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Risk assessment of large-scale winter sports sites in the context of a natural disaster

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ABSTRACT

Accidents induced by natural disasters at sports sites may cause catastrophic loss of great concern. However, previous studies on risk assessments of sports sites have only focused on operational risk and equipment failure. With the frequent occurrence of extreme disasters, the risk of domino chains caused by natural disasters at large-scale events, such as large-scale winter sports sites, cannot be ignored. In this study, a natural disaster-induced accident-chain evolution analysis model (NAEA model) is proposed. Based on the results of the NAEA model, a fuzzy Bayesian network for domino accidents triggered by an earthquake at large-scale winter sports sites was established. Through sensitivity analysis and scenario analysis, it was found that fire and explosion accidents and crowded stampede accidents are the main causes of serious loss in domino disaster chains in large-scale sports sites. Simultaneously, improving the early warning capability, reliability of electrical equipment, and automatic sprinkler systems are the most effective ways to prevent and control major accidents. In addition, an optimal safety strategy improvement analysis was performed to facilitate the decision-making of safety managers to prevent serious accidents and reduce accident loss.

1. Introduction

Large-scale sports events are held every year worldwide. Whether it is the Olympic Games or the World Cup, they are generally held in the city center and attract many spectators. Therefore, the safety of large-scale sports sites has become a major concern for sponsors. Recently, because of environmental deterioration, natural disasters are occurring more frequently. That being said, in addition to their frequency, the suddenness of disasters also determines the severity of the accidents they induce. As large-scale sports sites attract a large number of participants (spectators, contestants, and on-site staff), and have complex types of equipment, natural disaster-induced accidents at these sites present a multi-hazardous situation. For instance, if a natural disaster destroys the basic equipment at the stadium or causes it to malfunction, the resulting chain reaction (disaster chain) may cause catastrophic damage [1]. These accidents exhibit chain transmission under the action of the domino effect [2]. Thus, because domino effects can induce catastrophic consequences [3], consequence analysis becomes more complicated and significant when they are triggered. Due to the complexity of the weather system, the limitations of scientific cognition, and technological limitations, it is difficult to predict natural disasters very accurately [4]. Therefore, we should pay great attention to the risk of domino chains caused by natural disasters during large-scale events.

Previous research on the risk assessment of large-scale sports sites is relatively limited and is mainly divided into three aspects: identification and assessment of risk indicators or factors, prevention of accidents and disasters, and control of public health. In 2010, Wang and Yang used fuzzy analytic hierarchy [5] and the the decision making trial and evaluation laboratory (DEMATEL) method [6] to list natural disasters as an important factor affecting sports sites. Jia and Yang built a procedural risk assessment index system for large-scale sports sites before, during, and after a game by building a hybrid neural network [7]. In 2017, Gong proposed a risk assessment index system that classified natural disasters as major force factors based on fishbone diagrams [8]. Thereafter, a risk early warning safety model for sports sites was constructed by analyzing a back propagation (BP) neural network [9]. A hybrid human factors analysis and classification system (HFACS)-Bayesian network model was constructed in 2020 to quantitatively analyze the human and organizational factors in the Beijing 2022 Winter Olympics [10]. Moreover, research on accidents and disasters has mainly focused on the assessment of the risk of fire and explosion accidents (such as gas leakages) in large-scale sports venues [11] and the evaluation of the effect of fire protection design [12]. Studies on public health have mainly focused on

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the control of epidemic diseases, such as the dengue fever virus [13] and COVID-19 [14]. In previous studies, natural disasters were included in the risk assessment index system and have been the focus of many scholars. However, it is rare to consider natural disasters as the main research object of a study and conduct quantitative risk assessments on them. For example, spatial predictions of gale disasters at the Olympic Games have been made. However, the overall impact of natural disasters on large-scale sports sites has not been assessed.

Furthermore, studies such as Natech [15] have focused on the prevention and control of technical accidents induced by natural disasters. Natech risk analysis can be undertaken for risk-based prioritization and decisions regarding prevention and preparedness measures. However, regarding our study, using Natech risk assessment has its limitations. Although it is particular to accidents induced by natural disasters, it does not account for the high level of uncertainty—such as the various equipment categories, large numbers of people, and other factors—found in accidents at large-scale sports sites. In addition, many qualitative and quantitative risk assessment methods have been proposed. In general, among the risk assessment methods, qualitative methods are mainly represented by analyzing case databases [16], visiting or interviewing people in disaster areas [17], and using questionnaire surveys [18]. Quantitative methods are mainly represented by fault tree analysis [19], RAPID-N [20], the Bayesian network model [21], Monte Carlo simulation [22], and geographical information system-based methodologies [23]. These methods not only have a mature theoretical system but are also widely applicable, particularly in the field of natural disaster accident assessment. That being said, Bayesian networks [24] have a wide range of adaptations and can better deal with high levels of uncertainty. Thus, this method was preferable for our study.

As a result, we focused on developing a risk assessment model for a typical natural disaster in the context of large-scale winter sports sites based on a fuzzy Bayesian network. Furthermore, a NAEA model was proposed to analyze the domino chain induced by natural disasters. Section 2 describes the methods used in this study, and Section 3 considers an earthquake as an example to show the establishment process of the proposed model. Finally, Section 4 presents the results of risk analysis, while Section 5 presents our main conclusions.

2. Methodology

2.1. Bayesian network

Bayesian belief networks (BBN) are advanced graphical models that describe probabilistic relationships between variables [25]. A BBN can perform probabilistic inferences or belief updating based on data or observations using Bayes' theorem [26]. It is a directed acyclic graph. A network diagram contains multiple nodes that are connected by directed line segments. Nodes and directed connections represent elements in the system and the causal relationships between them. In Bayesian networks, there are three types of nodes. The first type is a node without a parent called the "root node". The second node, without children, is the "leaf node". The third has both root node and child node and is called the "intermediate node" [27].

The probability of the "root node" in the Bayesian network diagram is defined by unconditional probability, thus, the probability is generally derived from previous statistical data, literature, and expert judgment. The probability of the "leaf node" and "intermediate node" is determined by conditional probability. In other words, the relationship between the child and parent nodes is quantified using a conditional probability table. In a BBN, the joint probability distribution of child nodes can be written as the product of the local conditional probability of each parent node:

$$P(V_1, V_2, \ldots, V_K) = \prod_{1}^{K} P(V_i/\text{parent}(V_i)) \tag{1}$$

where $(V_1, V_2,\ldots,V_K)$ represents all the child nodes of an event and $P(V_1, V_2,\ldots,V_K)$ describes the joint probability of a child node. P (V_i/parent (V_i)) is the conditional probability of every parent node in this node. Given a new observation or evidence, the prior probability of variables can be updated. Then, the posterior probability of the variable can be obtained as (E is the evidence):

$$\mathrm{P}(V_1, V_2, \ldots, V_n|E) = \frac{P(V_1, V_2, \ldots V_n, E)}{P(E)} = \frac{P(V,E)}{\sum_X P(V,E)} \tag{2}$$

As a classic risk assessment method, Bayesian networks are widely used in various fields, such as chemical parks [28], natural gas pipeline networks [29], oil and gas pipelines [30], liquified natural gas (LNG) [31], and urban underground utility tunnels [32].

Table 1
Linguistic variables and fuzzy numbers.

Linguistic variables	Trapezoidal fuzzy numbers
Very High (VH)	(0.8,1, 1, 1)
High-Very High (H-VH)	(0.7,0.9,1,1)
High (H)	(0.6,0.8, 0.8,1)
Fairly High (FH)	(0.5,0.65, 0.65,0.8)
Medium (M)	(0.3,0.5, 0.5,0.7)
Fairly Low (FL)	(0.2, 0.35, 0.35,0.5)
Low (L)	(0,0.2,0.2, 0.4)
Low-Very Low (L-VL)	(0,0,0.1,0.3)
Very Low (VL)	(0,0,0,0.2)

2.2. Fuzzy set theory

Fuzzy theory with the fuzzy set principle as its core mainly solves the evaluation situation, which is difficult to judge by specific values, by introducing the concept of the evaluation degree [33]. The uncertain situation is defuzzified with the help of fuzzy equations and fuzzy numbers. As a result, evaluation results were obtained [34]. To deal with the uncertainty and lack of sufficient data, fuzzy set theory can be used to estimate the failure probability of the node. Therefore, a fuzzy Bayesian network is a combination of an expert opinion pool and fuzzy set theory values formed based on a Bayesian network. Fuzzy Bayesian combines the advantages of fuzzy logic, thus, this method is widely used in safety evaluations and risk assessments of various kinds. For example, this method can be used to evaluate the risks of gas tunnel construction [35], railway passenger transportation [36], and tunnel pipeline damage [37]. It can also be used to analyze the safety of human behavior [38], technological processes [39], and main ignition sources [40]. The process of calculating the prior and conditional probabilities of nodes in Bayesian methods using fuzzy set theory is as follows:

Step 1: Experts rely on experience using linguistic variables to estimate the probability of the nodes [41]. In this study, to make a more accurate assessment of the results, the authors used nine levels of linguistic terms (as shown in Fig. 1), namely: "Very High (VH)", "High-Very High (H-VH)", "High (H)", "Fairly High (FH)", "Medium (M)", "Fairly Low (FL)", "Low (L)", "Low-Very Low (L-VL)" and "Very Low (VL)". The fuzzy membership functions are shown in Fig. 2. Simultaneously, the linear opinion pool method [42] is used to calculate the weight of each expert, denoted by W_i .

