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An integrated framework for managing fire resilience of metro station system: identification, assessment and optimization

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Abstract:	As a sociotechnical infrastructure system composed of equipment and facilities, operational staff, and passengers, metro station systems (MSSs) manage threats of high-frequency fires in the city, but scant attention is drawn to how MSSs in operation systematically cope with fires. To improve the existing MSSs' poor performance across the fire lifecycle, the concept of fire resilience is proposed based on the system resilience theory. The disaster scene analysis, TOSE approach, and modified TOPSIS method are combined to identify critical fire resilience indexes. Then, a Bayesian network is developed to assess fire resilience and reveal critical causal chains in fire scenes. Furthermore, sensitivity analysis and dynamic Bayesian network with critical importance analysis are adopted to formulate optimization strategies for MSSs in different periods of operating life. The resulting integrated framework for managing fire resilience is applied to Nanjing MSS, providing operational staff and decision makers with practical tools to engage in long-term resilient operation of MSS against fires within a clear manageable scope. The results indicate that passengers' safety knowledge and behaviors, effectiveness of security screening operations, and skills of staff in emergency response team are the prime factors resulting in low fire resilience; meanwhile, economic resource allocation should be prioritized for optimization initially, but optimization priorities should be transferred to the less controllable passengers' escape skills and aging firefighting equipment as operating life increases. The integration of identification, assessment, and optimization methods can also be flexibly embedded into various infrastructure systems' operation management processes to optimize disaster resilience continuously.

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Dear Editors,

We would like to submit the enclosed manuscript entitled "An integrated framework for managing fire resilience of metro station system: identification, assessment and optimization", which we wish to be considered for publication in "International Journal of Disaster Risk Reduction". We claim that there is no conflict of interest in the manuscript and concerned materials have never been published or under consideration elsewhere. The approval by all the listed authors, including Yuchun Tang, Wei Bi, Liz Varga, Tom Dolan, and Qiming Li, for publication has been confirmed.

As a sociotechnical infrastructure system composed of equipment and facilities, operational staff, and passengers, metro station systems (MSSs) manage threats of high-frequency fires in the city, but scant attention is drawn to how MSSs in operation systematically cope with fires. To improve the existing MSSs' poor performance across the fire lifecycle, the concept of fire resilience is proposed based on the system resilience theory. The disaster scene analysis, TOSE approach, and modified TOPSIS method are combined to identify critical fire resilience indexes. Then, a Bayesian network is developed to assess fire resilience and reveal critical causal chains in fire scenes. Furthermore, sensitivity analysis and dynamic Bayesian network with critical importance analysis are adopted to formulate optimization strategies for MSSs in different periods of operating life. The resulting integrated framework for managing fire resilience is applied to Nanjing MSS, providing operational staff and decision makers with practical tools to engage in long-term resilient operation of MSS against fires within a clear manageable scope. The results indicate that passengers' safety knowledge and behaviors, effectiveness of security screening operations, and skills of staff in emergency response team are the prime factors resulting in low fire resilience; meanwhile, economic resource allocation should be prioritized for optimization initially, but optimization priorities should be transferred to the less controllable passengers' escape skills and aging firefighting equipment as operating life increases. The integration of identification, assessment, and optimization methods can also be flexibly embedded into various infrastructure systems' operation management processes to optimize disaster resilience continuously.

We would appreciate it that you can consider our manuscript and we are looking forward for any comments and suggestions from the reviewers. Should you need to contact me, please find my contact information as follows:

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Thank you very much for consideration.

Yours sincerely,
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Highlights

- Propose a model to identify fire resilience indexes for metro station system.
- Construct a Bayesian network to simulate formation and emergence of fire resilience.
- Perform critical importance analysis for dynamic optimization of fire resilience.
- The proposed methods are applied in a real-world case through investigating experts.

Manuscript

Title page

An integrated framework for managing fire resilience of metro station system: identification, assessment and optimization

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Abstract

As a sociotechnical infrastructure system composed of equipment and facilities, operational staff, and passengers, metro station systems (MSSs) manage threats of high-frequency fires in the city, but scant attention is drawn to how MSSs in operation systematically cope with fires. To improve the existing MSSs' poor performance across the fire lifecycle, the concept of fire resilience is proposed based on the system resilience theory. The disaster scene analysis, TOSE approach, and modified TOPSIS method are combined to identify critical fire resilience indexes. Then, a Bayesian network is developed to assess fire resilience and reveal critical causal chains in fire scenes. Furthermore, sensitivity analysis and dynamic Bayesian network with critical importance analysis are adopted to formulate optimization strategies for MSSs in different periods of operating life. The resulting integrated framework for managing fire resilience is applied to Nanjing MSS, providing operational staff and decision makers with practical tools to engage in long-term resilient operation of MSS against fires within a clear manageable scope. The results indicate that passengers' safety knowledge and behaviors, effectiveness of security screening operations, and skills of staff in emergency response team are the prime factors resulting in low fire resilience; meanwhile, economic resource allocation should be prioritized for optimization initially, but optimization priorities should be transferred to the less controllable passengers' escape skills and aging firefighting equipment as operating life increases. The integration of identification, assessment, and optimization methods can also be flexibly embedded into various infrastructure systems' operation management processes to optimize disaster resilience continuously.

Keywords: Metro station system; Fire resilience; Resilience capacities; Disaster scenes; Dynamic Bayesian network

1 Introduction

By the end of 2020, 538 cities worldwide had operational metros with a total length reaching 33346 kilometers [1]. As an urban lifeline infrastructure, metros provide cities with daily transportation services and disaster relief functions, such as emergency evacuation and emergency supply transportation, which guarantees cities' public safety. Furthermore, most metros are located in urban underground spaces and have complex structures and dense passenger flows, which dramatically increases various disaster risks [2]. According to incomplete statistics of metro operation accidents, metro stations have the highest accident rates in an entire metro system [3]; meanwhile, fire disasters are the accident type with the highest occurrence probability and the most severe consequences among all operation accidents [4]. Therefore, it is urgent to identify, assess and optimize metro stations' capacities to address fire disasters to minimize catastrophic economic losses and negative social impacts.

Current research on metro station fires mainly focuses on risk management with the goal of efficient fire prevention and emergency management with the goal of robust fire resistance, which emphasizes structural response to fires, but ignores the participation of operational staff and passengers during the fire recovery and adaptation [5]. Although fire resilience has gradually attracted attention, most related research aims only to address the functional continuity of equipment and facilities from structural perspective [6, 7], which ignores the role of operators and users in disaster resilience management of infrastructure systems. To fill the above gaps, this research applies system resilience theory to define the fire resilience of a metro station system (MSS) as the comprehensive capacities to absorb and resist negative impacts of fires, return to normal operations, and adapt to potential fires. Meanwhile, considering that the causality between the formation and emergence of fire resilience is usually neglected in existing resilience assessment tools [8, 9], this research integrates the disaster scene analysis and the technical, organizational, social, and economic (TOSE) approach to establish a standardized D-TOSE model to identify fire resilience indexes including assessment indicators and influential factors. In this model, assessment indicators reflecting fire resilience formation are identified as resilience capacities in the fire lifecycle scenes, and influential factors reflecting fire resilience emergence are identified from the TOSE dimensions. Then, the impacts of the emergence process of the influential factors on the formation process of resilience capacities are quantified by integrating resilience capacities with their influential factors and fire scene status into a Bayesian network (BN). Moreover, given that static BN model cannot be updated quickly according to the development or degradation characteristics of the system [10], dynamic Bayesian network (DBN) model is applied to capture the changing law of the failure probability of various influential factors as the MSS operating life increases. Finally, sensitivity analysis and critical importance analysis are combined to provide decision makers with current, short-term, and long-term optimization strategies of fire resilience. The above methods are integrated into a systemic framework for operational staff and decision makers to manage fire resilience of MSSs through scene-based identification, causality-based assessment, and time-based optimization. Such integration is applied in Nanjing MSS and advances comprehensive understanding of the system's existing fire resilience level and optimization strategy preferences, helping MSSs respond to fires with minor occurrence, less consequence, and faster recovery.

2 Literature review

2.1 Fire safety management for metro stations

Metro stations are characterized by complex fire compartmentation, limited evacuation paths, narrow emergency rescue space, etc. Once fires occur in metro stations, they quickly cause severe casualties and public property losses [11]. Therefore, studies on the fire safety management of metro stations have been extensively conducted with the following three aspects: (1) As for the existing studies on fire risk prevention for metro stations, they mainly propose targeted prevention measures of high-frequency hazards through statistical analysis and risk assessment [12, 13]. Many studies have found that fires breaking out in metro stations were mainly due to equipment faults and abnormal passenger behaviors [14, 15]; then, their likelihood, exposure, and consequence of triggering fires are assessed to develop rating early-warning measures in terms of human, technology, environment, and management aspects [13, 16]. (2) As for the existing studies on experimental and numerical simulation of fires in metro stations, they have mainly verified the reliability of the structural fire-resistance design and the evacuation efficiency of the walking equipment and facilities by simulating smoke movement and crowd evacuation behaviors under fires [3, 17]. (3) As for the existing studies on fire emergency management for metro stations, they mainly focus on emergency response plan optimization through multi-objective decision-making on disposal schedules, evacuation and rescue routes, and emergency resource allocation to minimize consequential losses [18–20].

It is concluded that most fire safety management schemes for MSSs ignore recovery and adaptation measures after fires [21]. As a result, an MSS usually wastes more time restarting operation services and suffers from recurring fires caused by the same influential factor, proving that scattered and unsystematic fire safety management measures struggle to make a difference when an MSS experiences fires. To address the above deficiencies, the concept of resilience is introduced into fire safety management, and four fire lifecycle scenes including prevention scene (pre-disaster), response scene (in-disaster), restoration scene (post-disaster), learning scene (after resuming operations) [22], and their corresponding influential factors are identified to manifests the formation and emergence process of fire resilience.

2.2 Resilience management for metro systems

Compared with traditional safety management theories, system resilience theory can better reflect the changing state of system performance when a system is attacked by various disturbances [23]. Therefore, resilience management for metro systems has increasingly gained ground in research on identification and assessment [24]. (1) Metro system resilience identification is mainly realized by capturing system responses to different disturbances at physical or topological level. From the perspective of physical equipment and facilities, the interruption consequences caused by technical faults of trains, tracks, and cables are often identified as resilience metrics [25–27]. From the perspective of topological networks, a metro system is usually modeled as a complex network loaded with various attack strategies, including node, edge, and space destruction. And changes in the topological attributes of a metro network are usually identified as resilience metrics [28, 29]. (2) Metro system resilience assessment is realized by quantifying system performance or resilience capacities [30, 31], in which the performance-based method assesses resilience by the geometric solution of the change curve of the system performance over time [32], and the capacity-based method assesses resilience by inferring the resilience capacity level [33]. Because of the limited data on damage to infrastructures, many studies support the capacity-based method and indicate that resilience capacities as assessment indicators can be adjusted more flexibly according to different types of systems and disasters, which makes it easier to collect basic data [34]. However, the existing capacity-based assessment indicators usually do not address all the resilience capacities formed throughout the disaster lifecycle, which causes final assessment results reflecting reliability, robustness, and vulnerability, instead of resilience [35]. Meanwhile, almost all indicators are static and cannot be automatically updated as operating life increases [36]. Hence, corresponding resilience assessment results cannot assist in decision-making for long-term system operations.

