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Safety Risks in Rail Stations: An Interactive Approach

Hui Xu[a,b], Yajian Zhang[b], Hongyang Li[c,d*], Martin Skitmore[e,f], Jun Yang[g], Fang Yu[a]

[a] School of Economics and Management, Chongqing University of Posts and Telecommunications, Chongqing 400065, China
[b] Department of Building, School of Design and Environment, National University of Singapore, 4 Architecture Drive 117566, Singapore
[c] School of Civil Engineering and Transportation, South China University of Technology, Guangzhou 510641, China.
[d] State Key Laboratory of Subtropical Building Science, South China University of Technology, Guangzhou 510641, China.
[e] School of Civil Engineering and Built Environment, Queensland University of Technology (QUT), Gardens Point, Brisbane Q4001, Australia
[f] Faculty of Computing, Engineering and the Built Environment, Birmingham City University, Birmingham, UK
[g] School of Transportation and Logistics, Southwest Jiaotong University, Chengdu 611756, China

Abstract

Rail systems in urban areas have been developing rapidly in recent years. Numerous risk events at rail stations reveal the vulnerability of rail system. The interdependent risks in the stations interact with each other and may further form risk interaction chains and networks. However, most of the studies treat risks independently. In response, this paper aims to explore the safety risk interactions in rail stations as they can be as serious as those in rail systems generally. This involves a four-step case study. In step I, 62 rail station risk events were collected from 62 stations worldwide. 25 risks are then identified from these events and 241 risk interaction chains extracted in steps II and III respectively. In the last step, the 241 chains are used to construct a Bayesian network to identify their sensitivity levels and the key risk chains. This shows there are 8 sensitive risks and 9 key risk interaction chains. This paper proposes a risk interaction analysis method for the operational risks in the rail station. The results provide a better understanding of rail station safety and are beneficial for formulating the safety management strategies of rail stations worldwide.

Key words: rail station; risk interaction chain; risk interaction network; influence strength; sensitivity analysis

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[*] Corresponding Author.
Email: li.terryhy@yahoo.com

1. Introduction

A number of transportation requirements currently need to be satisfied in parallel with growing cities experiencing rapid economic growth to avoid such associated negative impacts as increased congestion and pollution. The results of a survey conducted by the Peking University's National Development Research Institute, for example, indicate that Beijing loses 3.6% of its potential annual GDP due to traffic congestion-significantly higher than World Bank estimates of 1-3% (Gwilliam, 2002; Li et al., 2017). Traffic congestion can cause a variety of social, economic, and environmental problems; people's daily lives are restricted and urban development is also seriously influenced. Urban public transportation is therefore becoming the key to urban development by relieving the congestion problems (Beaudoin et al., 2015). As a main component of modern public transportation, urban rail, including metro and light rail, aligns with the principle of sustainable development and presents the advantages of a large capacity, high speed, energy saving, low pollution, increased convenience and comfort, etc. Thus, urban rail transit can provide a better choice to alleviate the traffic problems. With the growing demand for the efficient public transport systems, rail station construction is increasing worldwide. Over 200 cities worldwide are now equipped with operating metros. Also, urban rail has been developing quite fast in China. Over 4100 kilometers of urban rail in 30 cities were in operation in 2017, which ranks the first in the world in terms of operating mileage (Economy & Nation Weekly, 2017; Xu et al., 2018). As a result, progressively more cities in China are stepping into the "urban rail era".

Today, rail stations in many cities have become populated spaces, especially transfer stations with multiple rail lines. For example, in April 2017, the Shanghai metro entered a new stage, with a daily passenger flow of almost 12 million people (Dongfang Internet, 2017), while the daily passenger flow of Beijing's metro reached to 11.6 million people in August 2018 (Beijing Evening News, 2018). The real transportation capacity of some Beijing metro stations is around 130% of their designed long-time transportation capacity (Shi et al., 2012a). Besides, such as the Shinjuku station in Tokyo, Gyeongbokgung station in Seoul, Kievskaya station in Moscow, are world's most crowded subways, also with millions of ridership in daily operation (Kade, 2013). During the expansion of the rail system, the rail stations are also subject to various kinds of risks due to overcrowded carriages and the underground space (Xu et al., 2018). Catastrophic risk events occasionally occur. For instance, 18 people were injured in the 10 February 2017 Hong Kong metro fire, 1 person died and 28 people were injured in the 5 July 2011 Beijing metro elevator accident, and the 19 February 2003 Daegu metro fire resulted in 198 dead and 147 injured (BBC News, 2011; Wikipedia, 2017).

The existence of diverse and numerous facilities and passengers are strongly interrelated in rail stations, which constitute the main characteristics of complexity (Chu et al., 2003). Such complexity leads to the existence of interdependent risks (Danilovic and Browning, 2007), where a risk could cause, or be caused by, other risks (Fang and Marle, 2012). The nature of rail station safety is that the causes of a risk event may be found in the complexity of the relationships implicit in the facilities, equipment, operation, environment, etc. The interactions between different risks can pose threats to the safe operation of the rail station. Therefore, the studies of the interactions between risks are important and helpful to fully understand the risk events in rail stations.

From this standpoint, the purpose of this paper is therefore to identify the risk interactions for rail stations (rather than the entire rail network) as they can have serious consequences, and to provide a useful reference for formulating rail station safety management strategies. The paper is organized as follows. The second section contains the literature review. The third section describes the methodology, including the research design, research method, and data collection. In the fourth section, the research results for the collected risk cases are presented, with the risks of rail stations identified based on the collected risk events and risk interaction chains established through analyzing the interaction relationships. A risk interaction network is then constructed and analyzed based on a Bayesian network (BN), and the sensitive risks are determined, with the key risk interaction chains also listed. The research findings will be useful for the safety management of rail stations and an improved understanding of rail station safety.

2. Literature review

Urban rail provides significant transport services for the public. As an important part of the system, the rail station plays an essential role in the urban rail operation. The operation safety of rail stations is highly important and attracts much attention from government administration and academic research.

2.1. Safety analysis of rail stations

Safety analysis of rail stations was conducted in many studies. For instance, Kim et al. (2010) focused on the monitoring and diagnosis of air pollution risk in a subway station, and the multivariate and periodic characteristics of the indoor air samples were collected during each day. Gao et al. (2012) and Meng et al. (2014) analyzed the spread of fire-induced smoke in a subway station under different fire scenarios. Wan et al., (2015) carried out questionnaire surveys of metro passengers and metro station staff to explore the effects of 32 passenger behaviors and their relationship with accidents. These included riding time, number of stops experienced by a passenger, transgressions, and abrupt violations as important predictors of involvement in an incident. Xing et al. (2017) analyzed 950 escalator-related injuries in metro stations, finding the four most important reasons for injuries to be failing to stand firmly, passengers carrying out other tasks or not holding handrails, and unhealthy passengers, which provided an effective reference for reducing the severity and probability of such injuries. Zhao et al. (2017) conducted an operational risk analysis of block sections in the rail way network by developing an “operational risk index” based on statistical methods and railway simulation tools. Besides, Xu et al. (2018) conducted a field investigation and complex network analysis in determining the high-risk nodes in a complex urban rail transit station and provide useful suggestions for the daily management of rail stations.

