $P(U)$  of the variables in the network is based on Eq. (6).

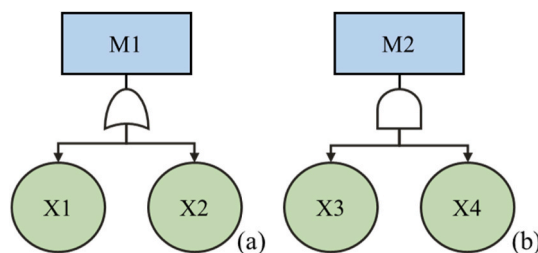


Fig. 3. “Or” gate (a) and “And” gate (b) for fault tree.

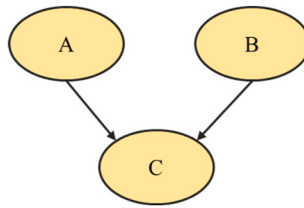


Fig. 4. Schematic diagram of the basic structure of Bayesian networks.

$$P(U) = \prod_{i=1}^n P[X_i|P_a(X_i)] = P(X_C|X_A, X_B)P(X_A)P(X_B) \tag{6}$$

where  $U$  represents the variable, and  $P(U)$  represents the joint probability of all the parent nodes to this child.  $P[X_i|P_a(X_i)]$  is the conditional probability of variable  $X_i$ .

The Bayesian network has the capacity to conduct dynamic risk analysis and update with emerging information [28]. However, the BN still needs to integrate with risk identification and illustration method like fault tree and Bow-tie, the corresponding BN mapping approach fully exploits both the dynamic properties of BN as well as the logical benefits of the fault tree to derive the accident scenario in a top-down strategy [29,30].

### 3. Risk identification based on egg model and FTA

#### 3.1. The modified egg model

The potential causes of an accident for a system or process can be identified by using the accident causation model [31]. Therefore, based on the accident causation theory, the primary causal factors that lead to campus accidents can be clarified into four categories: human, equipment, environment, and management. Based on the egg-aggregated model introduced in section 2.2, a modified egg model for campus risks is proposed in this section. Generally, eggshell, air, protein, and yolk are the major parts of an egg. Among them, the air inside an egg mainly connects the internal and external environments to assure growth. The function of the protein in an egg is to supply the essential nutrients for embryonic development. And the most nutrient-dense and easily observed part of an egg is the yolk. Therefore, along with different attributes of different parts of an egg, the modified egg model is proposed as shown in Fig. 5. As the most essential element of an egg, the yolk for an egg is similar to the equipment failure for campus accidents. Since the

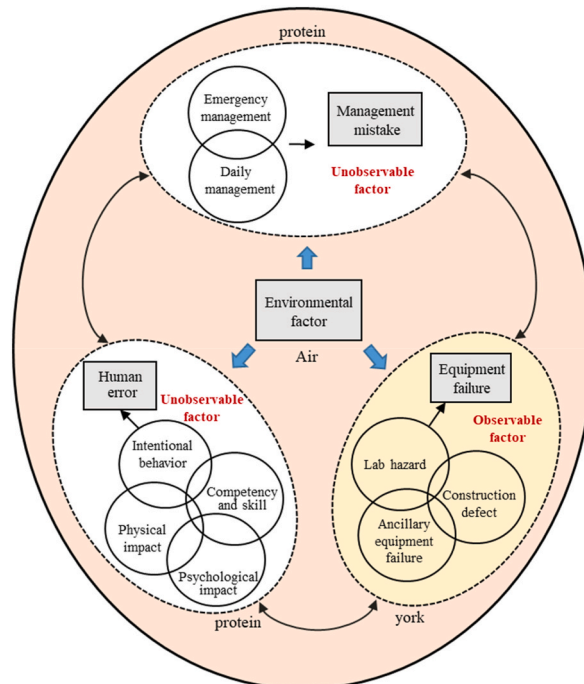


Fig. 5. The modified egg model for campus accidents.

management mistake and human error are hidden but important components that cannot be directly observed, the protein is introduced to symbolize them. Meanwhile, the environment can be seen as air because it acts as a link between each part of an egg.

### 3.2. Building fault tree

According to the principle of fault tree analysis, the “occurrence of a campus accident” is regarded as the top event of the fault tree to further identify causal factors layer by layer. Based on the literature review, statistics, accident causation theory, and the modified egg model [32–35], the causes of campus accidents are divided into four categories, human error, equipment failure, environmental factor, and management mistake. Moreover, various potential causes of the top event are extracted as intermediate factors, until all the primary causes are identified.

Based on the study of Reason [36], human error can be divided into two groups: intentional behavior and unintentional behavior. Unintentional behavior refers to the improper operation or response impacted by the actor’s physical condition, psychological condition, and competency failure. Meanwhile, intentional behavior always carries out a specific goal, and it can be divided into intentional violation and improper curiosity of staff or students on the campus. So, the fault tree of human error inside the college campus is proposed in Fig. 6.