In conclusion, the shortcomings of existing research are as follows: (1) Most research objects focus on metro systems' physical hardware and topological network, but there is a lack of attention to metro stations that are simultaneously equipped with service function and topological function [37]. In addition, metro system resilience is mainly assessed by simulating generalized attacks on metro networks without a characteristic analysis of specific disasters. Hence, the formation and emergence of various system resilience capacities against specific disasters are still black-box issues. (2) Most resilience optimization strategies fail to consider complex time-varying characteristics of metro system components' functional states and their gain or loss effects on resilience capacities over time [38]. To address the above deficiencies, this research selects metro station as the system and fire disaster as the disturbance, and then proposes the concept of fire resilience based on system resilience theory. Furthermore, resilience capacities with their dynamic influential factors are considered in BN model and DBN model to assess and optimize fire resilience of the MSS.

3 Methodology

3.1 Three-phase integrated framework

System resilience theory indicates that resilience is an inherent property of a system in operation; meanwhile, assessing and optimizing system resilience are premised on the basis of identifying the system, disturbance, time period when the system experiences the disturbance, required capacities of the system to handle the disturbance, and influential factors of required capacities [39]. It is worth noting that system resilience should be built not only in the technical and physical elements as in traditional engineering practices, but also in the social and organizational elements. Therefore, in this research, the MSS is defined as a sociotechnical system composed of "hard" parts including equipment and facilities as well as "soft" parts including operational staff and passengers [40–42]; the disturbance is fire disaster; the time period refers to the fire lifecycle, namely, prior-disaster, in-disaster, post-disaster and after resuming operation stages; the remaining two elements are resilience capacities as assessment indicators of fire resilience and their influential factors, reflecting the formation and emergence process of fire resilience, respectively. A three-phase integrated framework is proposed as shown in Fig. 1 to fulfill scene-based identification, causality-based assessment, and time-based optimization of fire resilience.

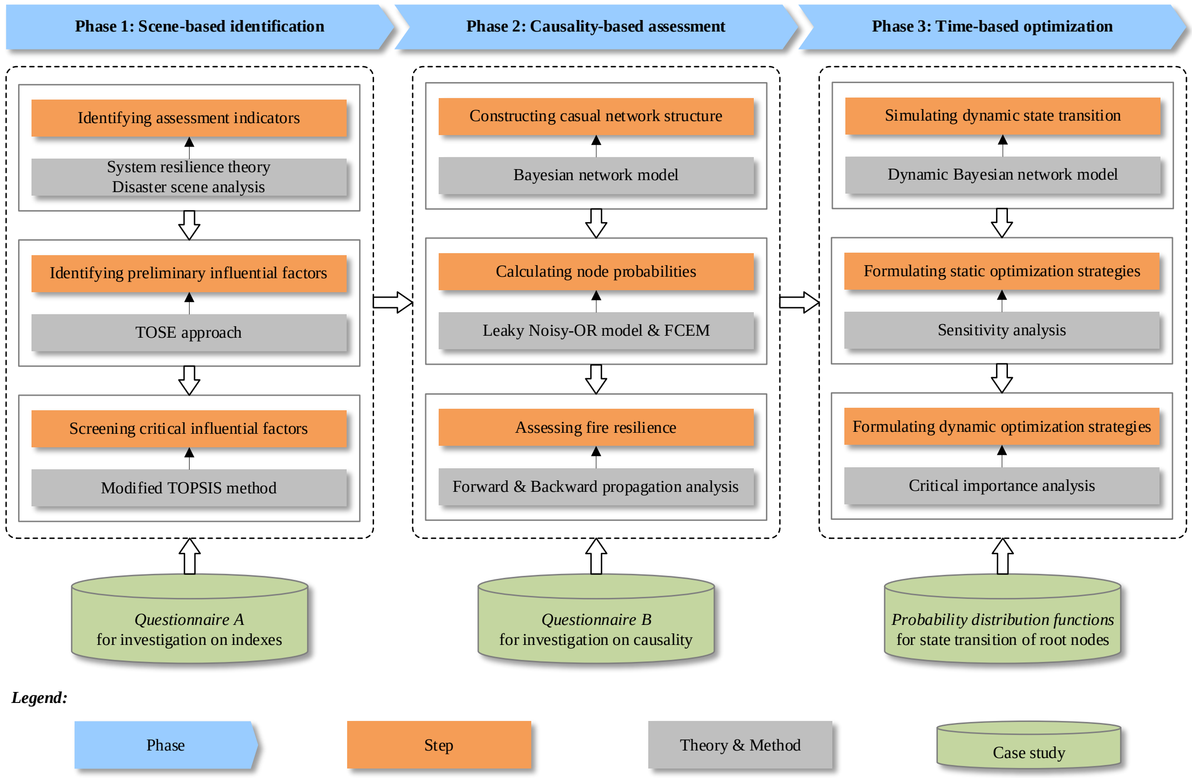


Fig. 1. A three-phase integrated framework for managing fire resilience

3.2 Identification methods in Phase 1

Phase 1 aims to identify fire resilience of the MSS based on fire lifecycle scenes. The disaster scene analysis and TOSE approach are integrated to construct the D-TOSE model for identifying fire resilience indexes, including assessment indicators and influential factors. Then, the modified technique for order preference by similarity to ideal solution (TOPSIS) is used to calculate influential factors' contributions on fire resilience for screening critical influential factors tailored to different MSSs. The identification methods in Phase 1 help operational staff and decision makers fully understand specific resilience capacities and influential factors involved in the fire lifecycle, which encourages them to engage in resilient operation of MSS within a clear manageable scope.

3.2.1 Disaster scene analysis to identify assessment indicators

To date, many studies have reached a basic consensus that the resilience capacities are effective assessment indicators to quantify disaster resilience of infrastructure systems [43], and they include absorption capacity to prevent disturbances, resistance capacity to minimize consequences, recovery capacity to return to normal operations, and adaptation capacity to learn from undesirable situations [44, 45]. However, the connotation of resilience capacities is still very abstract for front-line operational staff and decision makers, which easily causes inefficient resilience management due to significant understanding bias when assessing resilience capacities. Because the basis of analyzing the antecedents and consequences of disasters is to determine specific scenes (or scenarios), the scene analysis has been increasingly applied to infrastructure disaster management [46, 47]. It is worth noting that the scene analysis emphasizes that one scene should contain both “hard” and “soft” elements including physical space, awareness, and behaviors [48], which coincides with the system boundaries defined in system resilience theory. Hence, combing with specific disaster characteristics, one fire scene can be divided into reaction components, reaction time, reaction causes, reaction behaviors, and scene statuses to capture resilience capacity and its corresponding efficacy [49], which facilitates understanding and assessing resilience capacities through observing scene status of the MSS under its different reaction components’ reaction behaviors. The fire lifecycle is divided into the following four fire scenes as shown in Table 1:

(1) the prevention scene, where the absorption capacity forms, is characterized by the prevention status of unsafe passenger behaviors and unsafe equipment and facilities;

(2) the response scene, where the resistance capacity forms, is characterized by the response status of fire detection, evacuation, and extinguishment;

(3) the restoration scene, where the recovery capacity forms, is characterized by the reuse status of equipment, facilities and operation services;

(4) the learning scene, where the adaptation capacity forms, is characterized by the feedback status from the operation organization.

Table 1 Fire scene analysis of an MSS

Scene type	Prevention scene	Response scene	Restoration scene	Learning scene
Reaction component	• Equipment and facilities • Inspection team • Training team • Passengers	• Equipment and facilities • Emergency response team • Passengers	• Emergency response team • Maintenance team • Customer service team	• Technical service team • Data and analytics team • Duty manager
Reaction time	Pre-disaster	In-disaster	Post-disaster	After resuming operation
Reaction behavior	• Fire safety and emergency training • Security checks for flammable and explosive substances • Routine inspection of electrical equipment	• Fire alarm system warning • Coordination with internal and external rescue teams to fight fire • Evacuation commands for passengers	• Repair work on the site • Operation order recovery • Compensation for casualties	• Investigation of incidents • Summary of experience and knowledge • Rectification implementation
Scene status	Prevention status of • unsafe passenger behavior • unsafe equipment and facilities	Response status of • fire detection • fire evacuation • fire extinguishment	Reuse status of • equipment and facilities • operation services	Feedback status of • operation organization
Resilience capacity	Absorption capacity (Abs)	Resistance capacity (Res)	Recovery capacity (Rec)	Adaptation capacity (Ada)
Resilience efficacy	Prevent fires	Control the fire spread	Restart operation services	Avoid recurrence

3.2.2 TOSE approach to identify preliminary influential factors

It should be acknowledged that identifying influential factors of fire resilience not only emphasizes the disaster lifecycle, but also needs to focus on the whole system and systematically subdivide the influential factors to reflect different types of reaction components' contribution to resilience in fire scenes. In this research, the TOSE approach is applied to further subdivide all the influential factors into technical, organizational, social, and economic dimensions, which respectively represent physical hardware operation related to equipment working status and facility design features; operational management implementation related to all the internal work teams including inspection team, training team, emergency response team, maintenance team, customer service team, technical service team and data and analytics team; social organization interaction related to passengers and external organization access; and resource allocation related to decision makers' input of investments, equipment, and manpower [34, 50]. Then, four dimensions from the TOSE approach and four fire scenes from the disaster scene analysis are combined to establish the D-TOSE model, which provides a systematic classification matrix to identify influential factors. Moreover, the relevance of each influential factor to the 4R attributes of system resilience (namely, robustness, redundancy, resourcefulness, and rapidity [51]) should also be judged to guarantee that all identified influential factors are closely related to fire resilience, which can confirm when influential factors come into play, whether the MSS better resist various negative impacts of fire, possess more replaceable redundancy components, schedule resources more reasonably, and recover operational services faster.

3.2.3 Modified TOPSIS method to screen critical influential factors

The limited investment should be optimized the most critical influential factors of fire resilience; in addition, different operational management schemes and philosophies of metro stations in various cities lead to different preferences for critical influential factors. Therefore, it is essential to screen critical influential factors before the formal assessment and optimization of fire resilience of an MSS. The TOPSIS method has been gradually applied to screen the influential factors of engineered system resilience [52], and this research modifies traditional TOPSIS method by constructing the "degree of contribution" as the screening threshold for each influential factor and quantifying it by combining the "degree of importance" and the "degree of differentiation", where the "degree of importance" aims to find which influential factor is no longer important with technological development, and the "degree of differentiation" aims to find which influential factors are not differentiated for most metro stations. The steps of applying the modified TOPSIS method to screen the critical influential factors are illustrated as follows [53, 54].

(5) Step1: Construct the initial decision matrix X

Each influential factor has three attributes: likelihood of occurrence (p), severity of consequence (c), controllability of uncertainty (α), and they can be marked through questionnaire survey on a 5-point Likert-type scale as "*Unlikely=1, Seldom=2, Occasional=3, Likely=4, Frequent=5*", "*Negligible=1, Minor=2, Moderate=3, Major=4, Catastrophic=5*", and "*Very difficult =1, Difficult =2, Neutral=3, Easy=4, Very easy =5*" respectively. Meanwhile, p and c are positive, and α is negative; namely, the larger the value of p and c, the smaller the value of α, the more important this influential factor is [55]. The initial decision matrix

X is shown in Equation (1):

$$X=\begin{bmatrix} X_{11} & X_{12} & X_{13} \\ X_{21} & X_{22} & X_{23} \\ \vdots & \vdots & \vdots \\ X_{m,1} & X_{m,2} & X_{m,3} \end{bmatrix}=\begin{bmatrix} \frac{\sum_1^K x_{11}}{K} & \frac{\sum_1^K x_{12}}{K} & \frac{\sum_1^K x_{13}}{K} \\ \frac{\sum_1^K x_{21}}{K} & \frac{\sum_1^K x_{22}}{K} & \frac{\sum_1^K x_{23}}{K} \\ \vdots & \vdots & \vdots \\ \frac{\sum_1^K x_{m,1}}{K} & \frac{\sum_1^K x_{m,2}}{K} & \frac{\sum_1^K x_{m,3}}{K} \end{bmatrix} \tag{1}$$

Where i is the i^{th} preliminary influential factor $(i=1,2,\cdots,m)$; j is the j^{th} influential factor attribute $(j=1,2,3)$; X_{ij} is the value of j^{th} attribute of i^{th} influential factor, which is obtained by questionnaire survey with K experts.