2.2. Emergency evacuation research of rail stations

Emergency evacuation contributes much to avoiding loss of life and minimizing damage after an event. Research into emergency evacuation comprises a considerable part of the safety analysis of rail transit. Jiang et al. (2009), for example, studied the crowding in platform staircases during rush hours of a subway station, and the width of staircase and the maximum upstairs walking speeding are two key parameters in evacuation, Shi et al. (2012b) established a computational model to simulate the evacuation process in a metro station to guarantee evacuation safety, including the illustration of the evacuation route, evacuation time, and safety zone. Similarly, Kallianiotis et al. (2018) analyzed the performance of the evacuation process in an underground metro station, with results showing that computer modelling evacuation presents clear advantages for considering worst case scenarios, influence of exit choice, etc. Hong et al., (2018) innovatively combined the ripple effect principle and herd behavior hypothesis to model passenger self-evacuation in a metro station, which can also provide useful suggestions for optimizing evacuation strategies.

2.3. Network methodologies used for system safety analysis

System safety is related to system component interactions and the overall behavior that emerges from such interactions (Ottino, 2003; Dewilde et al., 2013; Li et al., 2017). Network methodologies were applied in many studies. The vulnerability of inner interactions within the entire urban rail system was mainly focused. For example, by analyzing the complexity of the 33 world's metro systems, Derrible and Kennedy (2010) applied network science methodologies to ascertain the metros' robustness and discuss their topological features. Yang et al. (2015) explored the topological properties of the rail system by establishing a mathematical statistical model and assessing the metro network's robustness under random failures and malicious attacks, to guarantee the operational safety. Based on complex network and graph theories, Sun et al. (2015) proposed a vulnerability evaluation model for application in a case study of the Shanghai Metro. In doing so, the metro operation hazard was established and measured through complex network theory, and demonstrating the robustness to random attacks and the vulnerability to deliberate attacks on the network. In addition, based on passenger flow, Xiao et al. (2018) analyzed the correlation between heterogeneity and vulnerability of subway networks, and identified the stations with high flow degrees.

According to the above review, the independent risk event, such as air pollution risk and fire-induced smoke were focused in the existing rail station safety studies. Besides, the effects of passenger behaviors and their relationship with accidents, the important reasons for injuries, and the high-risk nodes determination were explored for the rail station safety. For the different stages of the risk events, the emergency evacuation stage after the risk event was studied, including the main facilities in evacuation, emergency evacuation simulation, evacuation performance analysis, etc. It can be concluded that even there are a few studies focus on some risk interactions, such as fire-induced smoke, but most of the existing studies conducted the rail station safety research based on the consideration of the independent risk event, including the aspects of different kinds of risk events, the characteristics of risk events in rail station, the risk response in some specific stages, etc. The existing research on the comprehensive interactions among risks in rail stations is still lacking, and the questions that which risks most influence other risks, and how the interactions involved affect the safety operation of rail stations, are still to be answered. It is becoming a consensus that risk events are not only caused by an independent mistake or failure, but the confluence of a whole series of evolving risks (Ren et al., 2008). Risk interactions have also been showed in many risk events. Thus, the risk interactions deserves deep exploration. Accordingly, this paper mainly conducted the research on the safety risks in rail stations from the perspective of risk interaction, which presents the innovation compared with other related studies.

3. Methodology

3.1. Research design

The method used here is a case study. Actual rail station risk events form the basis of the analysis. Establishing and analyzing a rail station risk-interaction network involves four steps of collecting risk events, identifying risks, establishing risk interaction chains, and constructing and analyzing the risk interaction network. Historical risk-event information provides the foundation for constructing the risk interaction network. The rail station risk events were therefore firstly collected. These contain a great deal of information, including risk event causes, risk interaction conditions, and risk management strategies. After analyzing the risk events, the independent risks are identified and the relationships between the risks determined. The next two steps involve risk identification and establishing risk interaction chains. The interaction chains are matched with each other and thus the risk interaction network is constructed by using a Bayesian network (BN). This is then subjected to influence strength and sensitivity analysis in preparation for formulating rail station safety-management strategies. The stepwise procedure of the analytical framework is illustrated in Fig. 1.

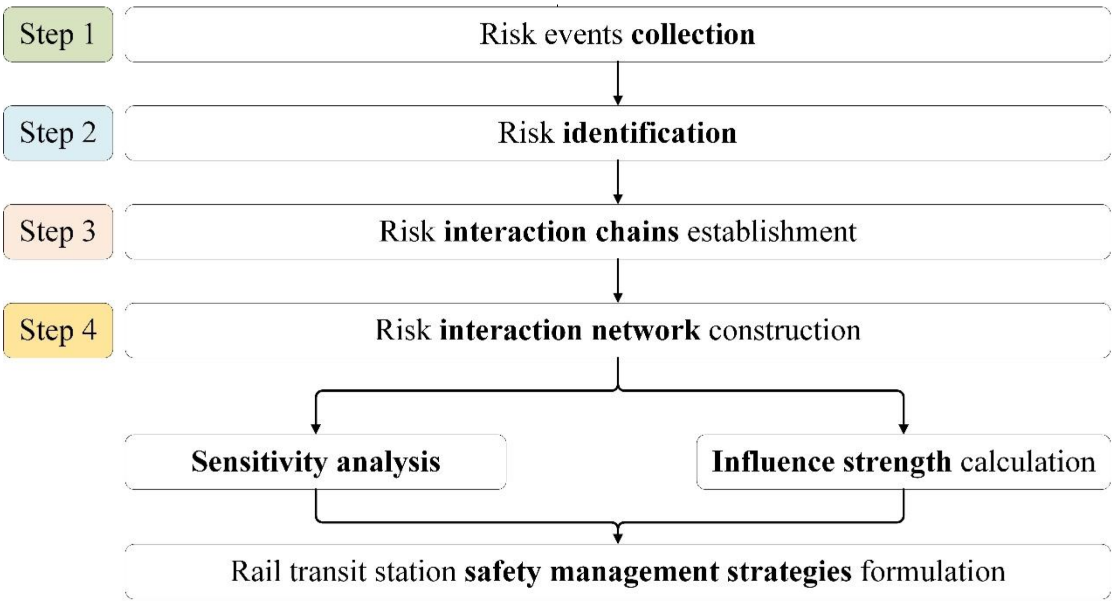

Fig. 1. Analytical Framework

3.2. Research method

The BN is used to establish the risk interaction network; it provides a qualitative, graphical illustration of the interactions between the variables it models (Oliver et al., 2000) and an intuitive network graph, in which the nodes denote random variables and arcs corresponding to the causal relations between the correlated variables (Holmes and Jain, 2008; Fan and Yu, 2004). The BN structure provides a probabilistic approach to inferencing, based on combining prior knowledge with observed data using *Bayes' rule*, which is used to calculate a specific probability distribution quickly (Friedman et al., 1997). Thus, the probability distributions of the variables are obtained with all possible combinations (Ghasemi et al., 2018). The *Bayes' rule* is