As the modified egg model illustrated, equipment failure is another kind of perceptual factor for campus risk. So, the fault tree of equipment failure is depicted in Fig. 7 as follows. Lab hazards, construction defects, and ancillary equipment failures are the three primary categories of equipment failure. Since there are multiple hazardous materials and frequent dangerous operations on the college campus, the laboratory hazard has been further elaborated as fire/explosion, toxicant leakage, and biological release.

The college campus is a kind of dynamic and huge system that interacts with both the outside and inside environments. Therefore, the environmental factor has been analysed in detail, including natural hazard, public health emergencies, and third-party interference, as shown in Fig. 8. There are 12 primary causes and 3 intermediate factors of a fault tree for environmental factors.

Since management mistake is a kind of unperceptual but essential factor, its primary causes should be determined systematically. So, management mistake has been separated into two categories: improper emergency management and improper daily management since they can either directly or indirectly lead to campus accidents. By further identifying their primary causing factors, 9 primary causes including the repeat “X45: Lack of inspection” are identified as shown in Fig. 9.

## 4. Risk interaction analysis based on DEMATEL

Based on the systematically identified risks in Section 3, the DEMATEL is then applied to elaborate on their risk interactions. In this work, 5 experts from universities, governments, and industries are invited to form an expert group to determine the influence of each pair of factors quantitatively to simplify the causation network for further BN modelling.

### 4.1. Risk interaction analysis of human error

First, the risk interaction analysis of human error is conducted. Based on expert elicitation, the average direct relation matrix  $A$  is obtained in Table 1 based on Eq. (1) after the consistency check. The average direct relation matrix indicates the influence strength of one factor on another. Then, based on Eq. (2) and Eq. (3), the total relation matrix  $T$  is proposed as shown in Table 2. Followed by using Eq. (4) and Eq. (5), the four relation indicators  $R$ ,  $C$ ,  $R + C$  (i.e. prominence), and  $R - C$  (i.e. relation) are calculated as shown in Table 3. As the influential relation map shown in Fig. 10,  $X1$  (Alcohol use),  $X6$  (Lack of safety education),  $X2$  (COVID pandemic), and  $X9$  (Intentional violation) are the most influential causes of human error. Since a limited number of causes are selected, the intermediate factors can be neglected for further analysis. Moreover, although the prominence of  $X7$  (Judgement error) is lower than the threshold (0.027) in this case, it’s worth noting that it more belongs to a consequence instead of a cause, according to the DEMATEL analysis.

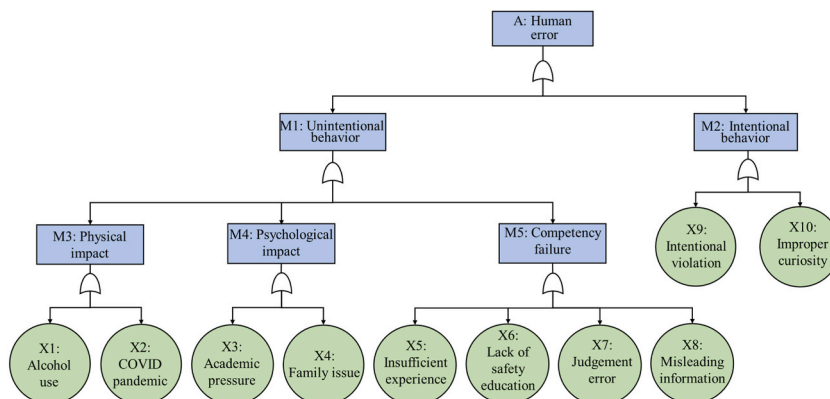


Fig. 6. The fault tree of human error.

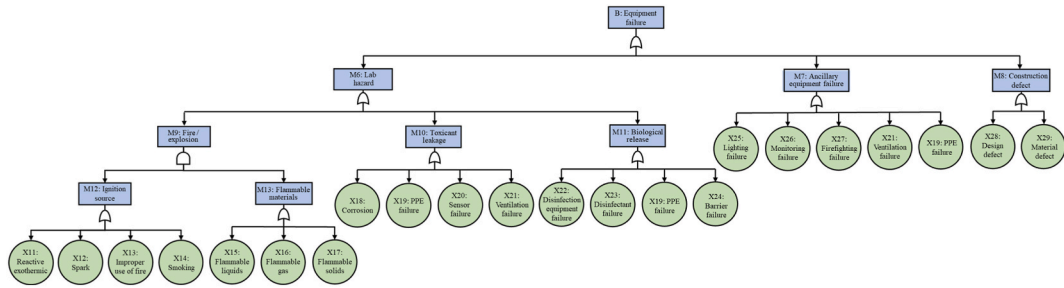


Fig. 7. The fault tree of the equipment failure.