Step 2: Convert linguistic variables into trapezoidal fuzzy numbers. The correspondence between the nine linguistic variables [43] and the trapezoidal fuzzy numbers is presented in Table 1.

Step 3: The aggregated fuzzy numbers are obtained by weighting the fuzzy numbers [44], as given in Eq. (3):

$$M_j = \sum W_i \times A_{ij} \tag{3}$$

where M_j is the "aggregated fuzzy numbers" of event j, W_i is the weighting score of experts i, and A_{ij} is the trapezoidal fuzzy numbers obtained from experts i about event j.

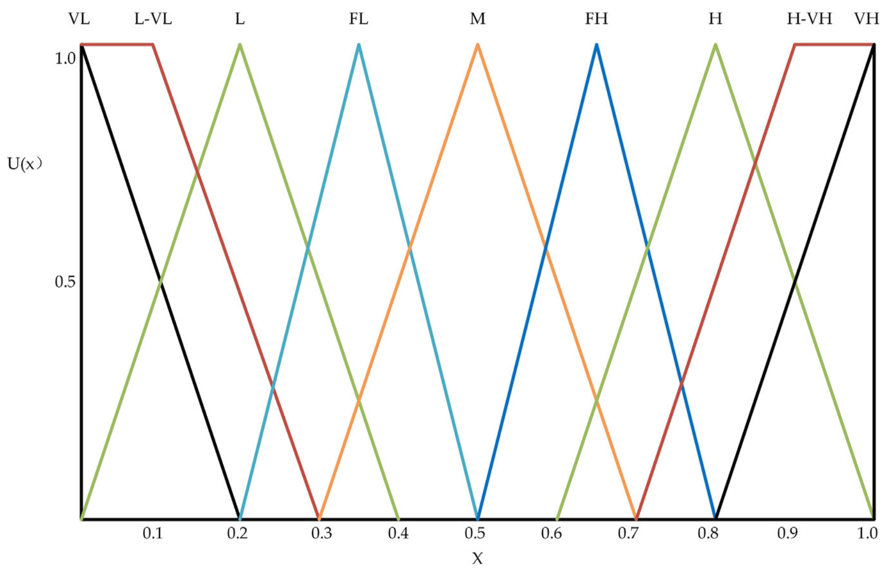
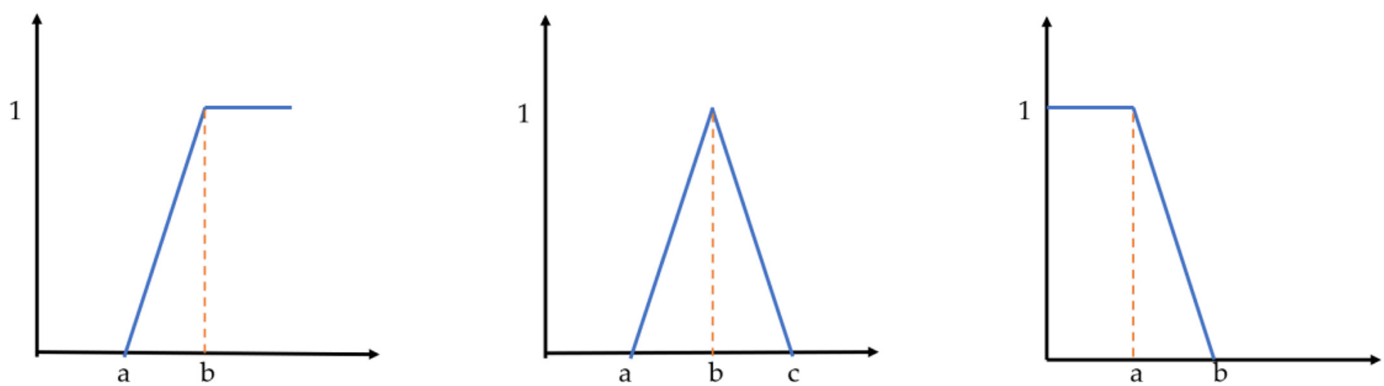


Fig. 1. Fuzzy membership functions.



$$F(x)=\begin{cases}0 & x<a\\ \dfrac{(x-a)}{(b-a)} & a<x<b\\ 1 & b<x\end{cases}$$

$$F(x)=\begin{cases}\dfrac{(x-a)}{(b-a)} & a<x<b\\ \dfrac{(b-x)}{(b-a)} & b<x<c\\ 0 & Other\end{cases}$$

$$F(x)=\begin{cases}1 & x<a\\ \dfrac{(b-x)}{(b-a)} & a<x<b\\ 0 & b<x\end{cases}$$

Fig. 2. Function distribution diagram and formulas.

Step 4: The center of gravity (COG) [45] method is used to defuzzify and calculate the final fuzzy probability [46]. In addition, the calculation formulas for the fuzzy probability (FPs) and fuzzy probability (FPr) are as follows:

$$\mathrm{FPs}=\frac{(a_3+a_4)^2-(a_3a_4)-(a_1+a_2)^2+a_1a_2}{a_3+a_4-a_1-a_2} \tag{4}$$

$$\mathrm{FPr}=\begin{cases}\frac{1}{10^k} & \mathrm{FPr}\neq 0\\ 0 & \mathrm{FPr}=0\end{cases} \quad K=\left(\frac{1-\mathrm{FPs}}{\mathrm{FPs}}\right)^{\frac{1}{3}}\times 2.301 \tag{5}$$

2.3. Integrated model of risk assessment

2.3.1. Framework of the integrated model

An integrated model is proposed for quantitative risk assessment of accidents induced by natural disasters that are formed on the basis of two sub-models (NAEA model and fuzzy evaluation model) combined with Bayesian modeling and analysis theory (shown in Fig. 3). First, a NAEA model was built to determine the structure of the Bayesian network. Second, the prior probabilities and conditional probability tables of the nodes that combine expert judgment and fuzzy set theory in the Bayesian network were determined. Finally, sensitivity and scenario analysis of the established Bayesian model were conducted using Netica (Netica 4.16, Norsys Software Corp., Vancouver, Canada). According to the above analysis, an accident that led to a huge loss of the domino disaster chain was found, and the importance ranking of the factors affecting critical accidents was determined. Furthermore, this study provides the optimal improvement ratio to reduce the probability of fire explosions or crowded stampede accidents through a safety strategy improvement analysis of the Bayesian network. Based on the foregoing, the comprehensive optimal improvement ratio of the Bayesian network is given as is the explored optimal change ratio to provide references and suggestions for safety management.

2.3.2. NAEA model

The suddenness, uncertainty, and catastrophe are the main characteristics of natural disasters. Currently, it is difficult to precisely predict and control the time and intensity of natural disasters due to scientific

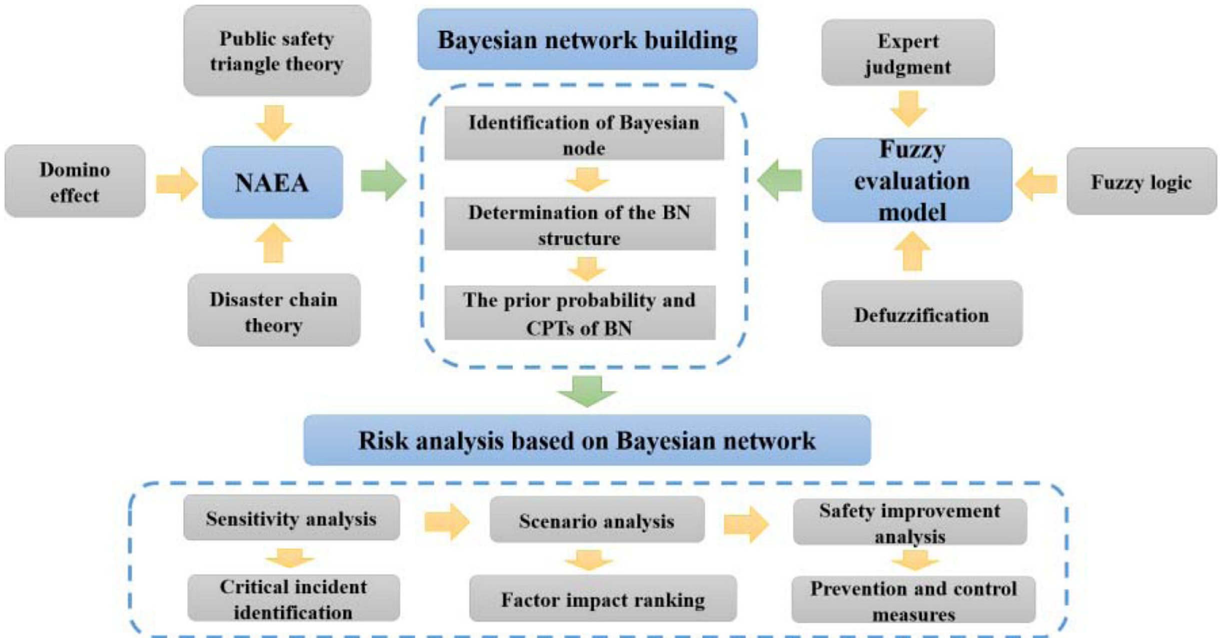


Fig. 3. The framework of the integrated model.