$$P(H \mid D) = \frac{P(D \mid H)P(H)}{P(D)} \tag{1}$$

where $P(D)$ is the prior probability of observing data D, $P(H)$ is the prior probability of hypothesis H, $P(D \mid H)$, called the *likelihood*, is the probability of observing D if hypothesis H holds, and $P(H \mid D)$ is the posterior probability of H after observing data D.

A BN (B) is a pair (G, Θ), where G is a directed acyclic graph in which the nodes represent random variables of interest and the edges denote probabilistic dependencies. Let $X = \{X_1, X_2, ..., X_n\}$ be a set of random variables, and let $\Theta = \{\theta_{x_i, Pa_i}\}$ be the set of parameters that represent conditional probabilities for the node X_i given its parents nodes Pa_i (the nodes pointing to X_i in the graph) in G, i.e. $\theta_{x_i, Pa_i} = P(X_i = x_i \mid Pa_i = pa_i)$. The distribution $P(X_i = x_i \mid Pa_i = pa_i)$ is called the local probability distributions. A BN represents a joint probability distribution over X as a product of local distributions (Friedman et al., 1997):

$$P(x_1, ..., x_n) = \prod_{i=1}^{n} P(x_i \mid pa_i) \tag{2}$$

BN contributes much to project risk management, which could model risk interactions, from multiple inputs to multiple outputs (Fang and Marle, 2012). There have been several papers on the application of BN in the field of project risk management in recent years. Ren et al. (2008), for instance, assessed offshore pipeline project risks using the combination of Reason's "Swiss cheese" model and BN; Wu et al. (2015) proposed a risk assessment method integrating interpretive structural modeling and BN applied in an offshore pipeline project; Lee et al. (2009) proposed a scheme for internal and external risks in large engineering project risk management based on a Bayesian belief network; and Vahid et al. (2007) applied BN to address both uncertainty and causality in project scheduling due to various sources of uncertainty. Moreover, a risk assessment methodology in the employment of Bayesian Belief Networks was established to evaluate and improve the performance of building construction projects for developing countries (Odimabo et al., 2017), and BN was also employed in risk management studies in the fields of natural gas stations (Ren et al., 2008), pressure drilling operations, supply chains, etc. (Abimbola et al., 2015)

In this study, the causal relations and interaction network of rail station risks are constructed through the software *GeNie*, in which the nodes are risks and connection lines denote the interaction relationships between risks. Influence strength and sensitivity analysis are conducted for the network.

3.3. Data collection

The statistics for the historical risk events provide a better understanding of rail station risks in the aspects of risk categories, risk causes, risk evaluation, risk response, risk interaction, etc. (Lyu et al., 2018; Li et al., 2010). Thus, historical risk events are useful for risk identification, risk analysis, and risk mitigation. Four categories of risk events pose threats to the safe operation of the rail station, comprising natural hazards, accident disasters, public health events, and social security events. More than one risk may be involved in each risk event. In fire accidents, for example, such risks as fire, collapse, and explosion may emerge simultaneously. Risks may interact with each other and form risk-interaction chains. Further, a network comprises many risk-interaction chains.

In this study, a rail station risk event database was established by gathering rail station risk events mainly from news, reports, and videos through internet searching. The key terms in risk event searching are the combination of “rail station” and “risk event”. As for the key term “risk event”, several words with similar meanings were also used in searching, including “accident”, “disaster”, and “hazard”. Besides, the corresponding Chinese characters for “rail station” that “地铁站”, “轨道交通站”, “轻轨站”, and for “risk event” that “风险事件”, “事故”, “事件” were also considered in searching rail station operational risk events in China. Four categories of risk event were considered, including natural hazards, accident disasters, public health events, and social security events. The internet explorers includes Google and Baidu. After inputting the key terms in the internet explorers, several relevant events were presented. The risk event cases were selected based on the criteria: (1) the risk event happens within the scope of rail stations instead of other such places in the rail system as the line between two stations; (2) every risk event comprises more than one risk; (3) the risk event leads to casualties or economic losses; and, (4) the risk event happens in the operation stage. As a result, a total of 62 rail station operational risk events were collected, including 25 cases in China and 37 cases in other counties/regions. The collected worldwide cases are in the time span of 1971-2018. Every risk event in the database contains six aspects of information–city, rail station, time, description of risk event, risk interaction chains, and risk event categories. Two examples of the collected risk events are shown in Table 1. Both the events occurred in rail stations, and comprise more than one risk and risk interaction chain.

Table 1

Two Examples of Risk Events

No.	City	Place	Time	Description of risk event	Risks interaction chains	Risk event categories
7	Beijing, China	Dongdan rail station	2008/ 3/4	On 4 March 2008, an escalator carrying hundreds of passengers suddenly made an unusual noise in the Dongdan rail station, causing passengers to flee. The emergency caused passengers to panic, fall, and stampede. 13 people were injured.	1. electrical device failure→panic→fall →stampede 2. electrical device failure→congestion →panic 3. electrical device failure→congestion →stampede	Accident disaster
26	Montreal , Canada	Montreal rail station	1971/ 12/1	On 1 December 1971, due to a signal malfunction, a train in Montreal, Canada crashed into the rear of a stationary train in the station, creating a short circuit in the locomotive, which caused a fire. One person was killed.	1. signal malfunction →train collision →Electrical device failure→fire 2. fire→asphyxiation 3. fire→panic→riot →stampede 4. fire→panic→ congestion→stampede 5. fire→passenger stranded→riot	Accident disaster

4. Results

4.1. Risk identification

The risk interaction chains and various risks are contained in the risk event database. The two main risk categories of risk events involved are accident disasters and social security events. A total of 25 risks are identified from the risk interaction chains, as shown in Table 2.