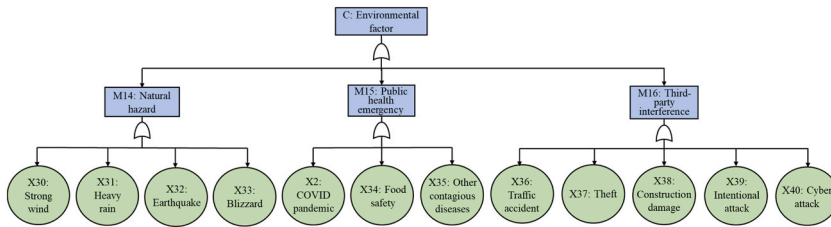


Fig. 8. The fault tree of the environmental factor.

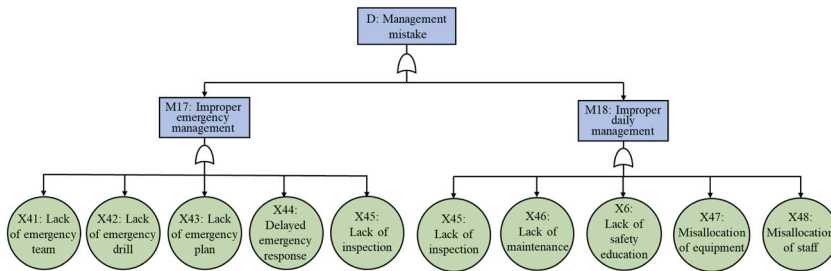


Fig. 9. The fault tree of the management mistake.

Table 1  
Average direct relation matrix of human error.

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	M1	M2	M3	M4	M5	A
X1	0	1	0	0	0	0	3.4	0.8	3.4	1.6	3	1.8	3.4	0.8	1.6	3.2
X2	0	0	0	0	0	0	2.2	1.6	0	0.8	2.8	0	3	1.2	1	3
X3	2.6	0.6	0	1	0	0	1	0.2	0.8	0.4	2.4	0.4	0	3	0.4	2.2
X4	1.2	0.6	0.4	0	0	0	0.6	0	0.6	0	1.2	0	0	2.4	0	1.6
X5	0	1.4	0	0	0	0	2	0.8	0	1	2.2	0	0	0.6	2.6	2.2
X6	1.6	2.4	0.8	0.2	0	0	2.2	1.4	1.6	2	2.4	1.6	0.6	1	3	3
X7	0	0	0	0	0	0	0	0	0	0	1.2	0	0	0.4	1	1.2
X8	0	0	0	0	0	0	0	0	1.2	1.4	1	1.6	0	0	1	1
X9	1	1.4	0	1	0	0	1	0	0	1	0.2	2.8	0.8	0	0.4	3
X10	0.8	1	0	0	0	0	0.8	0.6	1	0	0.8	3	1	0.4	0	2.2
M1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3.2
M2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2.4
M3	0	0	0	0	0	0	0	0	0	0	2.6	0.4	0	0.6	1	2.6
M4	0	0	0	0	0	0	0	0	0	0	2.2	1	0.8	0	1.2	2.6
M5	0	0	0	0	0	0	0	0	0	0	3.2	0	0	0	0	3.2
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

**Table 2**  
Total relation matrix of human error.

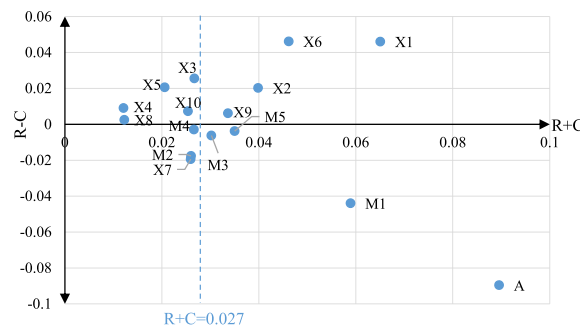
	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	M1	M2	M3	M4	M5	A
X1	0	0.0009	0	0	0	0	0.009	0.0005	0.0087	0.0021	0.0083	0.003	0.0091	0.0006	0.0023	0.0112
X2	0	0	0	0	0	0	0.0036	0.0019	0	0.0005	0.0068	0	0.0067	0.0011	0.0009	0.0085
X3	0.0051	0.0003	0	0.0008	0	0	0.001	4E-05	0.0006	0.0002	0.0054	0.0002	0	0.007	0.0002	0.0054
X4	0.0011	0.0003	0.0001	0	0	0	0.0003	0	0.0003	0	0.0014	0	0	0.0044	0	0.0026
X5	0	0.0015	0	0	0	0	0.0031	0.0005	0	0.0008	0.0044	0	0	0.0003	0.0052	0.0049
X6	0.0021	0.0046	0.0005	4E-05	0	0	0.0042	0.0016	0.0022	0.0033	0.006	0.0025	0.0005	0.0009	0.0074	0.0104
X7	0	0	0	0	0	0	0	0	0	0	0.0012	0	0	0.0001	0.0007	0.0013
X8	0	0	0	0	0	0	0	0	0.0011	0.0015	0.0008	0.0021	0	0	0.0007	0.0011
X9	0.0008	0.0015	0	0.0007	0	0	0.0009	0	0	0.0008	9E-05	0.0061	0.0006	0	0.0002	0.0082
X10	0.0005	0.0008	0	0	0	0	0.0006	0.0003	0.0008	0	0.0007	0.007	0.0009	0.0001	0	0.0047
M1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0075
M2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.0042
M3	0	0	0	0	0	0	0	0	0	0	0.0052	0.0001	0	0.0003	0.0007	0.0057
M4	0	0	0	0	0	0	0	0	0	0	0.0038	0.0007	0.0005	0	0.0011	0.0058
M5	0	0	0	0	0	0	0	0	0	0	0.0075	0	0	0	0	0.0081
A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