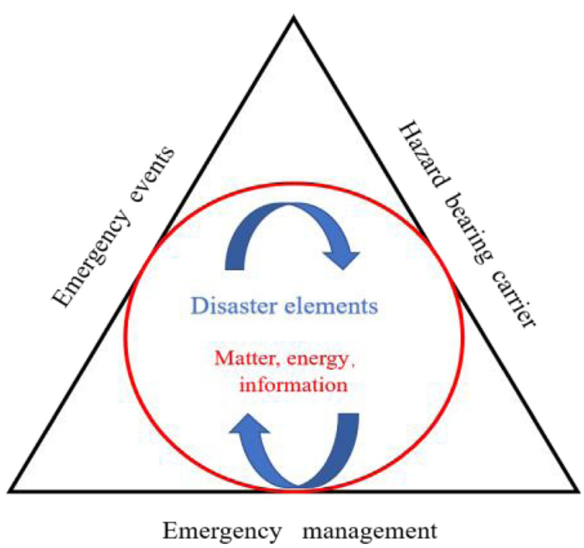


Fig. 4. Public safety triangle theory.

and technological capabilities. Thus, the probability of equipment damage and loss caused by accidents is uncertain. Regarding casualties and property loss, the damage to the accident chain caused by natural disasters is more serious than that of a single natural disaster or technical accident. Therefore, it is necessary to develop a model that can help users comprehensively analyze the development of an accident chain caused by natural disasters and provide emergency measures and suggestions. Therefore, a NAEA model was proposed and was developed using the public safety triangle theory [47]. In addition, it combines the domino effect and disaster chain theory.

The public safety triangle theory (illustrated in Fig. 4) states that a public safety system is composed of three parts: unexpected events, accident carriers, and emergency management. Unexpected events include natural disasters, accidents, public health incidents, and social security incidents. Therefore, this theory can be used to analyze accident chains caused by natural disasters. Any object that can be directly or indirectly affected by emergencies, such as people and technical equipment, is called an accident carrier. Emergency management not only includes measures to reduce the loss of life and property, but also measures to prevent accidents. Matter, energy, and information about an accident are collectively called disaster factors. Additionally, unexpected events, accident carriers, and emergency management influence each other through the interaction of disaster factors.

The overall structure of the NAEA model (shown in Fig. 5) is composed of four rings and two dashed circles. The four rings are filled with different colors, and from inside to outside are the disaster layer, disaster carrier layer, accident layer, and loss layer, respectively. The natural disaster contained in the disaster layer is a specific type of natural disaster that induces an accident chain, which is similar to an unexpected event in the public safety triangle theory. The disaster carrier layer is composed of several disaster bearings that include all people, equipment, or systems that may be directly or indirectly affected after a natural disaster occurs. The content of this layer is the refinement and upgrading of the disaster carrier in the public safety triangle theory. Furthermore, all the accidents caused by the disaster bearings were analyzed, and the specific accident types were given one by one in the accident layer. A loss layer was set up on the outermost layer of the NAEA model. Here, the specific accident loss is divided into four dimensions: casualties, property loss, social impact, and environmental pollution. The internal elements of the three-ring layers from the inside to the outside are connected by straight lines or curves according to disaster chain theory and the principle of the domino effect. Domestic and foreign scholars have emphasized the definition of a disaster chain. Among them, the concept accepted by most people is that the disaster chain is a series of disaster phenomena caused by certain hazardous factors or ecological environment changes. Additionally, the domino effect is a series of accident sequences. The spread of the physical effects of the initial event, such as fire, explosion, or leakage, leads to secondary accidents in other surrounding devices or equipment, and the overall consequences are more serious than the initial events. The chain relationship from the inside to the outside is triggered by a natural disaster, as the initial event is based on the principle of the disaster chain, whereas the transfer of influence between events or accidents is based on the domino effect. The two dashed circles in the model represent the disaster prevention circle (light blue) and disaster mitigation circle (dark blue), respectively. It should be pointed out that the disaster prevention circle will cut off the connection, which refers to the connection between the disaster bearings and the accident, or between different accident types. When the disaster prevention cir-

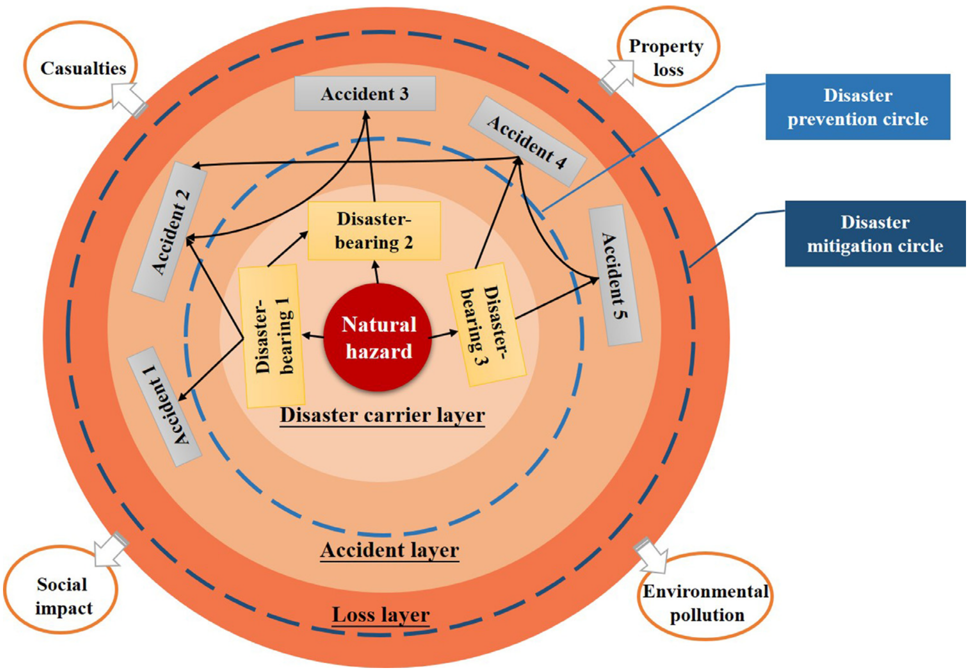


Fig. 5. NAEA model.

cle cuts a connection, a way to prevent a specific accident is provided. The meaning of the disaster mitigation circle refers to the situation in which an accident has occurred, and analysts consider measures from four dimensions to mitigate casualties, property losses, social impact, and environmental pollution.

3. Case study of earthquake-induced accidents in large-scale winter sports sites

3.1. Mapping the Bayesian network from the NAEA model

The NAEA model is suitable for technical accidents and public safety accidents induced by natural disasters. This study considered earthquake-induced accidents at large-scale winter sports sites as an example. The evolution results of the NAEA model are presented in Fig. 6, and the analysis results were used to determine the Bayesian network structure.

To use the NAEA model to analyze the development and results of this scenario, the specific situation of the disaster carrier layer must first be determined. Objects that can be used as disaster bearings for earthquakes in large-scale winter sports sites can be divided into two categories: people (spectators, contestants, and on-site staff) and structures. Furthermore, this study identifies four representative objects as the key structures: stadium buildings (including all stadium buildings built on flat ground and mountains), snowdrifts, auxiliary equipment, and mountains. For example, an earthquake affects the mountain (which is intermediate disaster-bearing), thereby affecting the stadium buildings and auxiliary facilities built on the mountain. However, this domino chain effect is more obvious at large-scale winter sports sites. The auxiliary facilities mentioned above mainly refer to lifelines, refrigerating plants, electric equipment, and ski lifts. These devices are all necessary for large-scale winter sports.

Next, we analyzed the accident layer of the NAEA model. The purpose of this stage is to analyze the direct and indirect accidents caused by each disaster-bearing body in the disaster carrier layer. For instance, at a large-scale winter sports event venue, an earthquake might cause damage to or collapse of the building, which could lead to trapped personnel, falling high-potential energy snow blocks or avalanches, or a stampede during evacuation–consequently causing casualties [48]. Moreover, earthquake damage to the lifeline systems (pipelines for water, electricity, and gas) of the venue may cause sewage, natural gas, and other toxic and hazardous substances to leak, which could lead to poisoning and suffocation accidents or fire and explosion accidents from an open flame (refrigeration systems at large-scale winter sports sites often uses liquid ammonia and carbon dioxide which is highly flammable and toxic). In addition, these sites use three-level transformers and regulator power stations that, if damaged, may result in fires or explosions. Lastly, the ski lift is a piece of necessary equipment for alpine ski resorts, which could trap people if damaged by an earthquake.

Using the NAEA model, five accidents, at the accident level, were analyzed from four aspects. These include casualties, property loss, social impact, and environmental pollution. It should be noted that all accidents at the accident level may cause casualties and property losses. However, large-scale winter sports sites are significant because if an accident occurs, it would most likely generate bad public opinion, which could impact a country's reputation. Serious accidents, such as the leakage of hazardous materials, fires and explosions, cause a certain degree of environmental pollution. Thus, this is also an aspect that must be considered in the analysis and evaluation of the accident chain caused by earthquakes.

The specific natural disasters, disaster bearings, accidents, and losses analyzed by the NAEA model will all become the nodes of the Bayesian network of accident chains triggered by the earthquake in the large-scale sports event context. Simultaneously, the domino effect formed by the elements becomes the basis for determining the node relationship of the Bayesian network (Bayesian network diagram shown in Fig. 7). Moreover, the three nodes of the automatic sprinkler, earthquake early warning, and emergency drill are elements of the disaster prevention layer in the model because they can effectively cut off the connection between the disaster bearing and the accident. "Medical rescue" is an element of the disaster reduction layer and effective on-site rescue work that can reduce the possibility of casualties.