Table 2

List of Identified Risks

No.	Risks	No.	Risks
1	Signal malfunction	14	Flood
2	Train collision	15	Derailment
3	Asphyxiation	16	Typhoon
4	Falling	17	Riot
5	Screen door failure	18	Electrical device failure
6	Poisoning	19	Stampede
7	Collapse	20	Fire
8	Bury	21	Panic
9	Passengers stranded	22	Terrorism
10	Power supply failure	23	Explosion
11	Congestion	24	Escalator failure
12	Earthquake	25	Epidemic
13	Suicide		

4.2. Risk interaction chain

The identified risks in Table 2 interact with each other to form interaction chains. More than one risk interaction chain can be extracted from every risk event. For example, earthquake→collapse→bury is an interaction chain extracted from one risk event. Earthquake→panic→riot→congestion→stampede is another risk interaction chain. Thus, the risk interaction chains in every risk event can be listed and may even be repeated in different events. The total number of the risk interaction chains is 241, or 97 excluding the duplicated chains, as shown in Table 3.

Table 3

Risk Interaction Chains from the Collected Cases

No.	Risk interaction chain	No.	Risk interaction chain
1	Collapse→Bury→Asphyxiation	50	Fire→Explosion→Passenger stranded→Riot
2	Collapse→Fall→Bury	51	Fire→Explosion→Power supply failure
3	Collapse→Fall→Train collision	52	Fire→Explosion→Riot→Stampede
4	Congestion→Fall→Stampede	53	Fire→Panic→Riot→Congestion→Stampede

5	Congestion→Riot→Stampede	54	Fire→Passenger Stranded→Riot
6	Congestion→Stampede	55	Fire→Power supply failure→Passenger stranded
7	Congestion→Stampede→Panic→Riot	56	Flood→Epidemic→Panic→Riot
8	Derailment→Fall	57	Flood→Passenger→Congestion→Stampede
9	Derailment→Fire	58	Power supply failure→Fire
10	Derailment→Fire→Panic→Stampede	59	Power supply failure→Fire→Electrical device failure
11	Derailment→Train collision	60	Power supply failure→Panic→Congestion→Stampede
12	Earthquake→Collapse→Bury	61	Power supply failure→Passenger stranded
13	Earthquake→Collapse→Fall→train collision	62	Power supply failure→Passenger stranded→Congestion→Stampede
14	Earthquake→Epidemic→Panic→Riot	63	Power supply failure→Passenger stranded→Panic→Riot
15	Earthquake→Panic→Riot→Congestion→Stampede	64	Riot→Congestion→Stampede
16	Electrical device failure→Fall	65	Riot→Panic→Stampede
17	Electrical device failure→Fall→Stampede	66	Riot→Panic→Terrorism
18	Electrical device failure→Fire	67	Riot→Stampede→Congestion
19	Electrical device failure→Panic→Congestion→Stampede	68	Screen door failure→Congestion→Stampede
20	Electrical device failure→Passenger stranded→Panic→Congestion→Stampede	69	Screen door failure→Fall
21	Electrical device failure→Passenger stranded→Riot	70	Signal malfunction→Train collision
22	Electrical device failure→Signal malfunction→Panic→Riot→Stampede	71	Signal malfunction→Train collision→ Derailment
23	Electrical device failure→Signal malfunction→Train collision	72	Signal malfunction→Train collision→Fire
24	Electrical device failure→Train collision→Explosion	73	Stampede→Fall→Bury
25	Electrical device failure→Train collision→Fire	74	Suicide→Explosion
26	Escalator failure→Fall→Congestion→Stampede	75	Suicide→Fall
27	Escalator failure→Panic→Congestion→Stampede	76	Suicide→Panic→Congestion→Stampede
28	Escalator failure→Panic→Riot	77	Suicide→Panic→Riot
29	Escalator failure→Panic→Stampede	78	Terrorism→Explosion
30	Escalator failure→Stampede→Riot	79	Terrorism→Explosion→Electrical device failure→Fire
31	Explosion→Fire	80	Terrorism→Explosion→Fire
32	Explosion→Fire→Asphyxiation	81	Terrorism→Explosion→Fire→Asphyxiation
33	Explosion→Fire→Panic→Congestion→Stampede	82	Terrorism→Fire
34	Explosion→Panic→Stampede	83	Terrorism→Fire→Asphyxiation
35	Fall→Panic→Congestion→Stampede	84	Terrorism→Fire→Panic→Congestion→Stampede
36	Fall→Panic→Riot	85	Terrorism→Panic→Congestion→Stampede
37	Fall→Passenger stranded	86	Terrorism→Panic→Riot
38	Fall→Passenger stranded→Congestion→Stampede	87	Terrorism→Poisoning
39	Fall→Passenger stranded→Panic→Riot	88	Terrorism→Poisoning→Asphyxiation
40	Fall→Passenger stranded→Panic→Stampede	89	Train collision→Electrical device failure→Fire
41	Fall→Passenger stranded→Riot	90	Train collision→Explosion
42	Fire→Asphyxiation	91	Train collision→Explosion→Fire
43	Fire→Congestion→Fall	92	Train collision→Explosion→Fire→Panic →Congestion→Stampede
44	Fire→Congestion→Riot	93	Train collision→Fire
45	Fire→Congestion→Stampede	94	Train collision→Panic→Congestion→Stampede
46	Fire→Electrical device failure→Explosion	95	Train collision→Passenger Stranded

47	Fire→Explosion	96	Train collision→Passenger stranded→Panic→Riot
48	Fire→Explosion→Asphyxiation	97	Typhoon→Flood→Passenger stranded
49	Fire→Explosion→Panic→Stampede		

4.3. Risk interaction network construction and analysis

The Access Database provides the base for the BN. As the BN probability distribution is directly related to the frequency of every risk in all the interaction chains, this is established by importing the 241 chains, in which every row contains one chain. The BN for the 241 risk evolution chains is then obtained by importing the data from the Access Database into *GeNie*. The influence strength and sensitivity analyses are described in the next two sections.

4.3.1 Influence strength

The connection lines in the BN are shown with different thicknesses depending on the influence strength between the parent nodes and child nodes. The higher the strength, the more influence the parent node has on the child node, and the thicker is the connection line. Influence strength demonstrates the distance between the probability distributions of the child node conditional on the parent node, which is obtained from the conditional probability table of the child node (Yu et al., 1999). The strength is represented as the Euclidean distance between the conditional probability distribution of a node given the parent node and the a-priori probability of the node (Theijssen et al., 2013) as

$$E(node, parent) = \frac{\sqrt{\sum_{n=1}^{N}(P_n(node|parent)\text{-}P_n(node))^2}}{\sqrt{2}} \tag{3}$$

where $P_n(.)$ denotes the n^{th} component of the discrete probability distribution $P(.)$. Since $P(.)$ is a unit length vector, the maximum distance between $P_n(node|parent)$ and $P_n(node)$ is equal to $\sqrt{2}$ when the two vectors are orthogonal. Therefore, division by $\sqrt{2}$ ensures that the resulting distance is between 0 and 1.