α



**Table 3**  
Results of four relation indicators of human error.

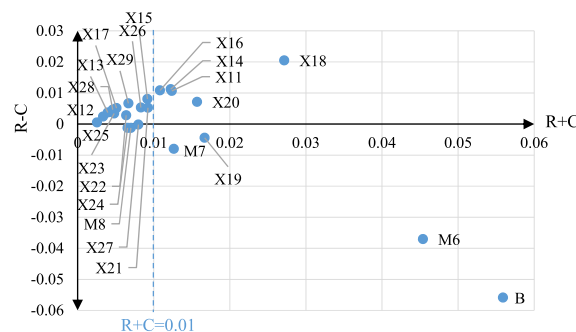
ID	Factor	R	C	R + C	R-C
X1	Alcohol use	0.0555524	0.0095035	0.0650559	0.0460488
X2	Covid pandemic	0.0300434	0.0097983	0.0398417	0.020245
X3	Academic pressure	0.0261091	0.0005862	0.0266953	0.0255229
X4	Family issue	0.0105646	0.0015256	0.0120902	0.009039
X5	Insufficient experience	0.0205806	0	0.0205806	0.0205806
X6	Lack of safety education	0.0461738	0	0.0461738	0.0461738
X7	Judgement error	0.003261	0.0226871	0.0259481	-0.019426
X8	Misleading information	0.0073851	0.0048812	0.0122663	0.0025038
X9	Intentional violation	0.0198957	0.0137371	0.0336328	0.0061587
X10	Improper curiosity	0.0163312	0.0090644	0.0253956	0.0072669
M1	Unintentional behavior	0.0074799	0.0514484	0.0589284	-0.043969
M2	Intentional behavior	0.0042075	0.0218121	0.0260196	-0.017605
M3	Physical impact	0.0119907	0.0182134	0.0302041	-0.006223
M4	Psychological impact	0.0118323	0.0147831	0.0266154	-0.002951
M5	Competency failure	0.0156067	0.0194101	0.0350168	-0.003803
A	Human error	0	0.0895636	0.0895636	-0.089564



**Fig. 10.** Influential relation map of human error.

4.2. Risk interaction analysis of equipment failure

Based on the same steps shown in Section 4.1, the average direct relation matrix, normalized direct relation matrix, and total relation matrix for equipment failure can be obtained and the four relation indicators can be calculated. As the influential relation map of equipment failure shown in Fig. 11, the X18 (Corrosion), X19 (PPE failure), X20 (Sensor failure), X11 (Reactive exothermic), X14, (Smoking), and X16 (Flammable gas) are the most influential causes for equipment failure. To better form a hierarchical structure causation network, M6 (Lab hazard) and M7 (Ancillary equipment failure) remain for further modelling. It is noticed that although X19 (PPE failure) affects a limited number of causes, it has a high influence strength on the B (Equipment failure) and is always affected by other causes, which results in a high prominence value of it.



**Fig. 11.** Influential relation map of equipment failure.

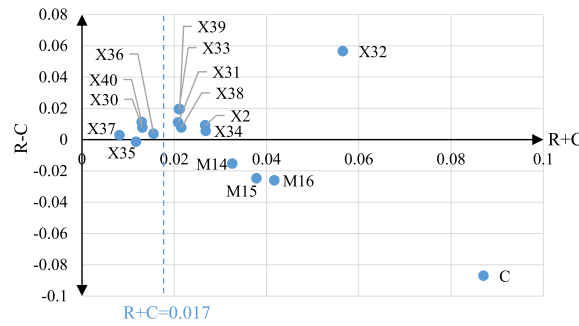


Fig. 12. Influential relation map of environmental factor.

4.3. Risk interaction analysis of environmental factor

Similarly, the risk interaction analysis of the environmental factor is conducted in this section. As shown in Fig. 12, there is a significant gap between X36 and the right-side group (X31, etc.). By introducing the prominence threshold of 0.017, the X32 (Earthquake), X34 (Food safety), X2 (COVID pandemic), X38 (Construction damage), X39 (Intentional attack), X33 (Blizzard), and X31 (Heavy rain) are determined as influential causes. Meanwhile, the three intermediate factors, M16 (Third-party interference), M15 (Public health emergency), and M14 (Natural hazard) are also collected as typical consequence factors with high prominence values. Also, the results indicate that the X32 (Earthquake) contributes far more than other causes, which should be paid more attention to handle.