(6) Step2: Calculate the weighted sum of squares of the distance between positive and negative ideal solutions $f_i(\omega)$

The questionnaire data X_{ij} is normalized to r_{ij} with Equation (2)-(3) for positive attributes (p, c) and negative attribute (α). The weights of p, c, and α are ω_1, ω_2, and ω_3 respectively, and the total weight is 1. Then, $f_i(\omega)$ is calculated with Equation (4):

$$r_{ij}=\frac{X_{ij}-min(X_{ij})}{max(X_{ij})-min(X_{ij})},\ \text{where } j=1,2 \tag{2}$$

$$r_{ij}=\frac{max(X_{ij})-X_{ij}}{max(X_{ij})-min(X_{ij})},\ \text{where } j=3 \tag{3}$$

$$f_i(\omega)=f_i(\omega_1,\omega_2,\omega_3)=\sum_{j=1}^{3}\omega_j^2\left(1-r_{ij}\right)^2+\sum_{j=1}^{3}\omega_j^2 r_{ij}^2 \tag{4}$$

When the distance is used as a limiting condition, a smaller value of $f_i(\omega)$ is better. To achieve this goal, the goal programming model is established as Equation (5), then Lagrange function is constructed as Equation (6) to calculate the optimal solution as Equation (7)

$$minf(\omega)=\sum_{i=1}^{3} f_i(\omega),\ \text{where } \sum_{j=1}^{3}\omega_j=1,\omega_j\geq 0, j=1,2,3 \tag{5}$$

$$F(\omega,\lambda)=\sum_{i=1}^{m}\sum_{j=1}^{3}\omega_j^2\left[\left(1-r_{ij}\right)^2+r_{ij}^2\right]-\lambda\left(1-\sum_{j=1}^{3}\omega_j\right) \tag{6}$$

$$\omega_j=\frac{\mu_j}{\sum_{j=1}^{3}\mu_j},\ \text{where } \mu_j=\frac{1}{\sum_{i=1}^{36}\left[\left(1-r_{ij}\right)^2+r_{ij}{}^2\right]}, j=1,2,3 \tag{7}$$

(7) Step3: Calculate the degree of importance I_i

Based on the weights calculated in Step 2, I_i is calculated with Equation (8):

$$I_i = \omega_1 x_{i1} + \omega_2 x_{i2} + \omega_3 (6 - x_{i3}), \text{ where } i = 1,2,\cdots,m \tag{8}$$

The threshold value of I_i is set to delete influential factors that are unlikely to occur, have negligible consequences, and are very easy to control. Hence, it is calculated as follows: $I_0 = \omega_1 \times 2 + \omega_2 \times 2 + \omega_3 \times (6-4) = 2$. When $I_i < I_0$, this influential factor is judged to be unimportant.

(8) Step4: Calculate the degree of differentiation D_i

The influencing proportion of i^{th} influential factor to the whole influential factor system is defined as k_i in Equation (9). Taking into account the differences in the relative importance of each attribute of i^{th} influential factor, the influential proportion of attribute j of i^{th} influential factor is defined as p_{ij} in Equation (10).

$$k_i = \frac{f_i(\omega)}{\sum_{i=1}^{m} f_i(\omega)}, \text{ where } i = 1,2,\cdots,m \tag{9}$$

$$p_{ij} = \frac{r_{ij}k_i}{\sum(r_{ij}k_i)}, \text{ where } i = 1,2,\cdots,m;\ j = 1,2,3 \tag{10}$$

Based on the entropy theory, entropy value H_i and entropy weight e_i can be combined to determine each influential factor's D_i with Equations (11)-(13):

$$H_i = -k \sum_{j=1}^{3} p_{ij} ln p_{ij}, \text{ where } k = \frac{3}{lnm} \text{ to make sure that } H_i \epsilon [0,1] \tag{11}$$

$$e_i = \frac{1-H_i}{m-\sum_{i=1}^{m} H_i}, \text{ where } i = 1,2,\cdots,m \tag{12}$$

$$D_i = \frac{e_i}{H_i} = \frac{1-H_i}{(m-\sum_{i=1}^{m} H_i)H_i}, \text{ where } i = 1,2,\cdots,m \tag{13}$$

The larger the value of D_i means that i is more beneficial for decision making. However, when H_i is infinitely close to 1, the contribution of each attribute is consistent, resulting in the influential factor i not having a substantial role compared with the other influential factors. Therefore, the maximum value of H_i is generally set to 0.8 as the threshold, and D_i's threshold value D_0 can be calculated accordingly [56]. When $D_i < D_0$, this influential factor is judged to be undifferentiated.

(9) Step5: Calculate the degree of contribution C_i

To ensure that influential factor i is important and differentiated to MSS fire resilience at the same time,

I_i and D_i are combined to calculate C_i with Equation (14):

$$C_i = \frac{I_i D_i}{\sum_{i=1}^{36} I_i D_i}, \text{ where } i = 1,2,\cdots,m \tag{14}$$

According to the threshold values of I_i and D_i, C_i's threshold value C_0 can be calculated to screen critical influential factors. When $C_i < C_0$, this influential factor is deleted.

3.3 Assessment methods in Phase 2

Phase 2 aims to assess fire resilience of the MSS based on causality inference. The BN model is applied to simulate complex causality between fire resilience capacities and their influential factors. Then fuzzy comprehensive evaluation method (FCEM) and Leaky Noisy-OR model are respectively applied to calculate the prior probabilities and conditional probabilities of nodes in the model according to questionnaire survey on causality among nodes. Finally, fire resilience is assessed through BN inference including forward and backward propagation analysis. The assessment methods in Phase 2 help operational staff and decision makers understand how fire resilience forms and emerges under complex causality, grasp MSS's current fire resilience level, and reveal the weakest chains in the fire resilience operation process.

3.3.1 Bayes theorem to construct the BN model

Considering the uncertainties of the fire lifecycle, this research applies the BN model and its inference rules to assess fire resilience. The BN model is a directed acyclic graph consisting of nodes and directed arcs, where the nodes represent various random variables and the directed arcs directing from the parent node to the child node quantify the conditional dependencies between nodes [57]. Additionally, a node not linked to any parent node is a root node, and a node not linked to any child node is a leaf node. In this research, fire resilience is regarded as the leaf node. Based on fire scene analysis of the MSS, fire resilience, four resilience capacities identified as assessment indicators, and influential factors identified from TOSE perspectives can be connected into one BN model with clear causality structure through fire scene status. The BN model can reveal how influential factors affect the emergence process of resilience capacities and how resilience capacities further affect the formation process of fire resilience during fire lifecycle. Supposing a BN model consists of n variables $X_1, X_2, X_3, \ldots, X_n$, the corresponding decomposition of the joint probability distribution of variables can be reported as Equation (15) based on Bayes theorem [58]:

$$P(X_1, X_2, X_3, \ldots, X_n) = \prod_{i=1}^{n} P(X_i | parents(X_i)) \tag{15}$$

where $parents(X_i)$ represents the parent node of variable X_i.

It is worth noting that when the data source used for Bayesian inference is from questionnaire survey, each node state is usually set with binary parameters [59, 60], which is consistent with the characteristics of participants' understanding and memory of causalities of historical events, guaranteeing the surveyed experts can accurately invoke the related work experience when they fill out questionnaires. Therefore, each node is equipped with two state parameters: "0" and "1", in which "1" indicates that the node fails, and vice versa. Then, in the BN model, the forward propagation analysis can be carried out to infer the probability of non-failure of the leaf node as the assessment result of MSS fire resilience; and the backward propagation analysis can be carried out to reveal the critical cause chain with the biggest contribution to the fire resilience failure.

3.3.2 Leaky Noisy-OR model to calculate node probability tables

After constructing the BN model, node probability tables (NPTs) consisting of the prior probability of the root nodes and the conditional probability of the non-root nodes should be calculated to infer the leaf node's non-failure probability as fire resilience. It is assumed that a child node Y has q parent nodes in $X_T = \{X_1, X_2, \ldots, X_i, \ldots, X_q\}$, and both the child node and its parent nodes have binary state parameters. Thus, 2^q questions need to be set in the questionnaire to obtain expert judgment for calculating the conditional probability of Y, which causes exponential growth of computational complexity [61]. To make the information obtained from experts reliable, the *Noise-OR* model is widely applied to simplify the calculation of the conditional probability of non-root nodes by only setting q questions about the failure probability of Y when only one of its parent nodes fails [62], and the simplified formula is shown in Equation (16):

$$Noisy\ OR\text{:}\ \ P(Y|X_T) = 1 - \prod_{i=1}^{q}\big(1 - P(Y|X_i)\big) \tag{16}$$

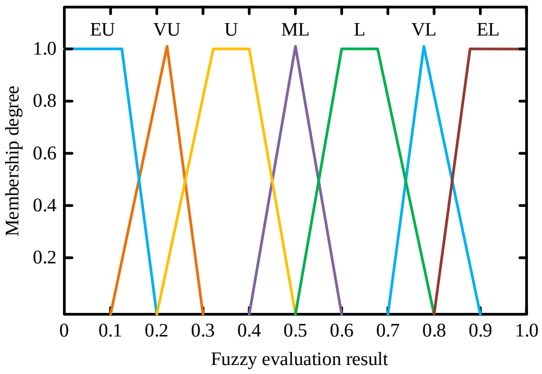
More importantly, considering that the fires occurring in MSSs are sometimes caused by unpredictable and accidental influential factors, a leaky node X_L is introduced to supplement possible factors that may be neglected. The basic assumption of the *Leaky Noisy-OR* model is that when all the parent nodes of a child node Y are in a non-failure state, it is possible that Y is in a failure state due to the existence of the leaky node [63]. The model is explained in Equation (17):

$$Leaky\ Noisy\ OR\text{:}\ \ P(Y|X) = 1 - \big(1 - P(Y|X_L)\big)\prod_{i=1}^{q}\frac{1-P(Y|X_i)}{1-P(Y|X_L)} \tag{17}$$

where $P(Y|X_L)$ represents the probability of the occurrence of Y in the absence of other causes listed in the BN structure. Considering the uncertainty of other unpredicted factors, it is assumed that $P(Y|X_L)$ is normally distributed with a confidence interval of 0.9; namely, $P(Y|X_L)$=0.1 [64].

Finally, the complete NPT of each node in the BN model can be obtained by experts only judging the failure probability of each root node and the probability that each parent node failure will cause its child node failure. Moreover, considering that the causality judgment should be more meticulous than the importance judgment of influential factors in *Section 3.2.3*, the failure likelihood of each root node and their causality with child nodes are measured through questionnaire survey on a scale of 1-7 points [65]. Then, all questionnaire data representing expert judgment are transformed into node probabilities through FCEM, and the specific data transformation process is shown in Table 2.