The user interface *GeNie* calculates the influence strengths for the arrows and presents the values visually by the line thickness in the network. Placing the mouse on the head of the arrow and the information relating the strength of influence is shown in a comment box, as shown in Fig. 2.

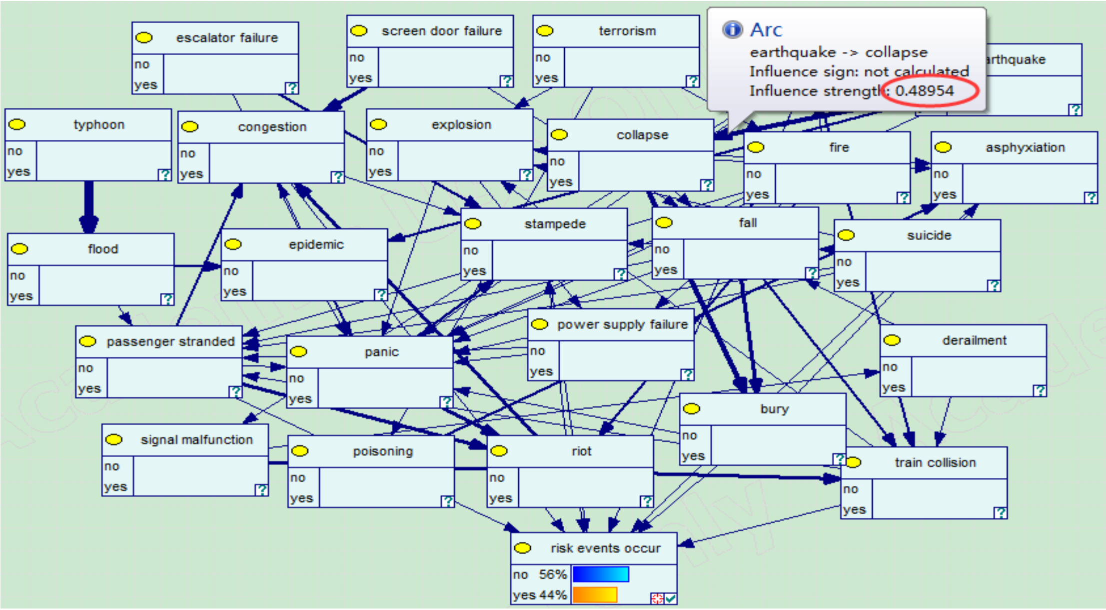

Fig. 2. Influence Strengths

Of the 64 parent-child paths contained in this network, the paths with the top 10 influence strengths are shown in Table 4.

Table 4

Highest Parent-child Path Influence Strengths

No.	Parent-child path	Influence strength
1	Typhoon → Flood	0.747934
2	Earthquake → Collapse	0.489540
3	Collapse → Bury	0.484985
4	Passengers stranded → Riot	0.392550
5	Signal malfunction → Train collision	0.378721
6	Riot → Congestion	0.363363
7	Fall → Bury	0.346096
8	Panic → Riot	0.305744
9	Screen door failure → Congestion	0.300863
10	Poisoning → Asphyxiation	0.267302

There are some common nodes among the 64 parent-child paths, which means that some child nodes in one path and could be parent nodes in another path. Thus, some different paths can be matched with each other. Based on the 10 strongest parent-child influence paths in Table 4, matching the different parent-child paths with common nodes identifies 9 key risk interaction chains, as shown in Fig. 3. While these 9 key risk interaction chains have a high influence strength, they are a reconstruction of the chains in Table 4.

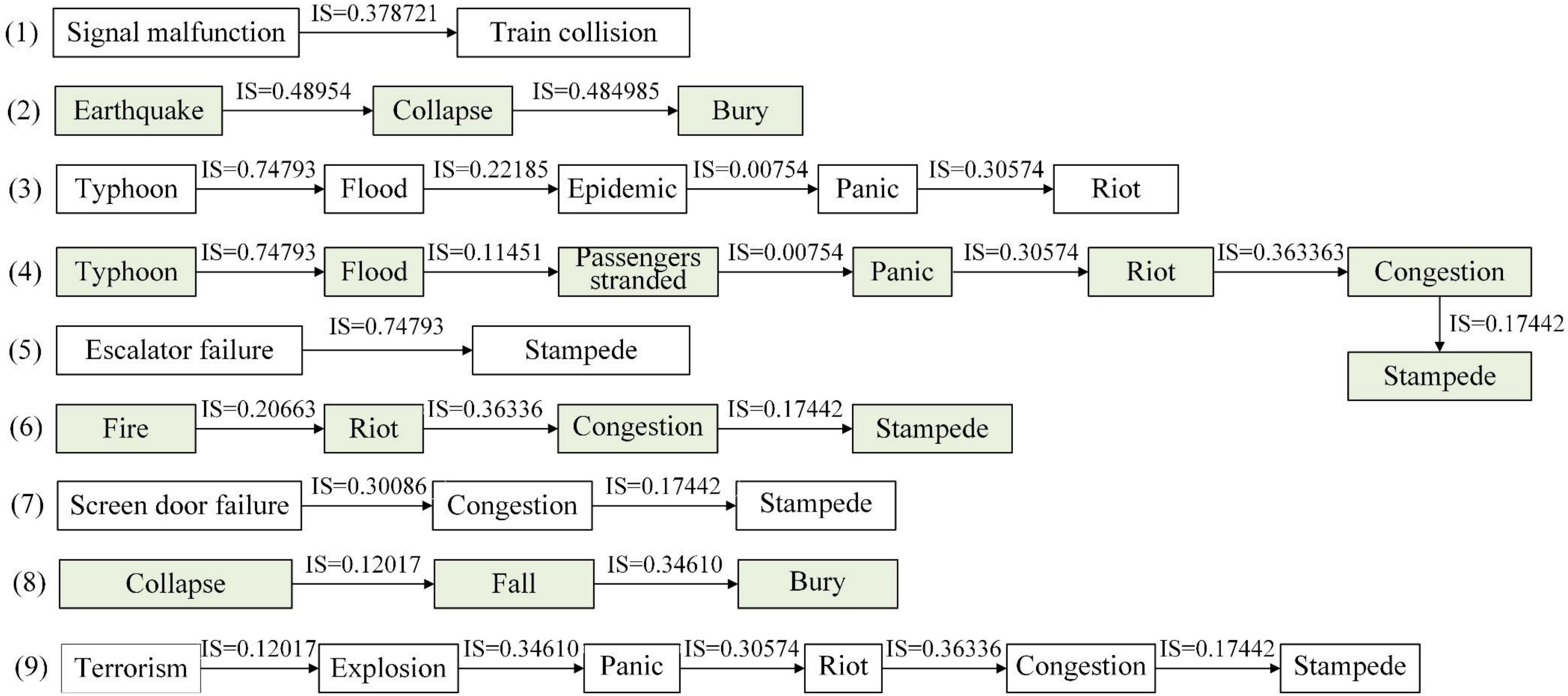

Fig. 3. Nine Key Risk Interaction Chains

4.3.2 Sensitivity analysis

Sensitivity analysis studies how sensitive a model's performance is to minor changes in the model and can be employed to demonstrate the changes in the posterior probability due to variations in the BN probability parameters (Castillo et al., 1997; Wang et al., 2002). The higher the sensitivity, the more significantly the parameters affect the results. This is obtained through the following functions (Laskey, 1995; Wang et al., 2002). Let B be a BN, x be a probability parameter, y be a query, and e be the evidence entered into B. The posterior probability $p(y \mid e)(x)$ is a fraction of two linear functions of x, where