4.4. Risk interaction analysis of management mistake

Meanwhile, the results of risk interactions of the management mistake are presented as follows. As shown in Fig. 13, X42 (Lack of emergency drill), X6 (Lack of safety education), X45 (Lack of inspection), X48 (Misallocation of staff), X41 (Lack of emergency team), and X44 (Delayed emergency response) are identified as the most influential causes for management mistake, whose prominence value all higher than 0.04. The results indicate that X42 (Lack of emergency drill) contributes most to management-related causes, which means that emergency drills should be organized more frequently and practically in the future. Although M17 (Improper emergency management) has a higher prominence value than M18 (Improper daily management), both should be attached importance since they highly interacted with each other.

5. Comprehensive risk assessment based on BN

Based on the results of DEMATEL analysis in Section 4, an interacted hierarchical structure of BN for campus risk is proposed in Fig. 14. Meanwhile, by integrating the data from administration, literature, media, etc., some prior probabilities of root nodes are objectively determined in Table 4 [37–45]. Due to the scarce data on campus accidents, other prior probabilities and conditional probabilities are determined by expert elicitation with 5 experts. The Delphi method and Cronbach’s  $\alpha$  coefficient are applied during the questionnaire to obtain more reliable and consistent results [30]. Based on the constructed BN, the result indicates that the risk of the college campus is 21.9% for high, 28.9% for medium, and 49.3% for low. But only the absolute posterior probability cannot support the risk reduction of the college campus. By utilizing the proposed BN, diagnosis analysis of causes, prediction analysis of consequences, and strategy analysis of management are presented in the following sections.

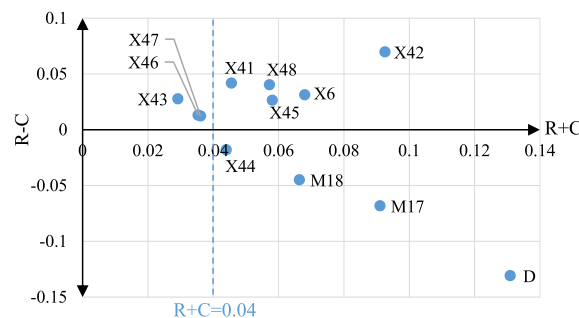


Fig. 13. Influential relation map of management mistake.

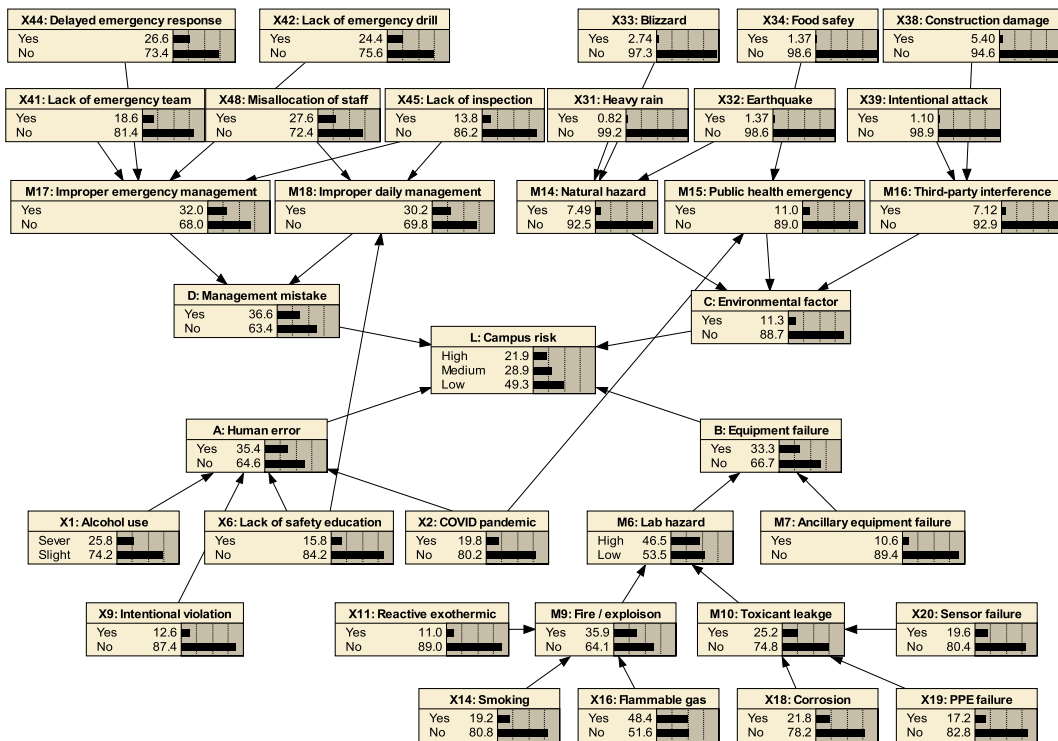


Fig. 14. The BN for campus risk.

Table 4  
The prior probability determined by statistics.