3.2. The prior probability and conditional probability table

Due to the lack of available information, this study used fuzzy statistics and expert opinion methods for the prior and conditional prob-

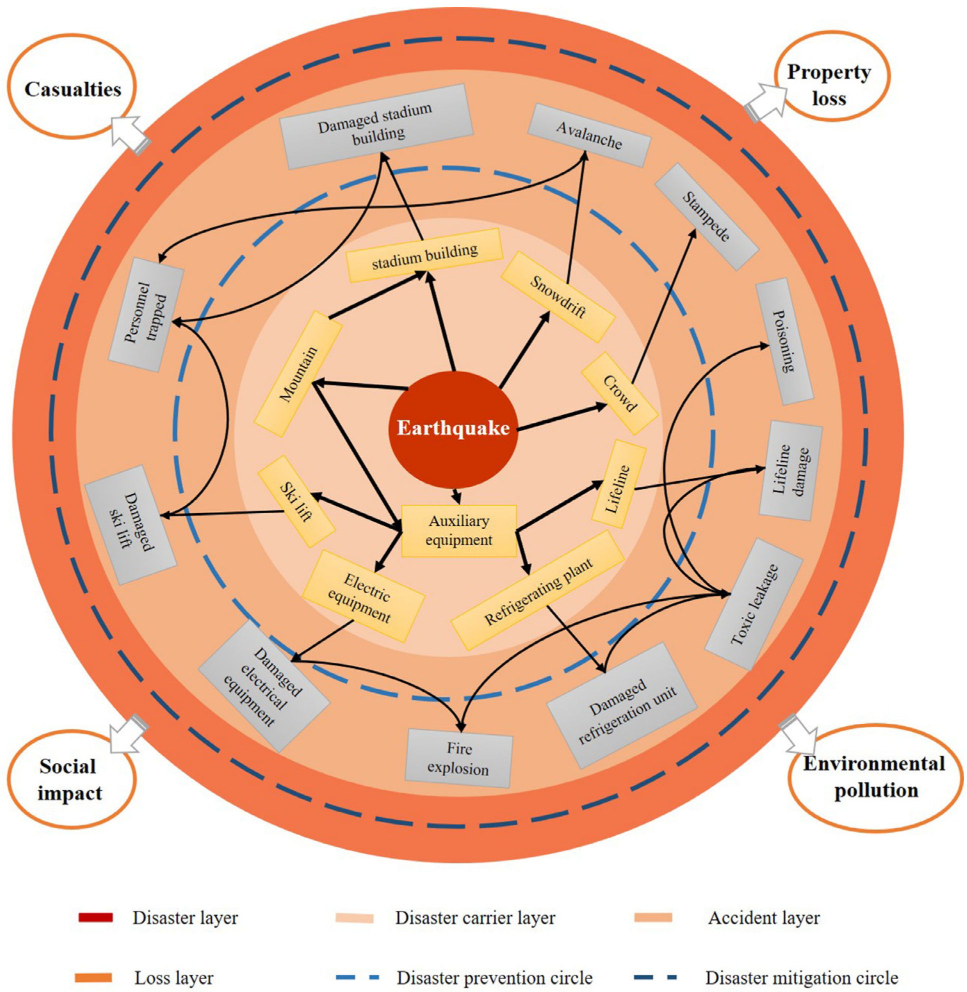


Fig. 6. The NAEA model of the large-scale winter sports sites.

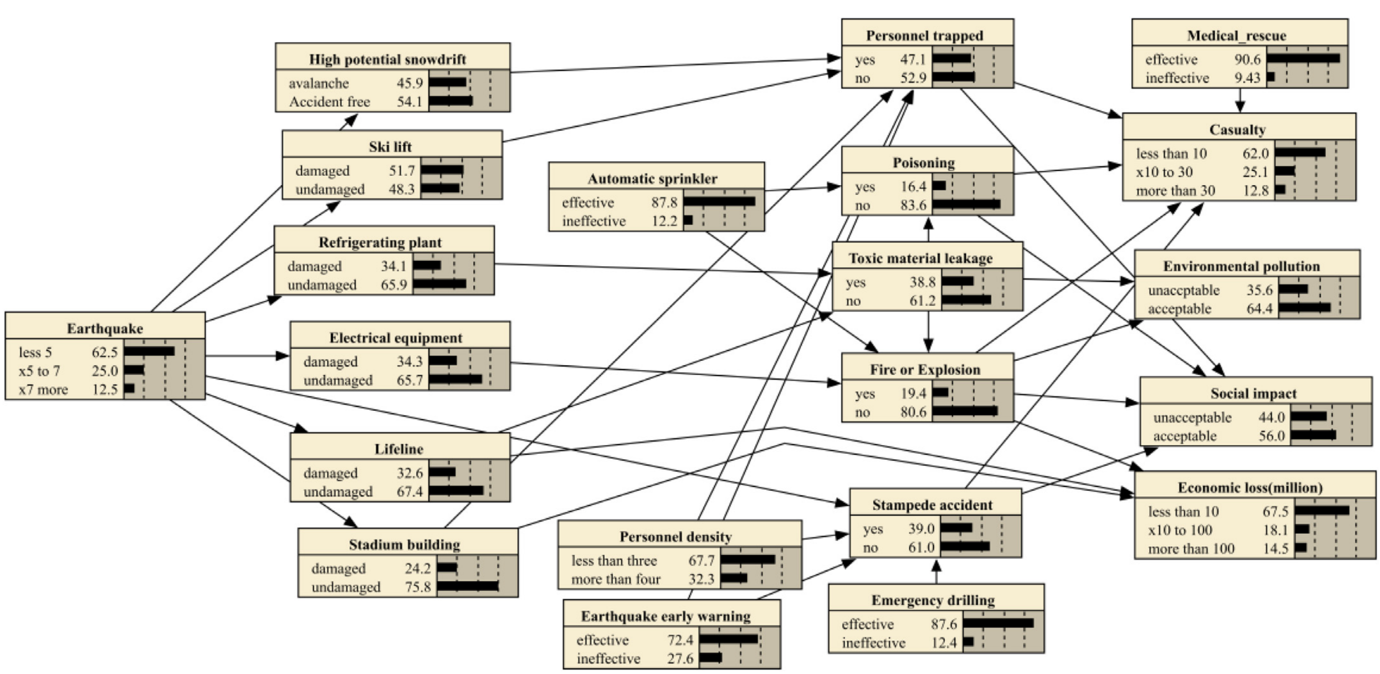


Fig. 7. Bayesian network of large-scale winter sports sites disaster induced by an earthquake.

Table 2
The prior probabilities obtained from domain experts' estimation.

Root nodes	Expert judgment			Aggregation of fuzzy numbers				K	FPs	FPr (%)
	1	2	3	a	b	c	d			
Earthquake less 5	VL-L	VL-L	M	0.09	0.16	0.23	0.43	3.43	0.2325	0.02
Earthquake 5 to 7	VL	VL	L	0	0	0.06	0.26	4.65	0.1083	0
Earthquake greater than 7	VL	VL	VL-L	0	0	0.03	0.23	5.23	0.083	0
Automatic sprinkler	VH	H	VH-H	0.71	0.91	0.94	1	1.19	0.8783	6.45
Personnel density less than 3 p/m^2	FH	M	VH-H	0.5	0.68	0.71	0.83	1.8	0.677	1.59
Earthquake early warning	FH	FH	VH-H	0.56	0.73	0.76	0.86	1.67	0.7239	2.14
Emergency drilling	VH-H	H	VH	0.7	0.9	0.94	1	1.2	0.8755	6.3
Medical rescue	VH-H	VH-H	VH	0.73	0.93	1	1	1.08	0.9057	8.27

abilities of all nodes in the Bayesian network [49]. This reflects the wide applicability of fuzzy Bayesian networks to objects with limited data. Thus, in this case, the fuzzy Bayesian network is superior to the ordinary Bayesian network. In this Bayesian network, there are six parent nodes and 15 child nodes, including four-leaf nodes and 11 intermediate nodes. All child nodes must determine the conditional probability. For child nodes with fewer parent nodes, it is easier to use fuzzy set statistics in the conditional probability table. However, nodes such as "person trapped", "crowded trampling accident", and "personal casualties", have a relatively large number of parents, which results in complicating fuzzy set statistical method calculation. Therefore, the author created fuzzy operations, a specific fuzzy probability calculation tool that considerably decreases computing difficulties and saves time.

The prior probability table of the parent node of the Bayesian network in this study is presented in Table 2. The contrast upgrade rule [24] can be used for complex conditional probability tables of child nodes. Take the node "personnel trapped" as an example, because this node has five parent nodes, there are 32 conditional probabilities that need to be determined. In this case, the "Contrast upgrade rule" believes that among the five parent nodes, "earthquake early warning" has a fundamental impact on the consequences of the crowded stampede accident. In other words, if an earthquake early warning is timely and accurate, the safety manager of a large-scale winter sports event can successfully evacuate the event, which would greatly reduce the possibility of crowded stampede accidents caused by panic and disorder. Therefore, in the case of other unchanged conditions, the possibility of personnel trapped accidents due to ineffective earthquake early warning can be raised by three levels. Concerning the "Contrast upgrade rule", experts only need to perform 16 evaluations of the conditional probability of the "personnel trapped" node, as shown in Table 2. The remaining 16 evaluations, relating to earthquake early warning failures, can be upgraded in sequence according to the above rules. For example, three experts' [27] opinions in the first row of Table 3 corresponding to the failure of the earthquake early warning are VH, VH, and VH. As H, VH-H, and FL were upgraded three levels, they reached the highest level of VH. Similarly, the conditional probabilities of all child nodes are given. Subsequently, a complete Bayesian network diagram was obtained based on an earthquake-induced accident chain at large-scale winter sports sites after the prior and conditional probabilities were input (shown in Fig. 7).