$$p(y \mid e)(x) = \frac{\alpha x + \beta}{\gamma x + \delta} \tag{4}$$

Then the partial derivative of $p(y \mid e)(x)$ on x can be expressed as

$$S(x \mid y, e) = \frac{\partial p(y \mid e)}{\partial x} = \frac{\alpha - \beta\gamma}{(\gamma x + 1)^2} \tag{5}$$

Parameter sensitivity helps identify the most important parameters in a BN (Wang et al., 2002), which are obtained here using *GeNie* based on the imported 241 risk evolution chains, as shown in Table 5.

The higher the sensitivity value of the risk, the more it affects the possibility of the final risk event. In this case, the risk with the highest sensitivity value is signal malfunction, which could further lead to the train collision child node, with a high influence strength of 0.378721, and derailment with low influence strength of 0.017955. As a child node, the risk signal malfunction could also be caused by the electrical device failure risk with an influence strength of 0.007955. The train collision risk has the second highest sensitivity value. This may lead to the child nodes of stranded passenger, panic, and explosion, all with low influence strength (<0.01). Risk asphyxiation ranks the third, with parent nodes of explosion, fire, poisoning, and bury, of which the influence strength from poisoning to asphyxiation of 0.267302 is obviously higher than others. These most sensitive risks need to be the main governance foci, in the formulation of mitigate strategies.

Table 5
Sensitivity Value of the Identified Risks

No.	Risks	Sensitivity		
		max	min	avg
1	Signal malfunction	0.086	0	0.022
2	Train collision	0.071	0	0.003
3	Asphyxiation	0.069	0	0.005
4	Fall	0.064	0	0.001
5	Screen door failure	0.057	0	0.029
6	Poisoning	0.057	0	0.018
7	Collapse	0.055	0	0.014
8	Bury	0.050	0	0.007
9	Stranded passenger	0.044	0	0.001
10	Power supply failure	0.034	0	0.005
11	Congestion	0.031	0	0.002
12	Earthquake	0.028	0	0.014
13	Suicide	0.027	0	0.014
14	Flood	0.027	0	0.007
15	Derailment	0.025	0	0.007
16	Typhoon	0.021	0	0.01
17	Riot	0.019	0	0.004
18	Electrical device failure	0.016	0	0.006
19	Stampede	0.015	0	0.001
20	Fire	0.012	0	0.004
21	Panic	0.01	0	0
22	Terrorism	0.005	0	0.002
23	Explosion	0.003	0	0
24	Escalator failure	0.002	0	0.001
25	Epidemic	0.002	0	0

5. Discussion

In this paper, 62 rail station operational risk events were collected. Accordingly, 25 risks were identified, and 241 risk interaction chains were extracted and inferred from the collected risk events. Excluding duplicated chains, a total of 97 risk evolution chains were obtained. The 241 chains were used for the construction of the risk interaction network through BN. The influence strength and sensitivity analysis were conducted for the network. Based on the parent-child paths with the ten strongest influences, nine key risk interaction chains were constructed.

The eight sensitive risks and the nine key risk interaction chains identified in this way will be vital for the establishment of the rail station safety management strategies from two aspects. One is for the mitigation of sensitive risks. Table 5 shows the sensitivities of the 25 risks identified in this study. The risks with highest eight sensitivities (greater than or equal to 0.05) belong to two categories of accident disasters and social security events. Signal malfunction, train collisions, falls, collapses, and burying are accident disasters, while poisoning is social security events. These risks could be triggered by failure operation of facilities and equipment, or management defects of the stations. Therefore, special attention needs to be paid to high sensitivity risks, with strategies established to guarantee the operational safety of the facilities and equipment in the stations and to respond to emergency social security events. The daily safety management should also be strengthened. These could be presented as handbooks, regulations, emergency plans, or other forms.

The second aspect of safety management strategy is to cut off the nine key risk interaction chains. For each chain, the prevention of one risk in the chain cuts off the rest of the chain, nullifying the subsequent risks in the chain. Thus, the strategies need to prevent the risks as early in the chains as possible. Of the nine chains, three originate from earthquake and typhoon, *force majeure* natural hazards that can only be predicted to some degree and impossible to prevent. Therefore, strategies for natural hazards mainly involve such emergency response and rescue measures as coordinating rescue forces, preventing the spread of epidemics, and caring for victims. The other six risk interaction chains originate from accident disasters and social security events. Handbooks, regulations, and emergency plans are also needed to prevent the risks as early as possible in the chains. Such strategies as regularly checking and renewing the escalators, screen doors, and other facilities would help to prevent equipment failure. Thus, the nine key risk interaction chains and sensitivity analysis results provide useful references for the establishment of safety management strategies for rail stations.

The foundation of this study is the 62 risk events, which were collected based on an utmost endeavor in risk event cases searching. The collected cases generally demonstrate the risk event conditions of the worldwide rail stations until now. Further research would involve collecting more rail station risk events, especially those occurring more recently. This paper proposed a risk interaction analysis method for the risks in the rail station. Through the analysis for the collected events, the sensitive risks and key risk interaction chains could be obtained, among which the key risk interaction chains could also be further applied in the analysis for new collected risk event cases, due to the common characteristics of the risk interaction. Besides, considering the operational risks of rail station in different countries or regions may be very different from each other, the analysis method proposed in this paper could be conducted in some specific scope repeatedly, and the corresponding sensitive risks and risk interaction chains could be presented accordingly. Collecting historical risk events in the scope of one country, one region, or even one rail station, and conducting the risk interaction analysis, then the sensitive risks and key risk interaction chains in the specific scope could be obtained. Some strategies for sensitive risks mitigation and key risk interaction chains cutting off could be formulated accordingly for the specific scope. Such an expanded analysis of the interactions involved would indeed help increase rail station robustness to operational interruptions.