ID	Factor	Prior probability/per year
X11	Reactive exothermic	1.10E-01
X31	Heavy rain	8.22E-03
X32	Earthquake	1.37E-02
X33	Blizzard	2.74E-02
X35	Food safety	1.37E-02
X40	Intentional attack	1.10E-02

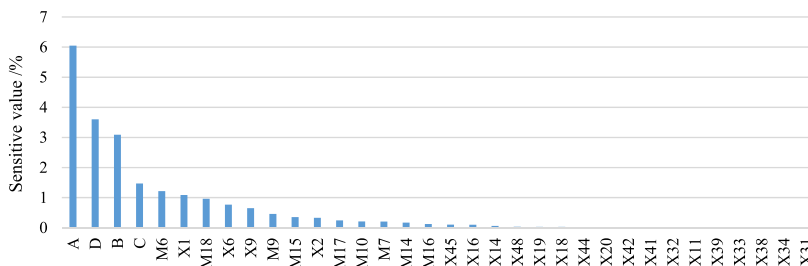


Fig. 15. Sensitivity of “Campus risk” to other findings.

### 5.1. Diagnosis analysis of causes

For such a probabilistic causation network, one of the most important abilities of BN is the diagnosis of causes. The single-finding sensitivity analysis is applied to calculate the sensitive value of each cause based on the calculation of entropy reduction and mutual information. First, the sensitive value of the leaf node L (Campus risk) to a finding at other causes is calculated in Fig. 15. The results indicate that A (Human error) is the most sensitive category with a 6.05% sensitive value, followed by D (Management mistake) for 3.6%, B (Equipment failure) for 3.09%, and C (Environmental factor) for 1.47%. The reason why human error-related causes

**Table 5**  
Results of sensitivity analysis of four category factors.

Category	Primary causes	Sensitive value
A: Human error	X1: Alcohol use	14.4%
	X9: Intentional violation	8.57%
	X6: Lack of safety education	6.64%
B: Equipment failure	X2: COVID pandemic	2.41%
	X16: Flammable gas	2.62%
	X14: Smoking	1.53%
	X19: PPE failure	0.824%
	X18: Corrosion	0.822%
	X20: Sensor failure	0.535%
C: Environmental factor	X11: Reactive exothermic	0.343%
	X2: COVID pandemic	2.44%
	X32: Earthquake	1.13%
	X33: Blizzard	0.822%
	X39: Intentional attack	0.769%
	X38: Construction damage	0.593%
	X34: Food safety	0.369%
D: Management mistake	X31: Heavy rain	0.131%
	X45: Lack of inspection	2.31%
	X6: Lack of safety education	0.985%
	X48: Misallocation of staff	0.822%
	X44: Delayed emergency response	0.521%
	X42: Lack of emergency drill	0.427%
	X41: Lack of emergency team	0.397%

contribute more to the campus risk could be the high prior probability of human category causes, compared with others.

To further elaborate on the impact of primary causes on the four category factors, sensitivity analyses of A (Human error), B (Equipment failure), C (Environmental factor), and D (Management mistake) to a finding at their corresponding primary causes are conducted in this section. And results of four sensitivity analyses are shown in Table 5. For the occurrence of human error, X1 (Alcohol use) is the most sensitive cause with a 14.4% sensitive value, followed by X9 (Intentional violation) and X6 (Lack of safety education). Moreover, X1 (Alcohol use) is also the most sensitive cause for campus risk, which means it should be prevented with the most priority. For the occurrence of equipment failure, X16 (Flammable gas) is the most sensitive cause with a 2.62% sensitive value, followed by X14 (Smoking) and X19 (PPE failure). As for environmental factors, X2 (COVID pandemic) is the most sensitive cause with a 2.44% sensitive value, followed by X32 (Earthquake) and X33 (Blizzard). For management mistakes, X45 (Lack of inspection) is the most sensitive cause with a 2.31% sensitive value, followed by X6 (Lack of safety education) and X48 (Misallocation of staff). Based on the results of the diagnosis analysis in this section, the management priority for mitigating campus risk can be quantitatively determined.

5.2. Prediction analysis of consequences

Since the most sensitive causes of each category (i.e. human, equipment, environment, and management) identified in the previous section are X1 (Alcohol use), X16 (Flammable gas), X2 (COVID pandemic), and X45 (Lack of inspection), the prediction analysis of

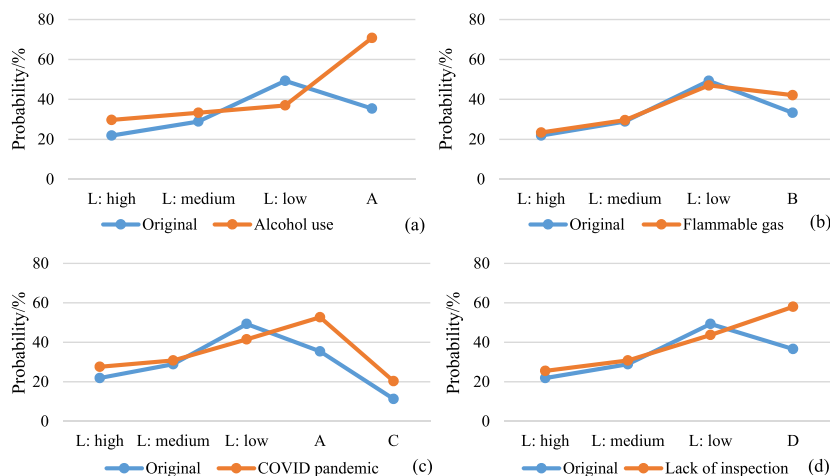


Fig. 16. The predicted posterior probabilities of single-cause occurrence.