Table 2 Data transformation process of expert questionnaire data

Linguistic term	Fuzzy number	Graphical presentation of the linguistic term
Extremely unlikely (EU)	(0, 0, 0.1, 0.2)	
Very unlikely (VU)	(0.1, 0.2, 0.2, 0.3)	
Unlikely (U)	(0.2, 0.3, 0.4, 0.5)	
More or less (ML)	(0.4, 0.5, 0.5, 0.6)	
Likely (L)	(0.5, 0.6, 0.7, 0.8)	
Very likely (VL)	(0.7, 0.8, 0.8，0. 9)	
Extremely likely (EL)	(0.8, 0.9, 1, 1)	

Questionnaire data processing step [66]	Specific formula, see Equations (18)-(23)
Step 1: Calculate the arithmetic mean of n experts' fuzzy evaluation results $F = (F_a^1, F_a^2, F_a^3, F_a^4)$	$F_a^1 = \frac{1}{n}\sum_{k=1}^{n} F_k^1,\ F_a^2 = \frac{1}{n}\sum_{k=1}^{n} F_k^2,\ F_a^3 = \frac{1}{n}\sum_{k=1}^{n} F_k^3, F_a^4 = \frac{1}{n}\sum_{k=1}^{n} F_k^4$ (18)
Step 2: Calculate the distance between each expert's fuzzy evaluation result F_k and the arithmetic mean of all experts' fuzzy evaluation results F_a	$d(F, F_a) = \frac{1}{4}(\lvert F_k^1 - F_a^1\rvert + \lvert F_k^2 - F_a^2\rvert + \lvert F_k^3 - F_a^3\rvert + \lvert F_k^4 - F_a^4\rvert)$ (19)
Step 3: Calculate the similarity between each expert's fuzzy evaluation result F_k and the arithmetic mean of all experts' fuzzy evaluation results F_a	$S(F_k, F_a) = 1 - \frac{d(F_k, F_a)}{\sum_{k=1}^{n} d(F_k, F_a)}$ (20)
Step 4: Calculate the weight of each expert	$\omega(F_k, F_a) = \frac{S(F_k, F_a)}{\sum_{k=1}^{n} S(F_k, F_a)}$ (21)
Step 5: Integrate the expert fuzzy evaluation results	$F = (F^1, F^2, F^3, F^4) = \sum_{k=1}^{n} \omega_k F_k = \sum_{k=1}^{n} \left(\frac{S(F_k, F_a)}{\sum_{k=1}^{n} S(F_k, F_a)} F_k\right)$ (22)
Step 6: Calculate the defuzzification value	$P = \frac{1}{4}(F^1, F^2, F^3, F^4)$ (23)

3.4 Optimization methods in Phase 3

Phase 3 aims to optimize fire resilience of the MSS. Considering the impacts of influential factors' time-varying characteristics on fire resilience, the DBN model is established through setting probability distribution functions for the state transition of different influential factors. Then, sensitivity analysis is conducted to formulate static optimization strategies based on diagnostic perspective, and critical importance (CI) analysis is applied to formulate dynamic optimization strategies based on predicted perspective. The optimization methods in Phase 3 incorporate the degradation and strength characteristics of various influential factors of fire resilience over time into the optimization strategy, which makes BN model be automatically updated to determine optimization priorities from both static and dynamic aspects.

3.4.1 DBN model to capture system state transitions

In the practice of resilience management through the BN model, decision makers have frequently ignored the change characteristics of system component states over time, which makes optimization strategies not appropriate for long-term system operations [67]. Therefore, to incorporate influential factors' state change rules into the decisions on optimization priorities, the Markov law is introduced into the traditional BN model to generate the DBN model with the following two assumptions [68]:

(1) The BN structure does not change over time, and the conditional probability remains the same;

(2) The probability distribution of the next state depends only on the current state and not on the sequence of events that preceded it.

A DBN model has two types of arcs, including normal arcs linking nodes at the same time slice and temporal arcs linking nodes at different time slices. The joint probability of $X = (X_1, X_2, \dots, X_i, \dots, X_n)$ at the $t + \Delta t$ time slice can be mathematically expressed as Equation (24):

$$P(X^{t+\Delta t}) = \prod_{i=1}^{n} P(X_i^{t+\Delta t} | X_i^t, Pa(X_i^t), Pa(X_i^{t+\Delta t})) \tag{24}$$

where $Pa(X_i^t)$ and $Pa(X_i^{t+\Delta t})$ represent parent nodes of X_i^t and $X_i^{t+\Delta t}$.

3.4.2 Sensitivity and CI analysis to determine optimization priorities

As an in-depth diagnosis method, sensitivity analysis is an indispensable step to quantify the impact of each influential factor on the target nodes in the BN model [69]. In this research, considering that the purpose of the sensitivity analysis is to determine the static optimization priorities of root nodes based on their current rank of nonfailure probabilities, hence, the prior probability of each root node is increased step by step with a 5% step length from the original probability to 100%, which simulates decision makers gradually increasing optimization inputs for this root node until it does not fail completely, and then the increments of four fire resilience capacities are observed as optimization effects. Furthermore, the optimization effects of four resilience capacity increments on fire resilience are also observed. Finally, the optimization priority of influential factors and resilience capacities can be ranked by calculating the average sensitivity coefficient (i.e., the percentage change in the nonfailure probability of the root note to the percentage change in the target nodes [70]).

Compared with static sensitivity coefficient, CI indicator, which is defined as the ratio of the change rate of the root node's failure probability to the leaf node's failure probability, can better grasp the dynamic influence of root node failure on leaf node failure from both perspectives of sensitivity and the failure probability itself. Meanwhile, CI reflects that optimizing a root node with a high failure probability is easier than a root node with a low failure probability [71, 72]. In this research, the rank changes in the CI of the influential factors are observed to determine dynamic changes in the optimization priorities, helping operational staff predict the contribution changes of different influential factors on fire resilience over increasing operating life, and make scientific decisions on breakdown maintenance and safety investments. The CI of the root node *i* at a specific time slice is calculated as Equation (25) [73]:

$$I_i = \frac{P(X_i = 1) * \left(P(R = 1|X_i = 1) - P(R = 1|X_i = 0)\right)}{P(R = 1)} \tag{25}$$

where X_i is a binary variable which represents the state of root node *i* (i.e., 1 and 0 represents failure state and reliable state, respectively); R represents the state of leaf node; $P(R = 1|\cdot)$ represents the conditional probability of the leaf node failure; $P(R = 1)$ represents the failure probability of the leaf node.

4 Case study results and discussion

4.1 Study case and data collection

Nanjing MSS has served about 3.5 million passengers daily since it opened in 2005, and it has real historical experience in coping with fire accidents. Therefore, Nanjing MSS was chosen as a real-life case application to demonstrate how the developed D-TOSE model, BN model, and DBN model assist operational staff and decision makers to identify, assess and optimize MSS fire resilience at city level, which can provide valuable references to other cities' MSS facing challenges of fire resilience management. Given that the number of participants who can make professional judgment on influential factors' importance and causality with sufficient relevant knowledge and practical experience is minimal, most case studies tend to choose 5-30 experienced experts to guarantee the validity of the questionnaire data [74-76].

To collect data for screening critical influential factors of fire resilience, a one-day facilitated workshop with *Questionnaire survey A* (see *Section Supplementary material*) that investigates the contribution degree of each influential factor was conducted in Nanjing with 51 participants, including front-line operational staff for station operation, line operation, and company management from the Nanjing metro operating company. And the selection of participants is strictly abided by the criteria suggested by Witkin and Altschuld to guarantee that all participants have a deep understanding of metro station fire in the operation phase [77]. The workshop started with a detailed presentation to introduce the preliminary influential factors and their corresponding failure modes identified through the D-TOSE model, then followed by a panel discussion for the 51 participants to supplement and revise the factors. Immediately after the facilitated workshop, the updated *Questionnaire A* was conducted among 51 participants independently to rate p, c, and α of each influential factor on a scale of 1 to 5 points. Among the 51 returned questionnaires, 15 invalid questionnaires were removed due to the participants' insufficient rating duration and lack of working experience (i.e., less than 3-year working periods). Finally, 36 valid questionnaires were collected, with a response rate of 70.6%.

To collect data for calculating the NPTs, an online *Questionnaire survey B* (see *Section Supplementary material*) was conducted to investigate the causality among the influential factors on a scale of 1 to 7 points. In this survey, the participant quality is more important than its quantity because the accuracy of causality judgment depends heavily on the participants' experience [78]. Hence, 25 out of 36 valid respondents to the *Questionnaire A* were selected to conduct *Questionnaire B* due to their post-fire treatment experience in Nanjing MSS. Participants need to individually judge the causality for each pair of nodes in the BN model. Finally, 7 invalid questionnaires were removed due to participants' carelessness for failing one attention test item set in *Questionnaire B*. Thus, 18 valid questionnaires were collected for further analysis, with a response rate of 72%. And the demographic information of valid respondents to the *Questionnaire A* and *Questionnaire B* is listed in Table 3.

Table 3 Demographic information of valid respondents to the *Questionnaire A* and *Questionnaire B*

Item	Type	*Questionnaire A*		*Questionnaire B*	
		Number	Percent	Number	Percent
Work experience	3 to 5 years	6	16.7%	2	11.1%
	5 to 10 years	23	63.9%	9	50.0%
	over 10 years	7	19.4%	7	38.9%
Educational level	Bachelor degree	19	52.8%	10	55.6%
	Master degree	14	38.9%	6	33.3%
	Doctoral degree	3	8.3%	2	11.1%
Job level	Station operation	21	58.3%	13	72.2%
	Line operation	10	27.8%	2	11.1%
	Company management	5	13.9%	3	16.7%
Department	Inspection and maintenance team	10	27.8%	4	22.2%
	Technical service team	5	13.9%	2	11.1%
	Emergency response team	9	25.0%	5	27.8%
	Analysis and tasking team	2	5.6%	2	11.1%
	Training and development team	3	8.3%	1	5.6%
	Customer service team	2	5.6%	1	5.6%
	Senior management team	5	13.9%	3	16.7%
Post-fire treatment experience	Involvement	25	69.4%	18	100.0%
	Non-involvement	11	30.6%	0	0.0%

4.2 Scene-based identification of fire resilience for Nanjing MSS

4.2.1 Preliminary influential factors

Based on the D-TOSE model, a total of 36 influential factors of fire resilience for Nanjing MSS are preliminarily identified from national codes issued by the Chinese Ministry of Transport, enterprise standards issued by the Chinese metro operating companies, and metro fire accidents reported by official news. Furthermore, 3 out of 36 influential factors were supplemented by participants through the facilitated workshop, i.e., $AbsT_3$, $ResO_6$, and $AdaO_3$. All influential factors' relationship with the 4R attributes of system resilience, and specific failure modes are illustrated in Table 4.