6. Conclusion

Urban rail, with its large transportation capacity, energy saving, low pollution, and high speed, is an ideal form of public transport, which facilitates people's lives and solves many transportation-related problems. For the rail station-a public space with crowded passengers and multiple facilities and equipment-safety is a critical issue that should be guaranteed for normal operations. Existing risk events show that one risk could be triggered by another, and some risks interacted with each other, which deserves more attention in future research. In response, this study focuses on the interactions between risks in rail stations. 62 risk events in the rail stations were collected, 25 risks identified, and 241 risk interaction chains extracted. BN was adopted in the construction of the risk interaction network. As a consequence, the sensitive risks and key risk interaction chains were obtained.

This research provides a specific guiding role for the safe rail station operation in two aspects. One is that this paper proposed a risk interaction analysis method for the operational risks in the rail station. The method is conducted based on the historical risk event data and could be used for the risk interaction analysis in different specific scope, such as one country, one region, or even one rail station. Based on the proposed methods, research into risk interactions could be continuously conducted for a specific scope when more cases become available, and obtain the sensitive risk categories and key risk interaction chains. The other aspect of the specific guiding role of the research is that the results could provide useful references for the establishment countermeasures in reducing or eliminating risk events in rail stations from the perspective of risk interaction. The risk interaction demonstrates the characteristics of risk events and is also an innovation of this research. The risk management proposed in this paper is not mitigating the happening of risk events, but preventing the further evolution from one kind of risk event to other kinds. The countermeasures formulated based on the consideration of risk interaction, such as the strategies that made for cutting off the key risk interaction chains, could play useful role for preventing risk spread or evolution after risk events happen, and guarantee the safety operation as far as possible.

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References

Abimbola, M., Khan, F., Khakzad, N., Butt, S., 2015. Safety and risk analysis of managed pressure drilling operation using Bayesian network. Saf. Sci. 76, 133–144. https://doi.org/10.1016/j.ssci.2015.01.010

BBC News, 2011. Beijing Metro Elevator Accident [WWW Document]. BBC News. URL https://www.bbc.com/zhongwen/trad/chinese_news/2011/07/110705_beijing_metro_accident (accessed 9.6.18).

Beaudoin, J., Farzin, Y.H., Lin Lawell, C.Y.C., 2015. Public transit investment and sustainable transportation: A review of studies of transit's impact on traffic congestion and air quality. Res. Transp. Econ. 52, 15–22. https://doi.org/10.1016/j.retrec.2015.10.004

Beijing Evening News, 2018. The average daily passenger flow of Beijing Metro exceeds 11.6 million [WWW Document]. China Natl. Radio. URL http://travel.cnr.cn/list/20180809/t20180809_524327501.shtml (accessed 9.3.18).

Castillo, E., Gutierrez, J.M., Hadi, A.S., 1997. Sensitivity analysis in discrete Bayesian networks. Ieee Trans. Syst. Man Cybern. Part a-Systems Humans 27, 412–423. https://doi.org/10.1109/3468.594909

Chu, D., Strand, R., Fjelland, R., 2003. Theories of complexity — common denominators of complex systems. Complexity 8, 19–30.

Danilovic, M., Browning, T.R., 2007. Managing complex product development projects with design structure matrices and domain mapping matrices. Int. J. Proj. Manag. 25, 300–314. https://doi.org/https://doi.org/10.1016/j.ijproman.2006.11.003

Derrible, S., Kennedy, C., 2010. The complexity and robustness of metro networks. Phys. A Stat. Mech. its Appl. 389, 3678–3691. https://doi.org/https://doi.org/10.1016/j.physa.2010.04.008

Dewilde, T., Sels, P., Cattrysse, D., Vansteenwegen, P., 2013. Robust railway station planning: An interaction between routing, timetabling and platforming. J. Rail Transp. Plan. Manag. 3, 68–77. https://doi.org/10.1016/j.jrtpm.2013.11.002

Dongfang Internet, 2017. The passenger volume of Shanghai metro reaches to 118.67 million on April 28, 2017 [WWW Document]. Dongfang Internet. URL http://sh.sina.com.cn/news/m/2017-04-29/detail-ifyetwtf8920845.shtml (accessed 7.17.18).

Economy & Nation Weekly, 2017. The urban rail transit of great China ranks the first in the world [WWW Document]. Econ. Nation Wkly. URL http://mp.weixin.qq.com/s?__biz=MjM5MTM5MTQ4MA==&mid=2652935138&idx=1&sn=5459863bd1100d68d7c467b3d1eff310&chksm=bd6278758a15f1635638ba30bde1191479328f26b25e06c857ba52fec95c44864f729c2c2040&scene=0 (accessed 9.1.18).

Fan, C.F., Yu, Y.C., 2004. BBN-based software project risk management. J. Syst. Softw. 73, 193–203. https://doi.org/10.1016/j.jss.2003.12.032

Fang, C., Marle, F., 2012. A simulation-based risk network model for decision support in project risk management. Decis. Support Syst. 52, 635–644. https://doi.org/10.1016/j.dss.2011.10.021

Friedman, N., Geiger, D., Goldszmit, M., 1997. Bayesian Network Classifiers. Mach. Learn. 29, 131–163. https://doi.org/10.1023/a:1007465528199

Gao, R., Li, A., Hao, X., Lei, W., Zhao, Y., Deng, B., 2012. Fire-induced smoke control via hybrid ventilation in a huge transit terminal subway station. Energy Build. 45, 280–289.

https://doi.org/10.1016/j.enbuild.2011.11.018

Ghasemi, F., Sari, M., Yousefi, V., Falsafi, R., Tamošaitienė, J., 2018. Project portfolio risk identification and analysis, Considering project risk interactions and using Bayesian Networks. Sustainability 10, 1609. https://doi.org/10.3390/su10051609

Gwilliam, K.M., 2002. Cities on the move : a World Bank urban transport strategy review. World Bank Publications.

Holmes, D.E., Jain, L.C., 2008. Innovations in Bayesian Networks: Theory and Applications. Springer Science & Business Media, Berlin.

Hong, L., Gao, J., Zhu, W., 2018. Self-evacuation modelling and simulation of passengers in metro stations. Saf. Sci. 110, 127–133. https://doi.org/10.1016/j.ssci.2018.05.013

Jiang, C.S., Deng, Y.F., Hu, C., Ding, H., Chow, W.K., 2009. Crowding in platform staircases of a subway station in China during rush hours. Saf. Sci. 47, 931–938. https://doi.org/10.1016/j.ssci.2008.10.003

Kade, A., 2013. World's Most Crowded Subways [WWW Document]. Travel + Leis. Mag. URL https://www.travelandleisure.com/slideshows/worlds-most-crowded-subways (accessed 10.10.18).