4. Results and discussion

4.1. Sensitivity analysis

Sensitivity analysis was used to analyze which nodes have a greater impact on the lost nodes and take measures to control the occurrence of accidental nodes, which achieved the goal of reducing loss. In other words, in the Bayesian network of this study, the author conducted a sensitivity analysis of the loss nodes (casualty, social impact, environmental pollution, and economic loss).

For the casualty node, the occurrence probability of the parent node (trapped personnel, poisoning, fire or explosion, and stampede accident) corresponding to different casualty states is presented in Fig. 8. It shows that as the state of injury and death becomes more and more serious, the probability of stampede accidents has the largest change, increasing from 27.5 to 59.9%. The probability chances of fire and explosion accidents and personnel trapped accidents are close, being 27.8% (10.4% to 38.2%) and 28.1% (36.5% to 64.6%), respectively. However, the probability of fire and explosion accidents has increased by nearly four times, whereas the probability of trapped personnel has doubled. Therefore, it is reasonable to assume that the sensitivity to fire and explosion is higher than that of trapped persons. In addition, the probability of accidental poisoning is minimal. The results of this analysis were reasonable. Although fire explosions and poisoning suffocations are more harmful than the other two accidents, the probability of these two types of accidents is lower. In addition, the locations prone to fire, explosion, and poisoning at large-scale winter sports sites are far away from crowded locations. In contrast, crowded stampede accidents occur in places with a higher density of people.

Regarding social impact nodes, we study the probability of unacceptable social impact and acceptable social impact in certain parent nodes. As shown in Fig. 9, it can be seen that the probability of unacceptable social impact caused by "fire or explosion" and "poisoning" accidents is even higher, at 79.9% and 79.7%, respectively. However, sensitivity analysis considers not only the severity of the accident but also the possibility of an accident. Therefore, taking all these factors into account, a "crowded stampede" accident is the most sensitive node to "social impact".

The sensitivity analysis of the four loss nodes is presented in Table 4. The sensitivity analysis results were consistent with the results of the previous analysis. Comparing the sensitive nodes of different loss nodes, "stampede accident" and "fire or explosion" are the most frequently occurring sensitive nodes. This also shows that these two nodes play a key role in the degree of loss from other angles. Therefore, it is necessary to conduct further sensitivity analysis for these two nodes. As shown in Table 4, improving the early warning capabilities of earthquakes can most effectively reduce the likelihood of crowded stampede accidents. Furthermore, enhancing the seismic performance of a lifeline or taking effective measures to control leakage can reduce the possibility of leakage of toxic and hazardous substances, thereby preventing fire or explosion accidents.

4.2. Scenario analysis

Scenario analysis of Bayesian networks involves determining the occurrence of certain key nodes and is an important and effective method for predicting potential consequences. The optimal path to prevent accidents and reduce loss can be determined by analyzing the relationship between and within each scenario.

Table 3
CPT for “personnel trapped” node.

precondition	BN nodes				Expert judgment			FPs
	High potential snowdrift	Ski lift	Stadium building	Personnel density p/m^2	1	2	3	
Effective early earthquake warning	√	√	√	≤3	H	VH-H	FL	68.63%
	√	√	√	>4	VH-H	VH	M	78.17%
	√	√		≤3	M	M	FL	45.31%
	√	√		>4	FH	FH	M	60.31%
	√		√	≤3	M	FH	FL	50.00%
	√		√	>4	FH	VH-H	FH	72.00%
	√			≤3	FH	FL	FL	46.25%
	√			>4	H	FH	M	65.94%
		√	√	≤3	M	FH	M	54.69%
		√	√	>4	FH	H	FH	69.69%
		√		≤3	L	VL	FL	20.52%
		√		>4	FL	L	M	35.00%
			√	≤3	FH	VL-L	L	31.31%
			√	>4	H	FL	L	47.19%
				≤3	VL-L	VL	VL	8.09%
				>4	VL-L	VL-L	VL-L	10.83%

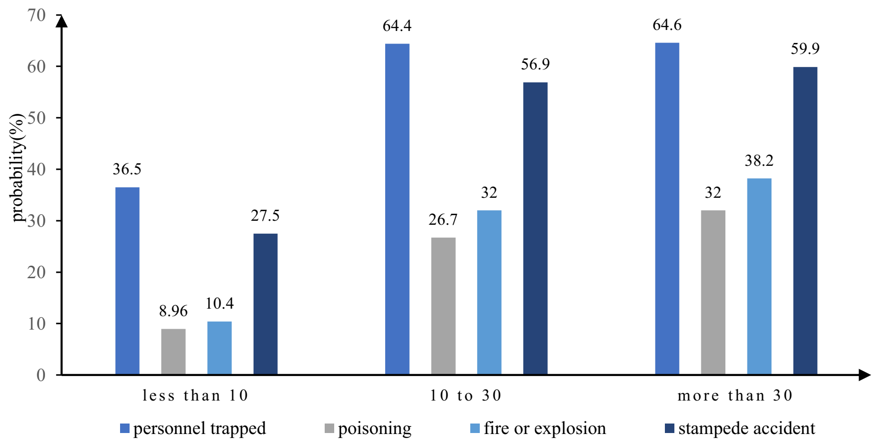


Fig. 8. Sensitivity analysis of “Casualty”.

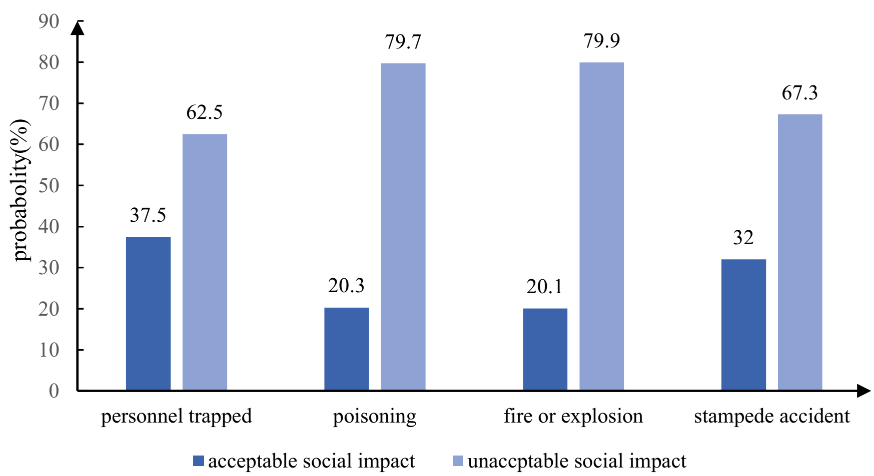


Fig. 9. Sensitivity analysis of “Social impact.”

4.2.1. Multi-hazard scenario analysis

As shown in the sensitivity analysis of the previous section, “earthquakes early warning” and “toxic material leakage” are the most sensitive nodes and lead to “stampede accident” and “fire or explosion accident” which will cause great loss, respectively. Considering the coupling effects of the above two accident types, six sub-scenarios based on actual conditions were designed from a macro perspective. Relating to the leakage of toxic and hazardous substances, the “refrigerating plant” and the “automatic sprinkler” were selected as the key nodes in this section. Therefore, this part of the scenario analysis sets “earthquake level”, “earthquake early warning,” “refrigeration plant”, and “automatic sprinkler” as the key nodes of scenario analysis. The specific settings of this scenario are listed in Table 5, and the probability state of the loss node corresponding to each scenario is shown in Fig. 10 (i.e., the Bayesian network of scenario one is shown in Fig. 10).

Table 5 shows only one key node’s state is changed at a time in the first four sub-scenarios to analyze the influence of each node. Overall, the first four sub-scenario states developed in the direction of serious

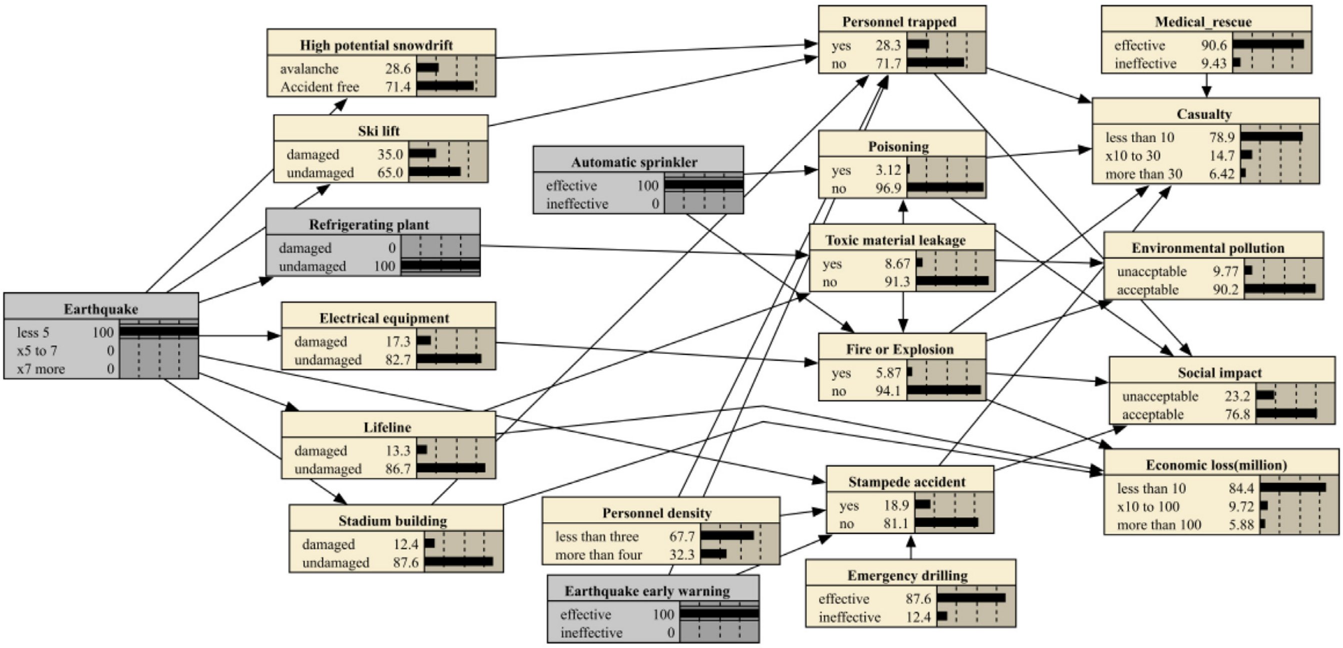


Fig. 10. Bayesian network of sub-scenario 1.