Table 4 Preliminary influential factors of fire resilience for the Nanjing MSS

Influential factor's dimension, relationship with 4Rs, coding, and contents			Failure mode (i.e., consequences of influential factor failure on fire scene)
Prevention scene for absorption capacity			
T (R1)	$AbsT_1$	Passenger and baggage security screening system	Undetected flammable or explosive items carried by passengers
	$AbsT_2$	Integrated supervision and control system	Lack of real-time monitoring and warning of fire hazards
	$AbsT_3$	Cigarette extinguisher	Passengers' unextinguished cigarette butts thrown at stations
O (R1)	$AbsO_1$	Inspection and maintenance of electrical equipment	Power failures such as short circuits of aging equipment
	$AbsO_2$	Fire safety and emergency training	Lack of fire prevention awareness and emergency management abilities
	$AbsO_3$	Effectiveness of security screening operations	Failure of checking all carry-on belongings of passengers due to negligence and careless attitudes
	$AbsO_4$	Compliance of hot-work procedures	Operation errors or missing protective measures in regular hot-work procedures
	$AbsO_5$	Inspection and maintenance of ancillary equipment	Disordered placement of wires and circuits in the auxiliary equipment room resulting in power failures
	$AbsO_6$	Stability control of the environment	Unsafe environmental conditions such as humidity, high temperatures, and extensive dust inside the station
S (R1)	$AbsS_1$	Passengers' safety knowledge and behaviors	Passengers smoking in the station, throwing unextinguished cigarette butts, carrying flammable or explosive items, etc.
	$AbsS_2$	Safe operation of underground commercial areas	Power usage, decoration materials, and firefighting equipment in the underground commercial areas without meeting fire safety requirements
E (R2, R3)	$AbsE_1$	Resource allocation for fire prevention	Fire occurrence due to irrational allocation of investments, equipment, and manpower in fire prevention
Response scene for resistance capacity			
T (R2, R4)	$ResT_1$	Fire alarm system	Delays in fire emergency response and rescue caused by the fire alarm system failing to warn in time
	$ResT_2$	Emergency safety equipment	Disordered emergency evacuation due to the failure or wrong use of emergency equipment such as the emergency lighting, broadcast system, and power supply
	$ResT_3$	Current evacuation design of the metro station	Low evacuation efficiency and high-frequency stampede accidents due to chaotic spatial layout or the imbalance between metro station's evacuation capacity and the current passenger flow
	$ResT_4$	Current fire-resistance design of the metro station	Rapid fire spread and severe equipment and facilities damage due to fire-resistance design defects
	$ResT_5$	Firefighting equipment	Inefficient and slow extinguishing due to insufficient supply or failure of firefighting equipment such as dry powder fire extinguishers
	$ResT_6$	Smoke ventilation and extraction system	Rapid rise in temperature, low visibility, and high concentration of poisonous gas in the metro station due to failures of smoke ventilation and extraction systems
O (R4)	$ResO_1$	Regular security detection of fire	Delays in fire emergency response and rescue due to negligence of fire detection
	$ResO_2$	Current fire emergency plan	Confusion at fire emergency site due to the absence of an effective fire emergency plan as a guide

	$ResO_3$	Coordination of the emergency response team	Inefficient firefighting and evacuation due to confused labor division, unclear emergency procedures, and information delay in emergency response and rescue
	$ResO_4$	Skills of staff in the emergency response team	Wrong or inefficient emergency work due to lack of skills and experience in emergency responses
	$ResO_5$	Implementation of emergency response actions	Aggravation of the fire consequences caused by missing or wrong critical emergency measures or procedures such as opening automatic ticket checkers and turning on emergency lighting
	$ResO_6$	Fire and rescue service access	Delays in firefighting and medical teams' rescue caused by the blockage of fire and rescue routes
S (R4)	$ResS_1$	Escape skills of the passengers	Increasing evacuation difficulty and casualties caused by passengers lacking basic escape knowledge and good psychological qualities
	$ResS_2$	Urban fire remote monitoring and networking system	Delays in external rescue and medical team receiving signals to arrive at the metro station and extinguish fires
E (R2, R3)	$ResE_1$	Resource allocation for firefighting	Prolonged burning fires due to irrational allocation of investments, equipment, and manpower in firefighting
Restoration scene for recovery capacity			
O (R2, R4)	$RecO_1$	Coordination of repair and rescue teams	Secondary and derivative accidents, the extension of the recovery time, and the increase in the recovery cost due to inefficient cooperation of various on-site repair and rescue teams
	$RecO_2$	Supplementary supply of emergency equipment	Insufficient new emergency equipment to replace the broken equipment after fires
	$RecO_3$	Implementation of operation recovery actions	Delays in fire recovery progress due to missing or wrong critical recovery measures and procedures such as arranging treatment for the injured, organizing resuming operational order and public services
E (R2, R3)	$RecE_1$	Resource allocation for fire recovery	Prolonged interruption due to irrational allocation of investments, equipment, and manpower in fire recovery
Learning scene for adaptation capacity			
O (R3)	$AdaO_1$	Fire cause investigation	Recurring fires due to the lack of detailed investigation into root causes of previous fires
	$AdaO_2$	Summary of lessons learned	Lack of experience and lessons resulting in the staff involved are still not clear about their responsibilities
	$AdaO_3$	Implementation and supervision of the rectification	Failure of rectification and supervision measures for the hazards triggering previous fires
	$AdaO_4$	Archive of fire history data	Missing historical data due to careless data collection and report
E (R2, R3)	$AdaE_1$	Resource allocation for rectification	Recurring fires due to irrational allocation of investments, equipment, and manpower in rectification

Notes: T, O, S, and E refer to technical, organizational, social, and economic aspects, respectively; R1, R2, R3, and R4 represent robustness, redundancy, resourcefulness, and rapidity, respectively.

4.2.2 Critical influential factors

Based on the scores of three attributes p, c, and α of each influential factor from the 36 valid questionnaires collected, all preliminary influential factors' degree of importance, differentiation, and contribution were obtained as shown in Fig. 2. Then, 5 influential factors including $AbsT_2$, $AbsO_6$, $AbsS_2$, $RecO_2$, and $AdaO_4$ were deleted according to the thresholds of importance, differentiation, and contribution calculated $I_0 = 2$, $D_0 = 0.0271$, $C_0 = 0.0118$ based on *Section 3.2.3*. Notably, these five influential factors were deleted due to low degree of differentiation, which indicates that these influential factors have been implemented with unified standardized operation by the whole Nanjing MSS. Finally, 31 critical influential factors applicable to Nanjing MSS were obtained.

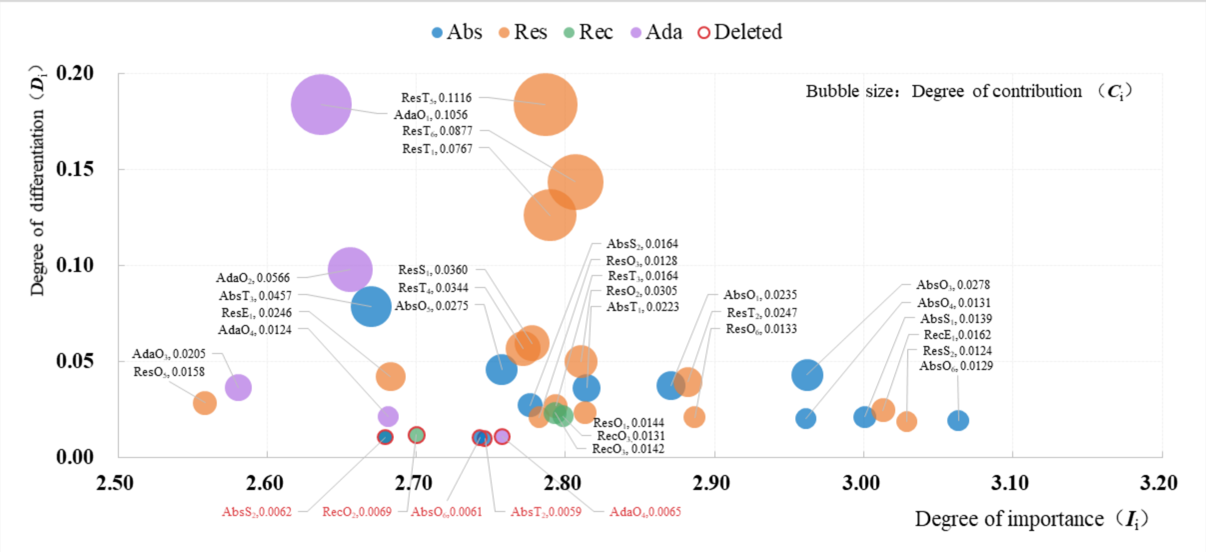


Fig.2. Degrees of importance, differentiation, and contribution of all preliminary influential factors

4.3 Causality-based assessment of fire resilience for Nanjing MSS

4.3.1 Constructed BN model

A BN model with 44 nodes integrating assessment indicators, fire scene status variables, and influential factors is constructed as shown in Fig. 3, and each node has two state parameters: fail (State 1) and not fail (State 0).

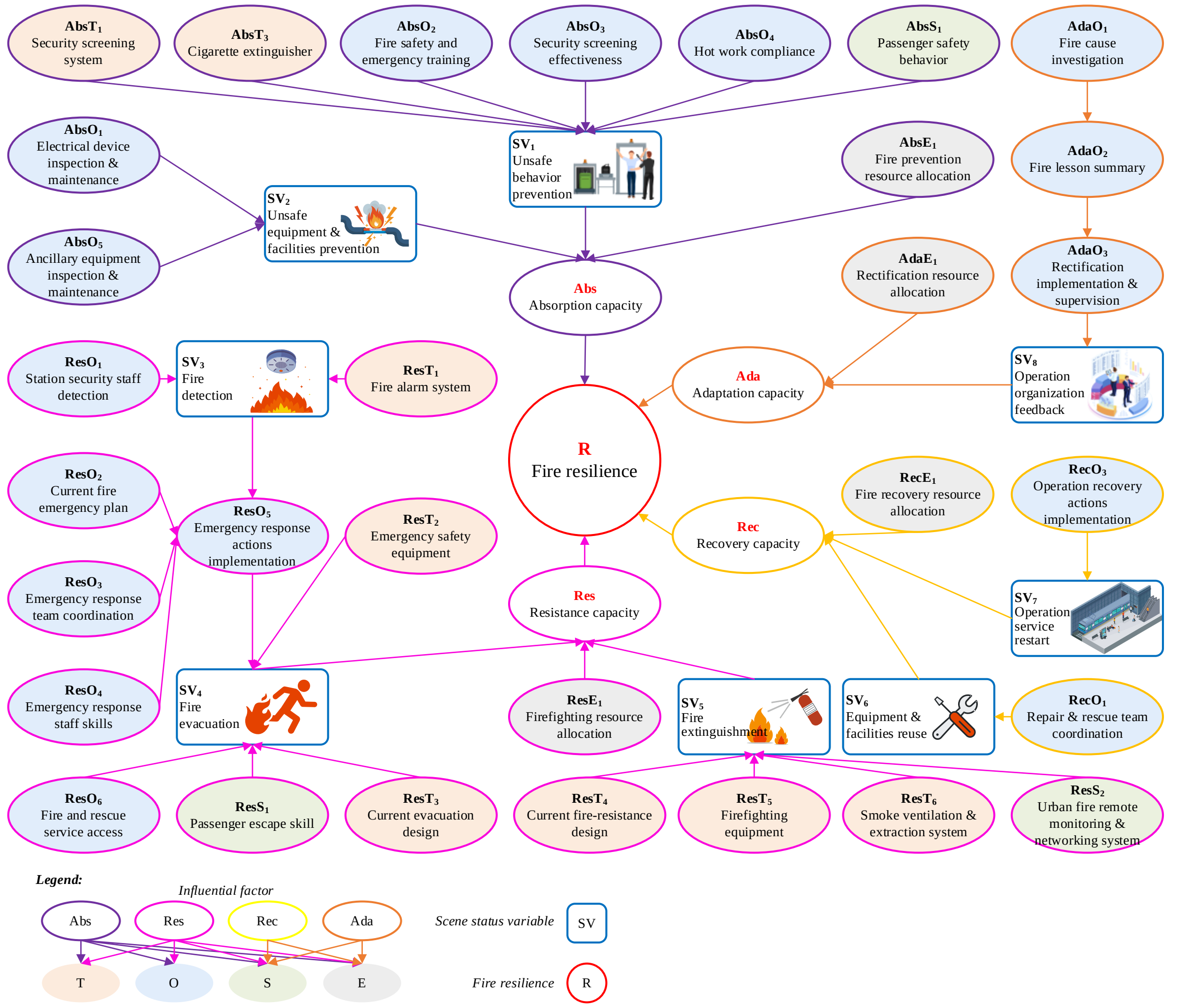


Fig. 3. BN model for assessing fire resilience of Nanjing MSS

All the participants agreed with the nodes and their causality established in this model. Meanwhile, all items rated by participants in the *Questionnaire B* reached the required level (inter-rater agreement $(R_{wg}) > 0.7$) proposed by James et al. [79], which confirms the validity of constructed BN structure. The meanings of various nodes in the BN model are as follows:

(1) 4 nodes represent fire resilience capacities, including absorption capacity (Abs), resistance capacity (Res), recovery capacity (Rec), and adaptation capacity (Ada); and the leaf node represents fire resilience (R);

(2) 8 auxiliary nodes represent fire scene status variables, including unsafe behavior prevention status (SV_1), unsafe equipment and facilities prevention status (SV_2), fire detection status (SV_3), fire evacuation status (SV_4), fire extinguishment status (SV_5), equipment and facilities reuse status (SV_6), operation service

restart status (SV_7) and operation organization feedback status (SV_8);

(3) 31 nodes represent influential factors of fire resilience. Among them, 27 nodes representing technical, organizational, and social influential factors determine fire scene status, then, fire scene status further affect fire resilience capacities; the remaining 4 nodes representing economic influential factors directly affect fire resilience capacities because the number of investments, equipment, and manpower allocated in the fire lifecycle can be directly applied to speed up fire resilience formation [80].

4.3.2 Forward propagation analysis

The process of the BN model to disseminate the effect of evidence through the network is defined as “propagation analysis” [81]. Propagation analysis helps to anticipate what kind of uncertainties might affect the underlying model. Forward propagation is a typical cause-to-effect analysis, where the probability of the target variable is inferred based on the probability of the cause variables and the propagation of the causality among them. According to the forward propagation analysis results shown in Fig. 4, the non-failure probabilities of Nanjing MSS's absorption capacity, resistance capacity, recovery capacity, adaptation capacity, and fire resilience are 75.5%, 70%, 76.9%, 84.8%, and 68.8%, respectively.

From the perspective of resilience capacities, it is evident that the Nanjing MSS has weak capacities to absorb and resist fires. $AbsS_1$ (passengers’ safety knowledge and behavior), $AbsO_3$ (effectiveness of security screening operations), and $ResO_4$ (skills of staff on the emergency response team) frequently fail with failure probabilities at 43.74%, 30.49%, and 27.07%, respectively, which rank in the top three among all the influential factors. From the perspective of the influential factor type, technical and economic factors are more reliable than organizational and social factors. Hence, it is necessary to strengthen operational staff skills through training and improve passenger safety awareness through regular broadcasts of safety knowledge in carriages [82].

4.3.3 Backward propagation analysis

Backward propagation is a typical effect-to-cause analysis to observe the leaf node, and the marginal probabilities of unobserved parent nodes are calculated by propagating the impact of the observed child node through the BN model in a backward fashion. In this research, the leaf node (i.e., fire resilience) is set to a complete failure state (i.e., $P(R = 1) = 1$) to identify the influential factors with high posterior probabilities in the BN model. According to the posterior probability results shown in Fig. 5, when the fire resilience of Nanjing MSS fails completely, the resilience capacity failure risks gradually increase in the order of adaptation, recovery, absorption, and resistance capacity, and their failure probabilities are 27.5%, 37.3%, 42.8%, and 50.6%, respectively. Moreover, the critical cause chain with the biggest contribution to the fire resilience failure was revealed, namely, "escape skills of passengers ($ResS_1$) → fire evacuation status (SV_4) → resistance capacity (Res) → fire resilience (R)". Hence, the resistance capacity was the most important guarantee for fire resilience formation in the Nanjing MSS, and the timely evacuation of passengers is the most effective measure to reduce casualties. Considering that fire evacuation efficiency is greatly affected by escape skills of passengers, it is also necessary to strengthen the publicity of fire knowledge and arrange professional command staff to help passengers evacuate quickly, which can avoid the cascading failure of the critical cause chain.

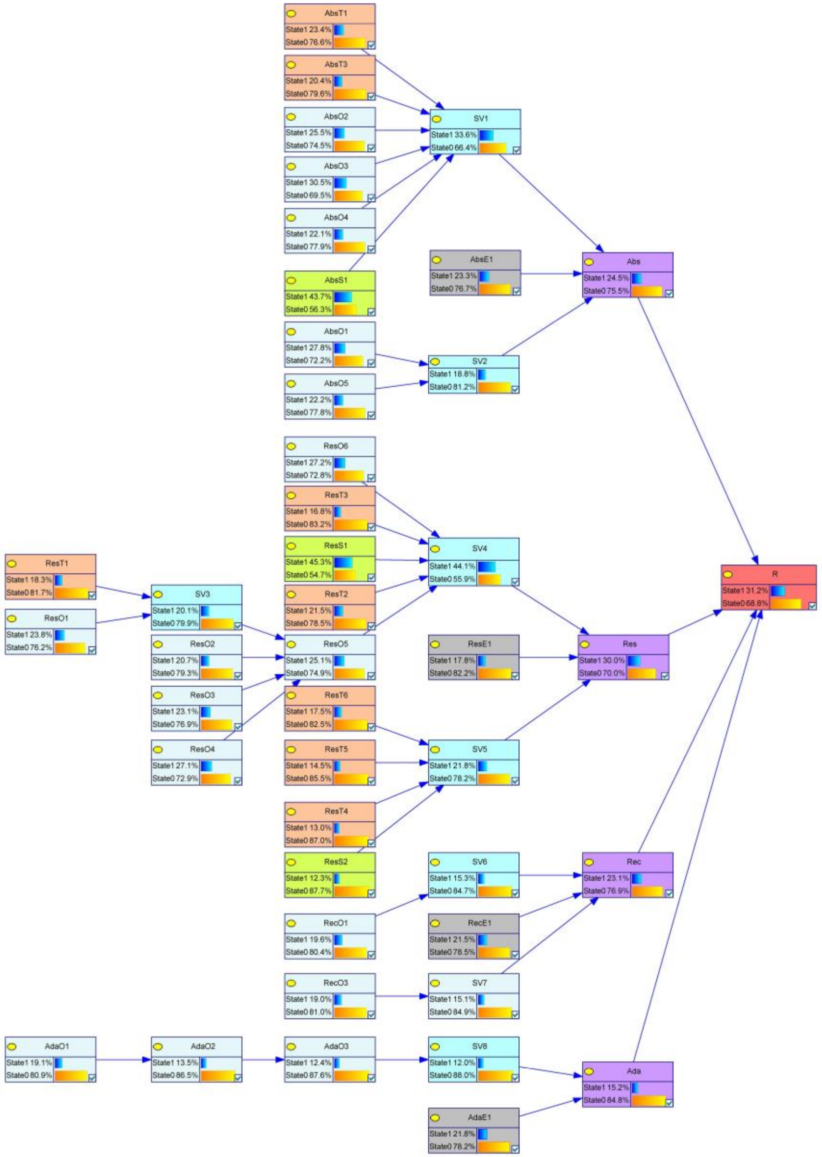


Fig. 4. Forward propagation analysis for assessing fire resilience

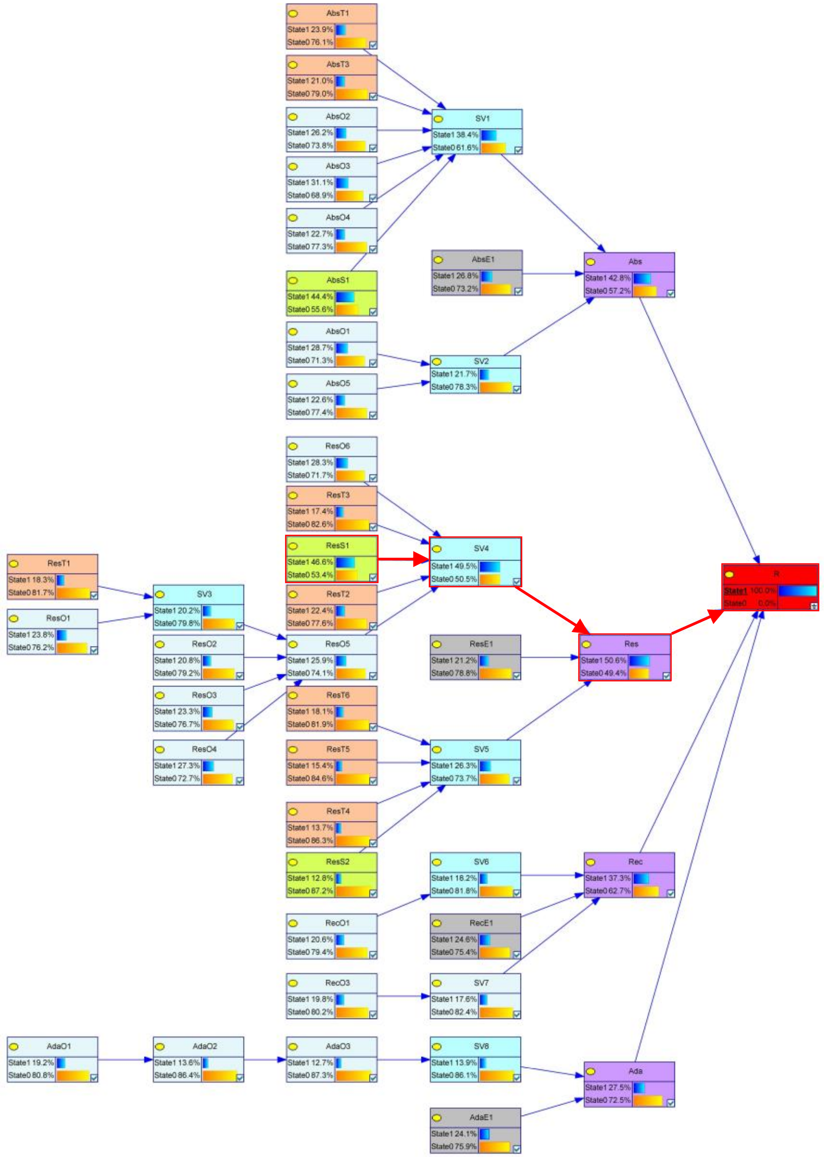


Fig. 5. Backward propagation analysis for revealing the critical cause chain

4.4 Time-based optimization strategies of fire resilience for Nanjing MSS

4.4.1 Static optimization strategies

To maximize fire resilience with limited resources, it is necessary to observe the effects of optimizing different root nodes on four resilience capacities [83]. The optimization priorities of rooted influential factors and resilience capacities can be ranked according to average sensitivity coefficients as shown in Fig. 6.