Kallianiotis, A., Papakonstantinou, D., Arvelaki, V., Benardos, A., 2018. Evaluation of evacuation methods in underground metro stations. Int. J. Disaster Risk Reduct. 31, 526–534. https://doi.org/https://doi.org/10.1016/j.ijdrr.2018.06.009

Kim, Y.S., Kim, M.J., Lim, J.J., Kim, J.T., Yoo, C.K., 2010. Predictive monitoring and diagnosis of periodic air pollution in a subway station. J. Hazard. Mater. 183, 448–459. https://doi.org/10.1016/j.jhazmat.2010.07.045

Laskey, K.B., 1995. Sensitivity analysis for probability assessments in Bayesian Networks. IEEE Trans. Syst. Man. Cybern. 25, 901–909. https://doi.org/10.1109/21.384252

Lee, E., Park, Y., Shin, J.G., 2009. Large engineering project risk management using a Bayesian belief network. Expert Syst. Appl. 36, 5880–5887. https://doi.org/10.1016/j.eswa.2008.07.057

Li, L., Wang, J., Leung, H., Jiang, C., 2010. Assessment of catastrophic risk using bayesian network constructed from domain knowledge and spatial data. Risk Anal. 30, 1157–1175. https://doi.org/10.1111/j.1539-6924.2010.01429.x

Li, Q., Song, L., List, G.F., Deng, Y., Zhou, Z., Liu, P., 2017. A new approach to understand metro operation safety by exploring metro operation hazard network (MOHN). Saf. Sci. 93, 50–61. https://doi.org/10.1016/j.ssci.2016.10.010

Lyu, H.M., Sun, W.J., Shen, S.L., Arulrajah, A., 2018. Flood risk assessment in metro systems of mega-cities using a GIS-based modeling approach. Sci. Total Environ. 626, 1012–1025. https://doi.org/10.1016/j.scitotenv.2018.01.138

Meng, N., Hu, L., Wu, L., Yang, L., Zhu, S., Chen, L., Tang, W., 2014. Numerical study on the optimization of smoke ventilation mode at the conjunction area between tunnel track and platform in emergency of a train fire at subway station. Tunn. Undergr. Sp. Technol. 40, 151–159. https://doi.org/10.1016/j.tust.2013.09.014

Odimabo, O., Oduoza, C., Suresh, S., 2017. Methodology for project risk assessment of building construction projects using Bayesian Belief Networks. Int. J. Constr. Eng. Manag. 6, 221–234. https://doi.org/10.1038/nature14486

Oliver, N.M., Rosario, B., Pentland, A.P., 2000. A Bayesian computer vision system for modelling human interactive. IEEE Trans. Pattern Anal. Mach. Intell. 22, 831–843. https://doi.org/10.1007/3-540-49256-9_16

Ottino, J.M., 2003. Complex systems. AIChE J. 49, 292–299. https://doi.org/10.1002/aic.690490202

Ren, J., Jenkinson, I., Wang, J., Xu, D.L., Yang, J.B., 2008. A methodology to model causal relationships on offshore safety assessment focusing on human and organizational factors. J. Safety Res. 39, 87–100. https://doi.org/10.1016/j.jsr.2007.09.009

Shi, C., Zhong, M., Nong, X., He, L., Shi, J., Feng, G., 2012a. Modeling and safety strategy of passenger evacuation in a metro station in China. Saf. Sci. 50, 1319–1332. https://doi.org/10.1016/j.ssci.2010.07.017

Shi, C., Zhong, M., Nong, X., He, L., Shi, J., Feng, G., 2012b. Modeling and safety strategy of passenger evacuation in a metro station in China. Saf. Sci. 50, 1319–1332. https://doi.org/https://doi.org/10.1016/j.ssci.2010.07.017

Sun, D., Zhao, Y., Lu, Q.C., 2015. Vulnerability analysis of urban rail transit networks: A case study of Shanghai, China. Sustainability 7, 6919–6936. https://doi.org/10.3390/su7066919

Theijssen, D., Bosch, L. Ten, Boves, L., Cranen, B., Van Halteren, H., 2013. Choosing alternatives: Using Bayesian Networks and memory-based learning to study the dative alternation. Corpus Linguist. Linguist. Theory 9, 227–262. https://doi.org/10.1515/cllt-2013-0007

Vahid, K., Norman, F., Martin, N., 2007. Project scheduling: Improved approach to incorporate uncertainty using Bayesian Networks. Proj. Manag. Jounal 38, 39–49.

Wan, X., Li, Q., Yuan, J., Schonfeld, P.M., 2015. Metro passenger behaviors and their relations to metro incident involvement. Accid. Anal. Prev. 82, 90–100. https://doi.org/10.1016/j.aap.2015.05.015

Wang, H., Rish, I., Ma, S., 2002. Using sensitivity analysis for selective parameter update in Bayesian network learning, in: In Proceedings of the AAAI Spring Symposium on Information Refinement and Revision for Decision Making: Modeling for Diagnostics, Prognostics and Prediction. pp. 29–36.

Wikipedia, 2017. Hong Kong Mass Transit Railway Fire [WWW Document]. Wikipedia. URL https://zh.wikipedia.org/wiki/2017年港鐵縱火案 (accessed 9.6.18).

Wu, W.S., Yang, C.F., Chang, J.C., Château, P.A., Chang, Y.C., 2015. Risk assessment by integrating interpretive structural modeling and Bayesian network, case of offshore pipeline project. Reliab. Eng. Syst. Saf. 142, 515–524. https://doi.org/10.1016/j.ress.2015.06.013

Xiao, X., Jia, L., Wang, Y., 2018. Correlation between heterogeneity and vulnerability of subway networks based on passenger flow. J. Rail Transp. Plan. Manag. 8, 145–157. https://doi.org/10.1016/j.jrtpm.2018.03.004

Xing, Y., Dissanayake, S., Lu, J., Long, S., Lou, Y., 2017. An analysis of escalator-related injuries in metro stations in China, 2013-2015. Accid. Anal. Prev. In Press. https://doi.org/10.1016/j.aap.2017.10.007

Xu, H., Jiao, L., Chen, S., Deng, M., Shen, N., 2018. An innovative approach to determining high-Risk nodes in a complex urban rail yransit station : A perspective of promoting urban sustainability. Sustainability 10, 2456. https://doi.org/10.3390/su10072456

Yang, Y., Liu, Y., Zhou, M., Li, F., Sun, C., 2015. Robustness assessment of urban rail transit based on complex network theory: A case study of the Beijing Subway. Saf. Sci. 79, 149–162. https://doi.org/10.1016/j.ssci.2015.06.006

Yu, D.C., Nguyen, T.C., Haddawy, P., 1999. Bayesian network model for reliability assessment of power systems. IEEE Trans. Power Syst. 14, 426–432. https://doi.org/10.1109/59.761860

Zhao, W., Martin, U., Cui, Y., Liang, J., 2017. Operational risk analysis of block sections in the railway network. J. Rail Transp. Plan. Manag. 7, 245–262. https://doi.org/10.1016/j.jrtpm.2017.09.003