consequences in the case of their occurrence is performed in this section by inputting the 100% prior probability of one or more causes as evidence. The consequence of various accident scenarios can be quantitatively predicted as follows.

First, consequences of single-cause occurrence are predicted respectively. By comparing the four sub-figures in Fig. 16, the occurrence of X1 (Alcohol use) can most significantly increase the campus risk. In the case of alcohol use, the probability of human error jumps from 35.4% to 70.8%, that of high campus risk increases from 21.9% to 29.7%, and that of medium campus risk also increases from 28.9% to 33.3%. Among all causes, it can be concluded that X1 (Alcohol use) is the most vital cause and may result in the most severe consequence. As for the occurrence of X2 (COVID pandemic), it will increase the probability of high campus risk to 27.6%, medium campus risk to 30.8%, human error to 52.7%, and environmental factor to 20.3%, which means the COVID pandemic can be recognized as the second most vital cause for campus risk.

Moreover, since the simultaneous occurrence of multiple causes is also possible, a prediction analysis of a multi-cause occurrence is performed as follows. As shown in Fig. 17, the co-occurrence of four sensitive causes significantly increases the probability of different accidents as well as the risk level of the college campus. In this case, the likelihood of human error reaches 79.7%, followed by 58% of management mistake, 42.1% of equipment failure, and 20.3% of environmental factor. Due to the synergy effect of these four causes, the posterior probability of human error, environmental factor, and high campus risk are all roughly doubled. It's worth noting that the high campus risk is the most likely consequence with a 39.4% probability, higher than 32.1% for medium risk, and 28.5% for low risk. It can be concluded that the co-occurrence of multiple causes can result in catastrophic consequences, so it should be avoided as much as possible.

### 5.3. Risk reduction analysis

Based on the sensitive causes and potential consequences determined by previous sections, the potential risk reduction strategy is proposed in this section. By inputting the reduced prior probability of the four sensitive causes as evidence, the posterior probability can be calculated. Then, the difference between the new posterior probability of high campus risk and the original one (21.6%) can be determined as a benefit indicator *B* of the risk reduction strategy. The lower the prior probability, the harder it is to be reduced. So, cost indicator *C* is introduced as Eq. (7). Furthermore, the efficiency indicator *B-C* can be proposed to identify the most efficient risk reduction strategy.

$$C = \sum_{i=1}^n \left( \frac{p_i - p_i'}{p_i} \right)^3 \tag{7}$$

where  $p_i$  is the original prior probability,  $p_i'$  is the reduced prior probability,  $n$  is 4 in this case.