Targeted node	Optimized node	Prior probability	Sensitivity coefficient (Rank)
Abs	$AbsT_1$	0.766	0.029 (7)
	$AbsT_3$	0.796	0.037 (4)
	$AbsO_1$	0.722	0.043 (2)
	$AbsO_2$	0.745	0.040 (3)
	$AbsO_3$	0.695	0.030 (6)
	$AbsO_4$	0.779	0.035 (5)
	$AbsO_5$	0.778	0.026 (9)
	$AbsS_1$	0.563	0.028 (8)
	$AbsE_1$	0.767	0.193 (1)
Res	$ResT_1$	0.817	0.001 (7)
	$ResT_2$	0.785	0.051 (3)
	$ResT_3$	0.832	0.048 (4)
	$ResT_4$	0.870	0.057 (2)
	$ResT_5$	0.855	0.075 (1)
	$ResT_6$	0.825	0.045 (5)
	$ResO_1$	0.762	0.002 (6)
Res	$ResO_2$	0.793	0.006 (7)
	$ResO_3$	0.769	0.008 (6)
	$ResO_4$	0.729	0.010 (5)
	$ResO_6$	0.728	0.056 (2)
	$ResS_1$	0.547	0.055 (3)
	$ResS_2$	0.877	0.053 (4)
	$ResE_1$	0.822	0.241 (1)
Rec	$RecO_1$	0.804	0.077 (2)
	$RecO_3$	0.810	0.066 (3)
	$RecE_1$	0.822	0.233 (1)
Ada	$AdaO_1$	0.809	0.001 (2)
	$AdaE_1$	0.785	0.146 (1)
R	Abs	0.572	0.310 (1)
	Res	0.494	0.306 (2)
	Rec	0.769	0.298 (3)
	Ada	0.848	0.249 (4)

Fig. 6. Sensitivity coefficients of the 28 root nodes and 4 resilience capacities

The simulation results show that the four resilience capacities' optimization priorities are the absorption, resistance, adaptation, and recovery capacities in descending order of the sensitivity to fire resilience, which reflects that Nanjing MSS has great optimization potential of effective fire prevention and rapid fire prevention response to fires. In addition, fire resilience capacities are the most sensitive to economic influential factors ($AbsE_1$, $ResE_1$, $RecE_1$, $AdaE_1$), which proves that increasing the investment, equipment and manpower in fire lifecycle scenes can directly reduce the consequences of fires because sufficient resource input can provide essential economic support to optimize technical, organizational and social influential factors [84]. Except for optimizing the resource allocation, the remaining static optimization strategies are as follows:

(1) The absorption capacity is the most sensitive to $AbsO_1$, which indicates that strengthening real-time

monitoring, regular inspection and maintenance of mechanical and electrical devices can optimize fire prevention effect to the maximum extent;

(2) The resistance capacity is the most sensitive to $ResT_5$, which indicates that adjusting and updating firefighting equipment types, quantities, and installation locations according to the lessons from historical fires and the latest fire safety requirements can maximize the efficiency of fire spread control;

(3) The recovery capacity is the most sensitive to $RecO_1$, which indicates that the timely arrival and efficient coordination of repair and rescue teams can avoid secondary accidents to the greatest extent and guarantee the rapid reopening of the MSS to the public;

(4) The sensitivity coefficient of the root node affecting adaptation capacity tends to be zero, indicating that the MSS has mature fire accident investigation and rectification process with little room for improvement.

4.4.2 Dynamic optimization strategies

Dynamic optimization strategies are proposed based on DBN simulation results considering system component states' change characteristics over time. The DBN model with three kinds of temporal arcs linking each root node from the current time slice t to the next time slice $t + \Delta t$ is shown in Fig. 7, in which 28 root nodes of fire resilience are divided into the following three categories [85]:

(1) Equipment and facility factors, including MSS internal equipment and facilities (all the technical root nodes: $AbsT_1$, $AbsT_3$, $ResT_1$, $ResT_2$, $ResT_3$, $ResT_4$, $ResT_5$, and $ResT_6$) and external equipment ($ResS_2$);

(2) Individual behavior factors, including operational staff's regulated behaviors for daily work and emergency work ($AbsO_1$, $AbsO_3$, $AbsO_4$, $AbsO_5$, $ResO_1$, $ResO_6$, $RecO_1$, and $RecO_3$) and passengers' behavior under current knowledge and skills ($AbsS_1$ and $ResS_1$);

(3) Management experience factors, including operational organization's emergency management capabilities ($AbsO_2$, $ResO_2$, $ResO_3$, $ResO_4$, and $AdaO_1$) and resource investment decision-making capabilities ($AbsE_1$, $ResE_1$, $RecE_1$, and $AdaE_1$).

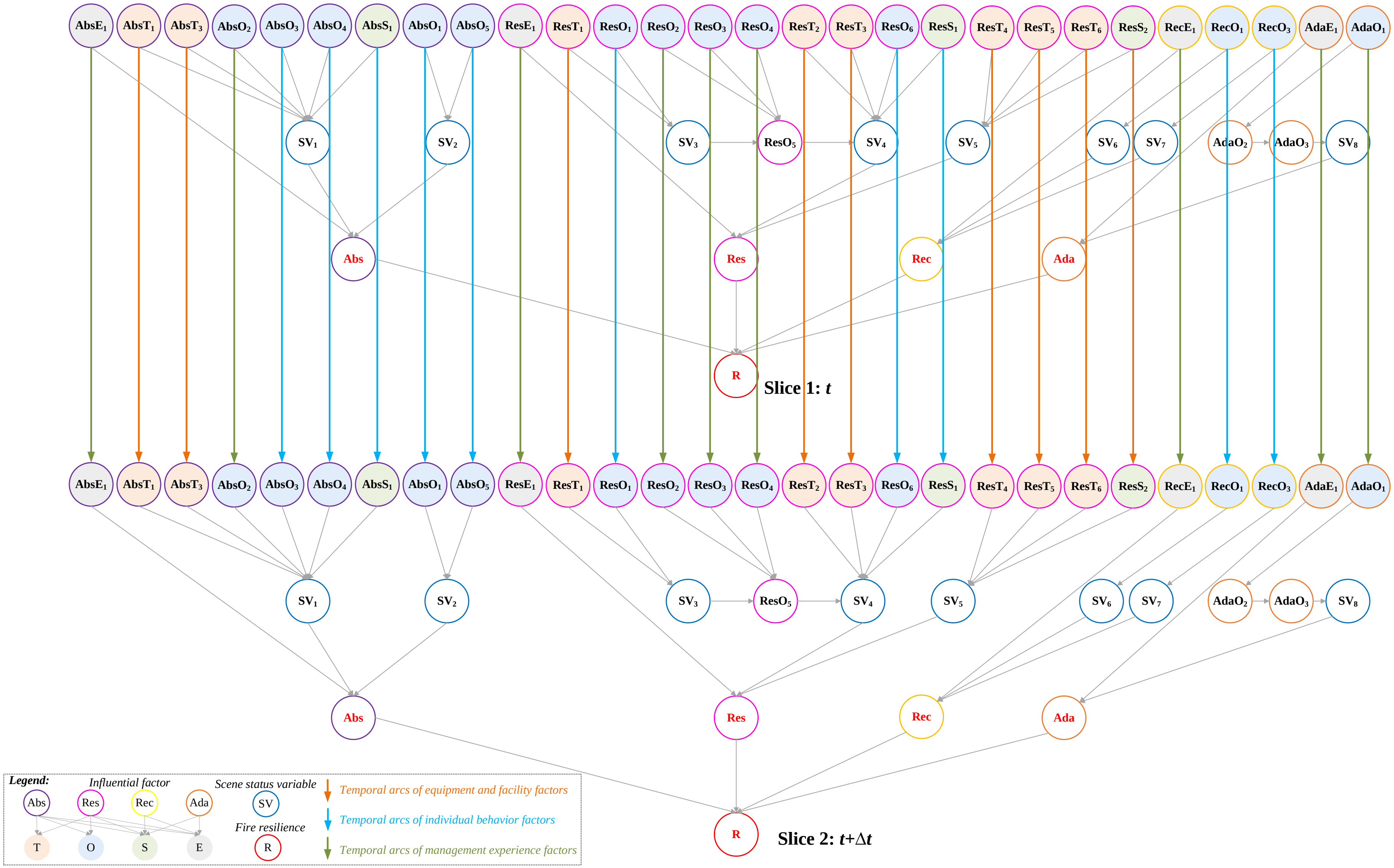


Fig. 7. DBN model for optimizing fire resilience of Nanjing MSS

In addition, considering that each root node's state transition in the DBN model complies with the hidden Markov model [86], the transition probabilities of three types of root nodes are defined as shown in Table 5 based on the following assumptions:

(1) For equipment and facility factors, all equipment and facilities work in one of two states: normal operation (State 0) or failure (State 1). As the MSS's operating life increases, equipment and facilities will age to a certain extent so that operational staff has to maintain all equipment and facilities regularly. It is assumed that the equipment and facility factor's failure rate due to aging is λ_1, and the repair rate due to regular maintenance is μ. Moreover, the failure rate and repair rate of the equipment and facilities are assumed to meet the exponential distribution [87].

(2) For individual behavior factors, all individuals execute tasks or instructions in one of two states: normative (State 0) or non-normative (State 1). Considering that human errors due to non-normative behavior belong to random events, it is assumed that such a random event is a counting process, in which the average number of human errors per unit time is λ_2 meeting the Poisson distribution [88].

(3) For management experience factors, all teams or organizations invoke management experience to make decisions, implement plans, and allocate resources in one of two states: rational (State 0) or irrational (State 1). Considering that as the establishment years of operational organizations increase, the management experience will become increasingly affluent through accumulation; the experience enhancement coefficient c is introduced to reflect the improvement in the decision-making level, implementation ability, and resource allocation rationality due to the enhancement of operational management experiences [89].

Table 5. Three types of root nodes' state transition probabilities

t	$t + \Delta t$	
Equipment and facility factors: *AbsT₁, AbsT₃, ResT₁, ResT₂, ResT₃, ResT₄, ResT₅, ResT₆, ResS₂*		
	State 0	State 1
State 0	$e^{-\lambda_1 \Delta t}$	$1 - e^{-\lambda_1 \Delta t}$
State 1	$1 - e^{-\mu \Delta t}$	$e^{-\mu \Delta t}$
Individual behavior factors: *AbsO₁, AbsO₃, AbsO₄, AbsO₅, AbsS₁, ResO₁, ResO₆, ResS₁, RecO₁, RecO₃*		
	State 0	State 1
State 0	$1 - \lambda_2 e^{-\lambda_2}$	$\lambda_2 e^{-\lambda_2}$
State 1	$e^{-\lambda_2}$	$1 - e^{-\lambda_2}$
Management experience factors: *AbsO₂, AbsE₁, ResO₂, ResO₃, ResO₄, ResE₁, RecE₁, AdaO₁, AdaE₁*		
	State 0	State 1
State 0	1	0
State 1	c	$1 - c$

Notes: (1) $\Delta t = 1$ represents 1 year; (2) $\lambda_1 = 12/365$ represents that equipment and facilities will breakdown 12 times a year, $\mu = 0.1$; (3) $\lambda_2 = 12$ represents that human errors will occur 12 times a year; (4) $c = 0.1$ represents that management experience enhancement can reduce the related influential factors' failure probability by 10%.

In this case study, the original static BN model is transferred ten times to form the DBN model with ten time slices, and then the CI of 28 root nodes from T_0 to T_{10} is obtained. Based on the numerical range of the CI, the optimization priorities are determined as follows: when $I_i > 0.03$, the corresponding root nodes are optimized with the first priority; when $0.015 < I_i \leq 0.03$, the corresponding root nodes are optimized with the second priority; and when $I_i \leq 0.03$, the corresponding root nodes are optimized with the third priority. According to the CI results of all the root nodes during ten time slices, the CI of root nodes ranked 11th to 28th at T_0 is lower than 0.015 in all the time slices. Therefore, the root nodes with the top 10 CI at T_0 are selected for dynamic CI analysis to help decision makers prioritize the critical influential factors at different stages of MSS operation. The dynamic optimization priorities of the critical influential factors from T_0 to T_{10} are shown in Fig. 8.