Table 4
The sensitivity of key nodes.

Analysis node	Sensitive node	Sensitive proportion (%)
Casualty	Stampede accident	5.06
	Fire or explosion	4.63
	Personnel trapped	4.1
	Poisoning	3.59
Social impact	Stampede accident	10.4
	Fire or explosion	9.47
	Personnel trapped	9.15
	Poisoning	7.58
environmental pollution	Toxic material leakage	51.5
	fire or explosion	20.6
economic loss	lifeline	17
	fire or explosion	12.4
Stampede accident	Earthquake early-warning	9.11
	Earthquake	5.45
	Emergency drilling	2.35
Fire or explosion	Toxic material leakage	14.7
	electrical equipment	12.1

loss. An in-depth comparison of the first four sub-scenarios, in terms of the state of casualties, showed that the transition from sub-scenario 1 to sub-scenario 2 caused the most obvious change. Under this change, the probability of moderate and severe casualties doubled, indicating that earthquake early warning plays a crucial role in controlling casualties. When focusing on environmental pollution, the state of environmental pollution showed a large increase (from 9.77% to 65.8%, the growth rate was close to seven times) when the transition from sub-scenario 2 to sub-scenario 3 occurred. Damage to refrigeration equipment that causes toxic and hazardous substances to leak into the environment, results in serious environmental pollution. Unsurprisingly, the transition from sub-scenario 3 to sub-scenario 4 results in the most distinct growth in the probability of serious economic loss. Furthermore, this accounts for the severe economic loss that would occur if the refrigeration device and the automatic spray system fail simultaneously. Thus, ensuring the reliability of the automatic sprinkler system can not only reduce the possibility of explosive and poisonous accidents but also effectively reduce property loss. Concerning social impact, the transition from sub-scenario 1 to sub-scenario 2 has the most obvious impact on society. The failure of early warning drastically increases the number of casualties, which results in a devastating social impact.

To ensure the completeness of the risk analysis, the author also supplemented each specific condition with other magnitudes for an analysis based on actual situations. The outcomes of these combinations and the probability of their loss nodes are shown in Fig. 11. Moreover, the significance of comparing sub-scenarios 5 and 6 with sub-scenario 1 is to predict the loss of a high magnitude earthquake. When comparing sub-scenario five and sub-scenario 1, the probability of serious casualties increased to 1.8 times, the economic loss increased to 2.8 times, the probability of causing serious environmental pollution increased to 3.6 times, and the probability of causing unacceptable social impact increased to 1.8 times. For sub-scenario 6, an earthquake of a magnitude greater than seven (which is rare), the probability of causing serious casualties and social impact increases by more than three times, while the probability of causing large economic loss increases by five times. Finally, the probability of causing unacceptable environmental pollution

Table 5
Node settings of multi-hazard scenario.

Sub-scenarios	Earthquake (Magnitude)	Earthquake earlywarning	Refrigerating plant	Automatic sprinkler
1	≤5	effective	undamaged	effective
2	≤5	ineffective	undamaged	effective
3	≤5	ineffective	damaged	effective
4	≤5	ineffective	damaged	ineffective
5	5 to 7	effective	undamaged	effective
6	>7	effective	damaged	ineffective

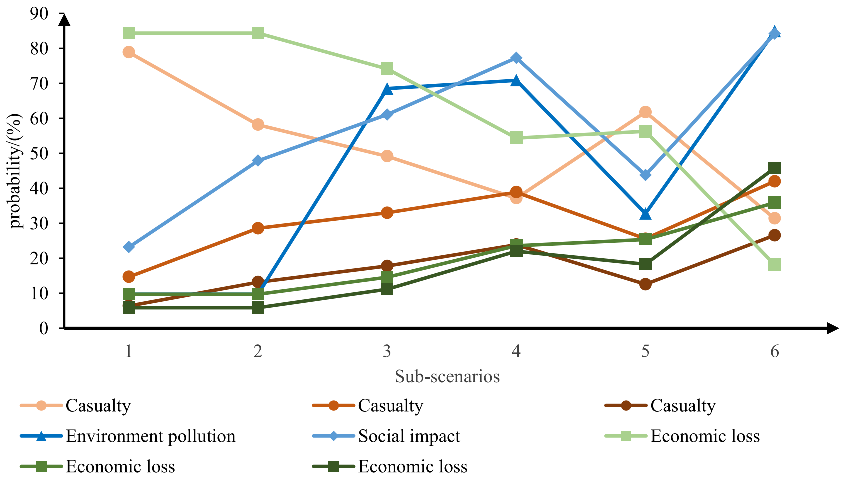


Fig. 11. Posterior probabilities of consequences in multi-hazard scenario.

Table 6
Node settings of explosion and poisoning scenario.

Sub-scenarios	Refrigerating plant	Electrical equipment	Lifeline	Automatic sprinkler
7	damaged	undamaged	undamaged	effective
8	undamaged	damaged	undamaged	effective
9	undamaged	undamaged	damaged	effective
10	undamaged	undamaged	damaged	ineffective
11	undamaged	damaged	undamaged	ineffective
12	damaged	undamaged	undamaged	ineffective

increases by 8.6 times. However, since the magnitude of the earthquake is a force majeure factor, we can devote ourselves to post-disaster relief and minimize loss.

4.2.2. Explosion and poisoning scenario analysis

"Fire or explosion" and "poisoning" are the most serious accidents in the accident chain caused by an earthquake during a large-scale sports event. In addition, from the sensitivity analysis results in the previous section, fire and explosion accidents are the main causes of great loss. Therefore, in this section, the parent node that can cause fire, explosion, or poisoning is listed as the research object, namely "Refrigerating plant", "Electrical equipment", "Lifeline", and "Automatic sprinkler" (seen in Table 6). Moreover, six sub-scenarios are described in this section based on whether the automatic sprinkler system is effective. Thus, the first three sub-scenarios and the last three sub-scenarios constitute two contrasting groups. The principle of the control variables is fully demonstrated in this way, which is more conducive to the accuracy of our scenario analysis.

The posterior probabilities of "fire or explosion", "poisoning", and "casualty" of the above four sub-scenarios are shown in Fig. 12.

In terms of fire and explosion, the accident probability was highest in sub-scenario 8 (caused by damage to electrical equipment, 21.4%), followed by sub-scenarios 7 (20.4%) and sub-scenario 9 (17%), in the first three sub-scenarios. When the automatic sprinkler system is ineffective, the probability of fire and explosion accidents caused by the damage to electrical equipment in an earthquake is highest (90.6%). Simultaneously, the possibility of fire and explosion accidents due to damage to refrigeration devices and lifelines has also doubled (20.4% to 52.8%, 17% to 44%). Thus, during an earthquake, the automatic sprinkler system can prevent the vaporization of liquid ammonia from causing an explosion (to a certain extent), and can also prevent the fire from further expanding due to electrical equipment and other reasons. In other words, if the automatic sprinkler system fails, all fire and explosion accidents or poisoning accidents tend to be uncontrollable. The importance of the causes of fire and explosion accidents is ranked as follows: power equipment damage, refrigeration equipment damage, and lifeline damage.

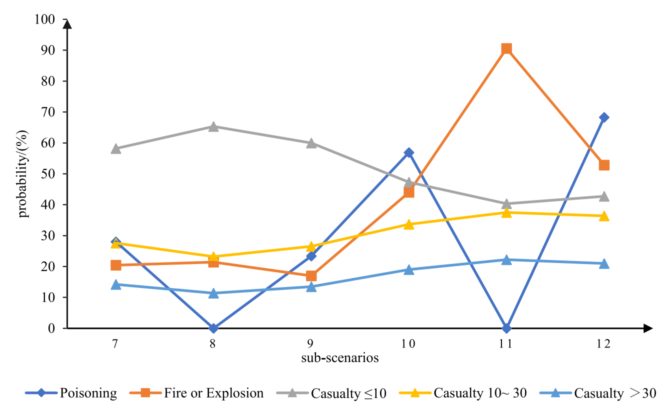


Fig. 12. Posterior probabilities of consequences in explosion and poisoning accident scenario.

Electrical equipment in the competition area might short-circuit or get damaged during an earthquake, thus sparking a fire (this is extremely common in earthquakes). As a result, because electrical equipment is the most widely used and largest installation area in large-scale sports sites, power facilities are also likely to be damaged by fire and explosion accidents induced by earthquakes Furthermore, if a refrigeration device or lifeline that stores liquid ammonia and carbon dioxide is damaged in an earthquake, toxic and hazardous substances can cause fire and explosion accidents.