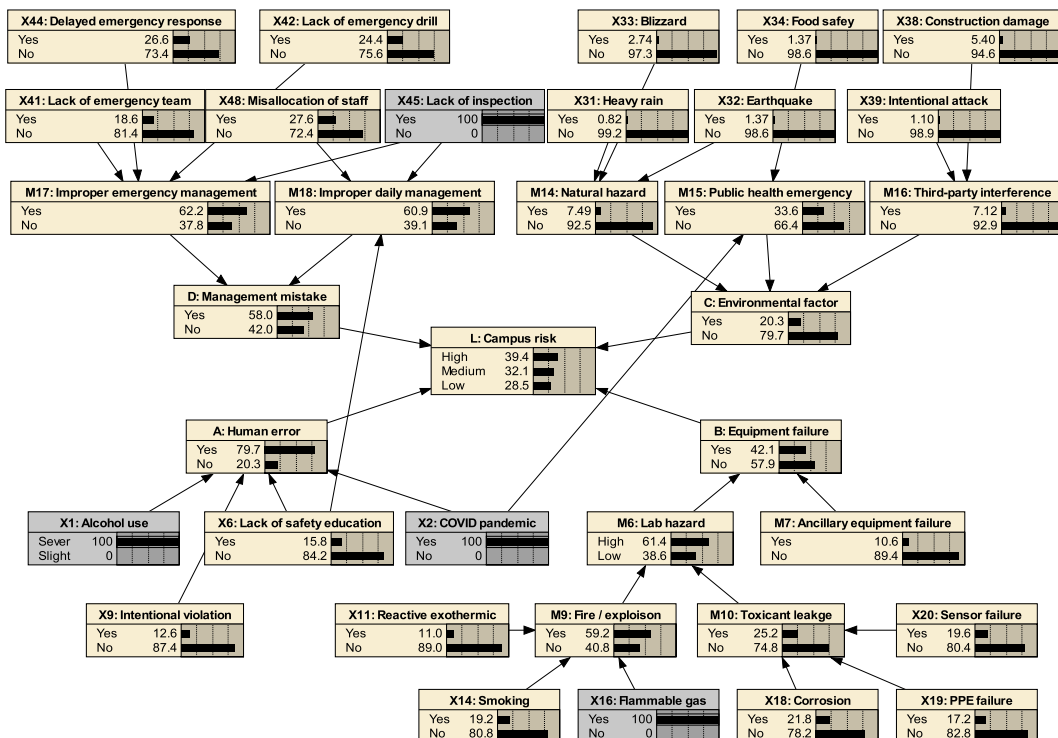


Fig. 17. The BN of multi-cause occurrence.

**Table 6**  
Efficiency results of different risk reduction strategies.

ID	Alcohol use	Flammable gas	COVID pandemic	Lack of inspection	B	C	B-C
1	-0.005	0	0	0	0.005	2.73E-04	4.73E-03
2	0	-0.005	0	0	0.002	1.18E-05	1.99E-03
3	0	0	-0.005	0	0.004	1.03E-03	2.97E-03
4	0	0	0	-0.005	0.002	6.24E-03	-4.24E-03
5	-0.009	-0.003	-0.007	-0.001	0.016	1.07E-02	5.31E-03
6	-0.009	-0.004	-0.006	-0.001	0.016	7.73E-03	8.27E-03
7	-0.008	-0.004	-0.006	-0.002	0.015	5.49E-03	9.51E-03
8	-0.007	-0.004	-0.006	-0.003	0.014	4.51E-03	9.49E-03
9	-0.006	-0.005	-0.005	-0.004	0.013	3.76E-03	9.24E-03
10	-0.005	-0.005	-0.005	-0.005	0.013	7.56E-03	5.44E-03

By comparing the results of strategies 1 to 4 (Table 6), the management priority (which is also the reduction priority) can be determined as alcohol use, the COVID pandemic, flammable gas, and lack of inspection. Based on the proposed priority, in the case of stable total reduction (-0.02), different reduction allocations are designed as strategies 5 to 10 follows. Although strategies 5 and 6 have the highest benefit indicator, their reduction costs are also high. Based on the proposed strategies, strategy 7 is the most efficient one, which can reduce the high campus risk by 0.0015 along with the highest efficiency indicator of 9.51E-3. More specifically, the most efficient strategy for a total 0.02 reduction is 0.009 for alcohol use, 0.003 for flammable gas, 0.007 for the COVID pandemic, and 0.001 for lack of inspection.

## 6. Conclusion

In the fast-developing age, more and more interacted emerging risks affect the vulnerable college campus and increase the comprehensive risk. There is no holistic work on comprehensive risks, although there are many separate works on lab safety, stampede, COVID, etc. Hence, there is still a need for a comprehensive risk assessment of the college campus considering risk interactions. Therefore, a model integrating the modified egg model, FTA, DEMATEL, and BN for assessing comprehensive risks on the college campus is innovatively proposed in this work. The main conclusions of this work are remarked as follows.

- (1) By integrating the modified egg model and FTA, a systematic and comprehensive risk identification of the college campus is innovatively conducted. First, inspired by the components of an egg, human error, equipment failure, environmental factor, and management mistake and their interactions with each other are determined. Then, four fault trees are elaborated to systematically identify the cause of campus accidents layer by layer. There are 18 intermediate factors and 48 primary causes in 4 categories identified for campus risks.
- (2) DEMATEL is then applied to quantify the complex risk interactions and determine the influential causes for further modelling. By calculating four relation indicators of DEMATEL, the most influential causes for each category are quantitatively determined. There are 20 primary causes of FTA are identified as influencing factors for further BN modelling. Moreover, the extracted risk interactions among different causes also support the following risk analysis.
- (3) The results indicate that BN is applicable for diagnosis analysis of causes, prediction analysis of consequences, and strategy analysis of management. The identified most sensitive causes are alcohol use, flammable gas, the COVID pandemic, and lack of inspection. In the case of the four sensitive causes simultaneously occurring, the probability of high campus risk will increase from 21.9% to 39.4%. Moreover, an efficiency analysis of different risk reduction strategies is performed to determine the most efficient risk reduction strategy.

The causal factors and accident cases considered in this paper are limited by computational resources and space. Meanwhile, this work focuses more on probability analysis with less effort on consequence modelling. Also, it could be interesting to conduct detection-based probability modelling and simulation-based consequence modelling in the future. Moreover, with more economic consideration of the cost of risk reduction strategies, the risk reduction strategy could be further optimized.

## Author contribution statement

Xinan Wang: Conceived and designed the experiments; Performed the experiments; Analysed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Xiaofeng Hu: Performed the experiments; Contributed reagents, materials, analysis tools or data.

## Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

## Data availability statement

Data will be made available on request.

## Declaration of interest's statement

The authors declare no conflict of interest.

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