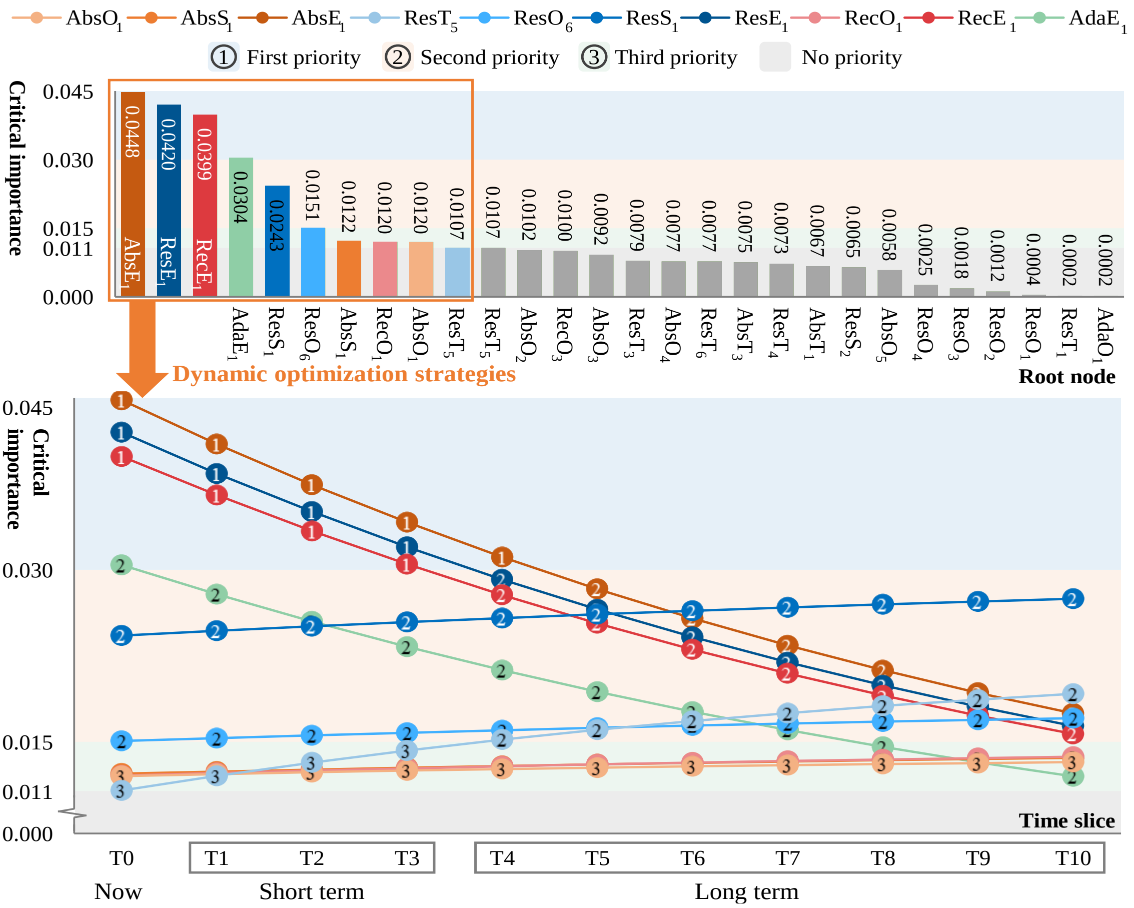


Fig. 8. Dynamic optimization priorities of the critical influential factors for Nanjing MSS

From the perspective of the influential factor type, the top 10 root nodes' dynamic optimization priorities are as follows:

(1) The CI of management experience factors ($AbsE_1$, $ResE_1$, $RecE_1$, and $AdaE_1$) decreases significantly.

(2) The CI of individual behavior factors ($ResS_1$, $ResO_6$, $AbsS_1$, $RecO_1$, and $AbsO_1$) increases slightly.

(3) The CI of equipment and facility factor ($ResT_5$) increases significantly.

The above predicted trend is consistent with the actual operation practice of Nanjing MSS, which reflects that as the operating life increases, the resource allocation becomes increasingly scientific with little room for further optimization; the failure probability of firefighting equipment and facilities increases due to aging; and human error occurrence increases, but human errors still belong to small probability events compared with technical failure.

From the perspective of the execution time of optimization strategies, the top 10 root nodes' dynamic optimization strategies are as follows:

(1) In the present moment T_0, it is necessary to increase the resource allocation strength ($AbsE_1$, $ResE_1$, $RecE_1$, and $AdaE_1$) with the first priority, facilitating rapidly building the absorption, resistance, recovery, and adaptation capacities. Then, less controllable passengers' escape skills ($ResS_1$) and easily overlooked fire and rescue service access ($ResO_6$) should be optimized with the second priority.

(2) In the short term, from T_1 to T_3, only the optimization priority of rectification resource allocation ($AdaE_1$) is degraded, mainly because rectification resources involve fewer investment items than the prevention, resistance, and recovery resources and are easier to optimize within the short term.

(3) In the long term since T_4, the optimization priorities of all resource allocations are degraded, which indicates that the resource allocation level of an MSS will be optimized to a relatively ideal state without further improvement potential after many years of MSS operation. Meanwhile, long-term optimization priorities should transfer to passengers' escape skills ($ResS_1$) that need to be continuously cultivated by playing various videos of escape skills in various media channels of the MSS, and firefighting equipment ($ResT_5$) that needs to be regularly maintained by establishing strict supervision process for monitoring, maintaining and updating firefighting equipment.

5 Conclusions and future work

5.1 Theoretical contribution

This study establishes an integrated framework for managing MSS fire resilience, which enriches the connotation of system resilience through disaster scene analysis and provides resilience management strategies with dynamic and long-term insights through combining BN and DBN. More importantly, this systemic integration of identification, assessment, and optimization methods can be extended to various infrastructures at asset, city, and national levels.

(1) For scene-based identification methods: system resilience theory, disaster scene analysis, and TOSE

approach are combined to establish a standardized D-TOSE model for identifying resilience capacities and their influential factors in the prevention, response, restoration, and learning scenes, which facilitates understanding the manageable scope of fire resilience and then screen out critical influential factors tailored to different cities.

(2) For capacity-based assessment methods: the formation and emergence process of fire resilience are simulated through the BN model linking resilience capacities with influential factors and fire scene status. This BN model reveals that the emergence level of influential factors affects fire scene status; then, fire scene status further affects resilience capacity formation; finally, the formation level of resilience capacities determines the fire resilience value. Moreover, considering that the BN model involves numerous conditional probability calculations and ignores the high uncertainty of influential factors, the Leaky Noisy-OR model is introduced to simplify the conditional probability calculation process and optimize the causality inference structure.

(3) For time-based optimization methods: from diagnostic perspective, static optimization strategies conforming to the MSS's current operation situation are formulated based on the sensitivity analysis; from predictive perspective, dynamic optimization strategies for short-term and long-term operations are formulated based on the DBN model with critical importance analysis, which addresses the impact of influential factors' time-varying characteristics on MSS fire resilience. The time-based optimization method delivers static and dynamic optimization strategies by ranking the optimization priorities of various influential factors, which helps decision makers flexibly adjust optimization strategies at different stages of operating life to maximize fire resilience.

5.2 Practical implication

The developed integrated framework is a practical management tool for the MSS's operational staff and decision makers. It can also flexibly adapt to the operation conditions of different metro stations in different cities by collecting questionnaire data on the influential factors' importance and causalities with fire resilience. Based on the case study of Nanjing MSS, the following results can be applied in practice.

(1) For identification results: 36 preliminary influential factors were identified based on the D-TOSE model, and among them, 3 influential factors including "cigarette extinguishers", "fire and rescue service access", and "implementation and supervision of the rectification" were supplemented in the facilitated workshop. However, 5 influential factors including "integrated supervision and control system", "stability control of the environment", "safe operation of underground commercial areas", "supplementary supply of emergency equipment", and "archive of fire history data" were deleted because their implementation status differed little in the current operational practice. Finally, 31 influential factors were selected to assess fire resilience of Nanjing MSS.

(2) For assessment results: the nonfailure probabilities of absorption capacity, resistance capacity, recovery capacity, adaptation capacity, and fire resilience were 75.5%, 70%, 76.9%, 84.8%, and 68.8%, respectively. These results reflect that the low fire resilience of Nanjing MSS resulted from poor system performance in the prevention and response scenes, where "passengers' safety knowledge and behaviors", "effectiveness of security screening operations", and "skills of staff on the emergency response team" had high failure probabilities. Meanwhile, the critical cause chain, "escape skills of passengers → fire evacuation status → resistance capacity → fire resilience" contributed the most to the failure of fire resilience. The above assessment results not only quantify Nanjing MSS's fire resilience value but also help operational staff confirm influential factors with the highest failure probabilities and the bottleneck existing in the fire resilience emergence process.

(3) For optimization results: from the perspective of resilience capacities, the optimization priority ranking is absorption, resistance, adaptation, and recovery capacities; from the perspective of influential factors, in addition to increasing resource allocation strength in four fire scenes, assigning the optimization

priorities to the remaining top 10 influential factors for the sensitivity to fire resilience, namely, “firefighting equipment” from the technical dimension, “fire and rescue service access”, “coordination of repairs and rescue teams”, and “inspection and maintenance of electrical equipment” from the organizational dimension, and “escape skills of passengers” and “passengers’ safety knowledge and behaviors” from the social dimension, can maximize the optimization effect. More importantly, incorporating dynamic impacts of aging equipment and facilities, human error randomness, and the reinforcement of operational management experience, dynamic optimization priorities applicable to the long-term Nanjing MSS operation conditions should transfer from resource allocation to passengers’ escape skills that need to be continuously cultivated and firefighting equipment that needs to be maintained regularly.

5.3 Limitations and future work

This study aims to improve the understanding and optimization effect of fire resilience for operational staff and decision makers of the MSS, but the proposed integrated framework still has the following limitations:

(1) For identification methods: the interactions between the MSS and other systems (such as tunnel systems and bus systems) are not discussed in the influential factor analysis because fire resilience is regarded as the inherent capacity of an MSS.

(2) For assessment methods: considering that the causalities among resilience capacities, influential factors, and scene status are quantified by questionnaires data which is dependent on the accuracy of the fire handling experience invoked by experts, the states of all nodes in the BN model have to be set with binary parameters to match the experts’ memory characteristics of historical fire disasters.

(3) For optimization methods: the existing probability distribution functions are used to simulate the state transition process of the equipment and facility factors, individual behavior factors, and management experience factors, which does not accurately describe a specific MSS’s status change rules of various

influential factors as the operating life increases.

Our future research will focus on addressing the above limitations. First, influential factors representing the interdependencies of other systems interacting with an MSS will be introduced into the BN model. Second, one pilot study will be conducted by installing sensors and cameras in a specific metro station to accumulate operation and maintenance data of equipment and facilities as well as behavior data of operational staff and passengers. Finally, each influential factor's practical state distribution and transition rules will be fitted based on real-time data for precise assessment and efficient optimization of fire resilience, realizing automatic decision-making and resilient operation.

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Supplementary material

(1) *Questionnaire A*: Investigation on influential factors of fire resilience of metro station system

(2) *Questionnaire B*: Investigation on causality among influential factors of fire resilience of metro station system

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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