The toxicity and quantity of toxic and hazardous substances in refrigeration devices are greater than those in lifelines. As a result, the probability of poisoning accidents in sub-scenario 7 (28%) will be higher than that in sub-scenario 9 (23.4%). When the automatic sprinkler system is ineffective, the probability of poisoning and suffocation accidents leading to damage to refrigeration devices and lifelines doubles (28% to 68.3%, 23.4% to 56.9%). Therefore, the reliable design and maintenance of refrigeration devices and lifelines are key to preventing poisoning and suffocation accidents. In addition, controlling the amount of

Table 7
Node settings of the stampede and trapped accident scenario.

Sub-scenarios	Personnel density p/m^2	Earthquake early-warning	Emergency drilling
13	≤3	effective	effective
14	≤3	effective	ineffective
15	>4	effective	ineffective
16	>4	ineffective	ineffective

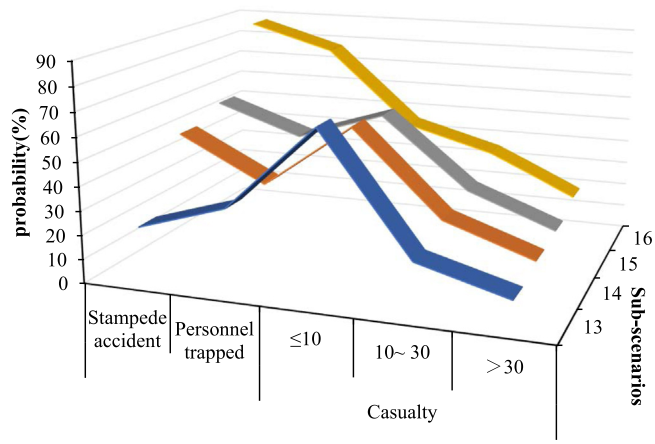


Fig. 13. Posterior probabilities of consequences in stampede and trapped accident scenario.

toxic and hazardous substances in a refrigeration system is also a way to prevent poisoning accidents.

Focusing on casualties, in the first three sub-scenarios, sub-scenario 7 caused the most serious casualties, and sub-scenario 9 was more severe than sub-scenario 8. The fire, explosion, and poisoning incidents caused by the damage to the refrigeration device will be higher than all other scenarios regarding impact and fatality rate, which are inseparable from the number of harmful substances. However, in the last three subscenarios, the casualties caused by damaged electrical devices are the most serious because the probability of fire and explosion accidents induced by damaged electrical devices is extremely high. Therefore, improving the reliability and seismic resistance of refrigeration and electrical equipment is the most effective way to reduce casualties.

4.2.3. Stampede and trapped accident scenario analysis

Stamped accidents are a secondary cause of serious loss. A scenario analysis of this accident is presented in this section. In the Bayesian network, "personnel density", "earthquake early warning", and "emergency drilling" were the nodes that affected crowd stampede accidents (Table 7). A trapped personnel accident is a fourth largest accident that causes serious system loss and has an overlapping parent node with a stampede accident. Therefore, we also analyzed trapped personnel accidents. This section used the scenario-progressive node-setting mode to analyze accidents.

The results of this analysis are shown in Fig. 13, which shows the transition from sub-scenario 13 to sub-scenario 14 increased the accident probability by 29.8%. The probability increased by 5.8%, from subscenario 14 to subscenario 15. Furthermore, an increase of 30.1% occurred in the change from sub-scenario 15 to sub-scenario 16. Thus, the first and third transitions have a greater impact on the occurrence of accidents and the possibility of stampede accidents will be reduced with effective earthquake early warning and adequate emergency drills. Regarding "personnel trapped", the third time has the largest change in probability (32%), and the second time has the second-highest change in probability (11.9%). In other words, in addition to improving early warning capabilities, effective evacuation methods and personnel density control measures can also reduce the possibility of people being trapped. The changes in the state of casualties are similar to those in crowded stampede accidents, which also shows that early warnings and emergency drills can control casualties to a large extent. It should be noted that the aforementioned points of concern relating to the possibility of accidents occurring, however, the severity of the accident is also worth investigating.

4.3. Safety strategy improvement analysis

In the previous sensitivity analysis and scenario analysis, the "fire or explosion" and stampede accidents were identified as the most vital causes of serious loss. Moreover, the influence of the parent node on the two accident types was also discussed. However, in actual safety management of large-scale winter sports sites, only a quantitatively detailed prevention plan can guide decision making, which cannot be obtained from the previous sections. Thus, this section explores the optimal change ratio of parent nodes to prevent fires or explosions, stampede accidents, and the entire system. Finally, the optimal prevention ratio is provided as a reference for real safety management.

4.3.1. Safety strategy improvement analysis of fire or explosion

The sensitivity analysis shows that the most sensitive nodes to the "fire or explosion" node are "toxic material leakage" and "electrical equipment". In fact, the prevention of accidents requires intervention in disaster bearings. Therefore, refrigeration devices and lifelines that cause poison leakage must be evaluated. In addition, through scenario analysis, the importance of the cause of fire or explosion accidents was ranked as follows: "electrical equipment failure", "refrigeration device failure", and "lifeline damage". Simultaneously, the scenario analysis also shows that the automatic sprinkler system can impact casualties effectively. According to the sensitivity and influence degree of the four parent nodes to the "fire or explosion" node, the changes to the four parent nodes are biased. Therefore, the largest degree of change in the parent node of the fire and explosion accident should be electrical equipment, followed by the refrigeration device, lifeline, and automatic sprinkler system. This degree of change was set to be consistent with the global sensitivity results of the "fire and explosion" node.

The nature of each node is different, thus, the difficulty of changing different nodes also differs when the degree of change is the same. The difficulty of change includes the difficulty of technological breakthroughs, the difficulty of maintaining equipment stability, and the economic investment required. Therefore, this article defines the "difficulty coefficient" (denoted as "d") to describe the diversity in the difficulty of intervention between different parent nodes. Furthermore, after investigating the data and interviewing experts, it was determined that the change difficulty coefficients of the four facilities of electrical equipment, refrigerating plant, lifeline, and automatic sprinkler were 2.3, 3, 3.5, and 1, respectively.

Taking a total change of 10% as an example, the specific prior probability changes (denoted as "C") of the four nodes are determined according to the change degree requirements of different parent nodes, as shown in the first column of Table 8 (if the overall investment increases, the probability of fire and explosion accidents will increase exponentially when the same node changes the proportion). For Case 1, the amount of change in the prior probability is $C_1:C_2:C_3:C_4 = 4:3:2.5:0.5$

Based on the value of the original prior probability (as shown in Fig. 7), the updated prior probabilities for electrical equipment (denoted as "Ele"), refrigeration devices (denoted as "Ref"), lifelines (denoted as "Lif") and automatic sprinkler systems (denoted as "Aut") are presented in columns 3 to 6 of Table 8. In addition, there are 11 cases in Table 8 where the prior probability of the four parent nodes changes proportions, and each case has a different difficulty index (denoted

Table 8
Improvement cases of fire or explosion.

Case	Change ratio	Difficulty index	Ele	Ref	Lif	Aut	P	K
1	4:3:2.5:0.5	2.825	30.3	31.1	30.1	88.3	19.3	54.52
2	4:3:2:1	2.7	30.3	31.1	30.6	88.8	19.2	51.84
3	4:3.5:1.5:1	2.675	30.3	30.6	31.1	88.8	19.2	51.36
4	4.5:3:1.5:1	2.65	29.8	31.1	31.1	88.8	19.1	50.62
5	4.5:3.5:1.5:0.5	2.75	29.8	30.6	31.1	88.3	19.2	52.8
6	5:2.5:1.5:1	2.625	29.3	31.6	31.1	88.8	19.2	50.4
7	5.5:2:1.5:1	2.6	28.8	32.6	31.1	88.8	19.2	49.92
8	5.5:2.5:1.5:0.5	2.7	28.8	31.6	31.1	88.3	19.1	51.57
9	6:2.5:1:0.5	2.65	28.3	31.6	31.6	88.3	19.1	50.62
10	6.5:2:1:0.5	2.625	27.8	32.1	31.6	88.3	19.1	50.14
11	7:1.5:1:0.5	2.6	27.3	32.6	31.6	88.3	19.0	49.4

as “D”). The definition of the difficulty index is given in Eq. (1).

$$D_j = \sum_{i=1}^{4} C_i \times d_i \ j = 1, 2, \dots, 11 \tag{1A}$$

After updating the prior probabilities of the four parent nodes and outputting the posterior probability of fire and explosion accidents, denoted as “P” in Table 8, this paper introduces a comprehensive evaluation index “K” to evaluate the optimization of 11 different schemes,. The comprehensive evaluation index is defined as the product of the difficulty index (D) and posterior probability (P) of the fire and explosion nodes (Eq. (2)).

$$K_j = D_j \times P_j \ j = 1, 2, \dots, 11 \tag{2A}$$

When the difficulty index and accident probability are considered equally important, the lower the comprehensive evaluation index, the better the optimization effect. According to Table 8, the comprehensive evaluation index of case 11 is the minimum, the accident probability is the lowest, and the difficulty index is also the lowest. Thus, it is the optimal ratio to prevent accidents: $C_1:C_2:C_3:C_4 = 7 : 1.5 : 1 : 0.5$.

Based on the above results, disaster-bearing and disaster prevention measures in the domino chains where the fire and explosion nodes are located are prevented and controlled. As shown in Table 8, 70% of all the efforts (including manpower, material, and financial resources) should be assigned to electrical equipment, 15% to refrigeration equipment, 10% to changing the lifeline system, and 5% to the automatic sprinkler system.

4.3.2. Safety strategy improvement analysis of stampede accident

Regarding stampede accidents, there are four parent nodes in a Bayesian network. However, because the magnitude cannot be changed, the probability of “personnel density”, “earthquake early warning”, and “emergency drills” can be intervened. It can be seen from the sensitivity analysis and scenario analysis above that the early warning of earthquakes has the most significant impact on stampede accidents, followed by emergency drills, and finally, the density of people. Therefore, the amount of change in the prior probability should also follow the above principles to ensure that the amount of change in the earthquake early warning is the largest, followed by emergency drills and personnel density. In this section, we consider the a priori probability change of 10% as an example. According to the above principles, all the possible change ratios of the three parent nodes are listed in the first column of Table 9, and the updated posterior probabilities of the three parent nodes are shown in the third to fifth columns of Table 9. In addition, the difficulty coefficients of “earthquake early warning” (denoted as “E-w”), “emergency drilling” (denoted as “E-d”), and “personnel density” (denoted as “P-d”) are 7, 1, 2, respectively. The calculation results of the difficulty index (D) are listed in the second column of Table 9. The comprehensive evaluation index (K) after outputting the posterior probability of a stampede accident is shown in Table 9. By comparing the comprehensive evaluation indexes of the 11 schemes, it is known that the lowest evaluation index is K^*=144.99. Therefore, the change ratio of the prior probability of the parent node corresponding to this index was the optimal change path. As shown in case 11 in Table 9: $C_1:C_2:C_3:C_4 = 5 : 4.5 : 0.5$.

By combining the above analysis results, the actual prevention and control of stampede accidents show that the best tendency to change is: 50% of the effort (including manpower, material, and financial resources) being used to improve the earthquake early warning capability, 45% being used to implement emergency drills, and the remaining 5% used to control the density of personnel. Under such changes, the effect of preventing and controlling stampede accidents is optimal.

4.3.3. Safety strategy improvement analysis of overall network

The first two sections analyze the optimization methods for fire or explosion’ and stampede accidents. This section aims to optimize the entire network based on the optimal change ratio of the priority probability obtained in the first two sections. Although the two types of accidents occur in a Bayesian network, they are relatively independent of each other. Therefore, this study determines the optimal change ratio under the coupling effect of the two accidents. This section selects the two representative nodes of “earthquake early warning” and “power equipment” as the coupled connection nodes. Taking a change of 20% as an example, the prior probabilities of the two representative nodes are adjusted separately, and the other nodes are adjusted accordingly to the optimal change ratio obtained above. Then, all possible allocation ratios are shown in the first column of Table 10. Furthermore, the values are assigned according to the proportion of change in Table 10, and the prior probabilities of the seven parent nodes are updated. Thereafter, the loss status (i.e., probability of unacceptable states) of each case is determined (the values of “casualty” (denoted as “C”), “environmental pollution” (denoted as “P”), “social impact” (denoted as “S”) and “economic loss” (denoted as “E”) in Table 10. Considering that the nature of each loss node is different, this study stipulates the weights of the four loss nodes. Among the four types of losses, casualties are the most important, followed by economic loss, environmental pollution, and social impacts. Therefore, the weight ratios of “casualty” (w_1), “environmental pollution” (w_2), “social impact” (w_3), and “economic loss” (w_4) are set to:$w_1:w_2:w_3:w_4 = 5 : 1.5 : 1 : 2.5$. The weighted calculation results of the four types of loss nodes are referred to as the comprehensive loss index, denoted as “L” in Table 10.

Further, the difficulty of changing two representative nodes was compared and the ratio of the two change coefficients was set to 2:3. Therefore, the remaining five nodes were adjusted according to the optimal change ratio to obtain the coupling optimization prior probability change ratio: $d_1:d_2:d_3:d_4:d_5:d_6:d_7 = 2 : \frac{2}{7} : \frac{4}{7} : 3 : \frac{18}{5} : \frac{21}{5} : \frac{6}{5}$. The difficulty index for each program was calculated using Eq. (1). Subsequently, the comprehensive evaluation index was calculated using Eq. (3).

$$K'_j = (L_j * D_j)/100 \ j = 1, 2, \dots, 9 \tag{3A}$$

Table 9
Optimization cases of stampede accident.

Case	Change ratio	Difficulty index	E-w	E-d	P-d	probability	K
1	4:3.5:2.5	3.65	76.4	91.1	70.2	36.3	132.495
2	5:3:2	4.2	77.4	90.6	69.7	36.1	151.62
3	5:3.5:1.5	4.15	77.4	91.1	69.2	36	149.4
4	5:4:1	4.1	77.4	91.6	68.7	35.9	147.19
5	5:4.5:0.5	4.05	77.4	92.1	68.2	35.8	144.99
6	6:3:1	4.7	78.4	90.6	68.7	35.8	168.26
7	6:3.5:0.5	4.65	78.4	91.1	68.2	35.7	166.005
8	6:2.5:1.5	4.75	78.4	90.1	69.2	35.9	170.525
9	7:2:1	5.3	79.4	89.6	68.7	35.7	189.21
10	7:2.5:0.5	5.25	79.4	90.1	68.2	35.6	186.9
11	8:1.5:0.5	5.85	80.4	89.1	68.2	35.5	207.675

Table 10
Optimization cases of overall network.

Case	Change ratio	D	E-w	E-d	P-d	Ele	Ref	Lif	Aut	C	P	S	E	L	K'
1	2:1.8:0.2:18: 3.9:2.6:1.3	85.15	74.4	89.4	67.9	16.3	30.2	30	89.1	33.4	33.9	37.6	28.4	32.65	27.80
2	4:3.6:0.4:16: 3.4:2.3:1.1	80.48	76.4	91.2	68.1	18.3	30.7	30.3	88.9	33.2	34.5	37.4	28.8	32.72	26.33
3	6:5.4:0.6:14: 3:2:1	76.29	78.4	93	68.3	20.3	31.1	30.6	88.8	33	35.1	37.1	29.3	32.8	25.02
4	8:7.2:0.8:12: 2.6:1.7:0.9	72.09	80.4	94.8	68.7	22.3	31.5	30.9	88.7	32.7	35.8	36.8	29.7	32.83	23.66
5	10:7.2:1:10: 2.1:1.4:0.7	66.91	82.4	100.2	68.9	24.3	32	31.2	88.5	32.3	36.4	36.2	30.2	32.78	21.93
6	12:7.2:1.2:8: 1.7:1.1:0.6	42.20	84.4	102	69.1	26.3	32.4	31.5	88.4	32.3	37	36.1	30.6	32.96	13.91
7	14:7.2:1.4:6: 1.3:0.9:0.4	57.80	86.4	103.8	70.1	28.3	32.8	31.7	88.2	32.2	37.6	35.9	31	33.08	19.12
8	16:7.2:1.6:4: 0.9:0.6:0.3	53.09	88.4	105.6	70.3	30.3	33.2	32	88.1	32.1	38.2	35.8	31.4	33.21	17.63
9	18:7.2:1.8: 2:0.4:0.3:0.1	47.91	90.4	118.2	70.5	32.3	33.7	32.3	87.9	32.1	38.8	35.7	31.9	33.42	16.01

As the comprehensive evaluation index is the overall measurement value of the difficulty of the scheme and the probability of accidents, the expected scheme can be considered low in difficulty and probability. When comparing all schemes in Table 10, the minimum comprehensive index is K^*=36.66. Therefore, the optimal a priori probability adjustment ratio of the overall network is from Case 6: $C_1:C_2:C_3:C_4:C_5:C_6:C_7 = 12 : 7.2 : 1.2 : 8 : 1.7 : 1.1 : 0.6$.

When considering the Bayesian network system of all large-scale winter sports sites, based on the above analysis results, we see that the focus should be on improving earthquake early warning capabilities, power equipment, and emergency drills. Specifically, 37.7% of all available efforts (including manpower, material, and financial resources) should be used to improve earthquake early warning capabilities, of which 25.2% of efforts should be used to improve the reliability of electrical equipment, and 22.6% of energy should be used to practice emergency drills.

5. Conclusion

In this study, a NAEA model is proposed to analyze the domino accident chains induced by natural disasters at large-scale winter sports sites. Using an earthquake as an example, sensitivity analysis, scenario analysis, and safety strategy improvement analysis for large-scale winter sports sites were carried out by integrating fuzzy set theory and the Bayesian network. The main conclusions are as follows:

(a) The NAEA model was established based on the public safety triangle theory, disaster chain, and domino theory to analyze typical Natech events and safety events caused by natural disasters. By determining the hazard carrier and considering disaster prevention and mitigation measures, the possible accidents, evolution chains, and chain-broken measures are determined.

(b) The results of the sensitivity analysis indicate that “Stampede accident” and “Fire or explosion” are the dominant causes of significant loss, which should be given more attention to improving early warning.

(c) When the automatic sprinkler system fails in large-scale winter sports sites, the posterior probability of fire and explosion accidents will increase from 17% to 44%, and that of poisoning accidents from 23.4% to 56.9%. Simultaneously, the number of serious casualties also increases by 12.7 %. Therefore, the reliability of automatic spraying devices should be a priority.

(d) To quantitatively optimize the allocation of safety resources (manpower, material resources, and financial resources), a safety strategy improvement analysis of different targets was conducted by comprehensively considering the difficulty and effect of changing the parent nodes. For example, 70% of all the efforts (including manpower, material, and financial resources) should be assigned to electrical equipment, 15% to refrigeration equipment, 10% to changing the lifeline system, and 5% to the automatic sprinkler system.

Declaration of Competing Interest

The authors declare no conflict of interest.

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