

Intelligent Bayesian analysis Based on Knowledge Graph and Graph Neural Network for Subway Fire Risk

Changhong Wang

ch_wang@shu.edu.cn

Shanghai University

Tao Jin

Shanghai University

Deyong Cai

Shanghai University

Baolin Hu

Shanghai University

Research Article

Keywords:

Posted Date: October 23rd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11286494/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Intelligent Bayesian analysis Based on Knowledge Graph and Graph Neural Network for Subway Fire Risk

Abstract: As critical urban public transport infrastructure, metro systems have been confined by narrow spaces and dense crowds, attracting global research attention of fire safety. Existing metro fire risk assessment methods have obvious defects: Knowledge Graphs (KG) rely merely on node-edge topology and ignore entity attribute correlations, leading to poor reasoning; classical Bayesian Networks (BN) built by manually selected nodes carry strong subjective bias. To tackle these limitations, this study proposes an intelligent inference framework integrating KG, Graph Neural Network (GNN), and BN. Firstly, a metro fire KG containing 666 nodes is built from historical fire records. Following metro fire codes, Natural Language Processing (NLP) extracts 215 fire characteristic keywords and 6 risk accident labels, embedding feature and label attributes into the KG topology to form a complete dataset. A three-layer Graph Convolutional Network (GCN) is trained for node classification, combined with confidence weighting and K-means clustering. Based on the trained KG-GNN model, an objective data-driven automatic BN node selection approach is put forward, which can intelligently take out metro fire risk evaluation.

Keywords: Subway Fire; Risk Assessment; Graph Neural Network (GNN); Knowledge Graph (KG); Bayesian Networks (BN)

1. Introduction

As one of the core infrastructure of urban public transportation, subway networks carry approximately 30% of the daily commuting population in major cities worldwide. As of 2025, the total length of operational subway globally exceeded 25,000 kilometers, with China contributing 9,507.5 kilometers, ranking first in the world. Statistics show that between 2000 and 2020, a total of 118 subway fire incidents were recorded globally, resulting in 1,363 fatalities and 4,155 injuries, averaging 11 deaths and 35 injuries per incident. Notably, developing countries showed a more pronounced trend of frequent accidents due to peak passenger flow and high pressures of operational maintenance. Regarding the spatiotemporal patterns, subway fire poses higher risk during winter. Additionally, weekend experience increased passenger flow, which can cause equipment overload, known as the

Friday effect. Tunnel sections and subway stations make up 72% of all fire incidents.

Amid the rapid advancement of the internet and Industry 4.0, research on subway fire accidents lacks a real-time, data-driven system of dynamic risk assessment. Incidents that cause no major casualties are often overlooked, allowing hidden risks to accumulate over time. Technological advancement has lowered traditional equipment failure rates, the complexity of human factors, such as terrorist attacks and operational errors, has introduced a new category of heightened risks. Current methodologies for risk assessment of subway fire are primarily categorized into three groups: physics-based model analysis, multi-criteria comprehensive evaluation, and probabilistic graphical models. The analytical method emphasizes fire dynamics simulation and the quantitative analysis of accident consequences. Lu et al. used computational fluid dynamics and Fire Dynamics Simulator (FDS) to analyze fire scenarios and temperature characteristics in three typical subway stations. Li et al. conducted numerical fire simulations using FDS for the concourse and double-island platform in a subway station, performing optimization for key factors such as ceiling opening rate, smoke reservoir utilization, and orientation of smoke exhaust vent. In winter and summer, Xu et al. investigated the influence of outdoor temperature on fire in a double-height atrium-style subway station based on full-scale experiment and numerical simulation. Teodosiu et al. developed a full-scale numerical model based on computational fluid dynamics to predict airflow, temperature, and the concentration of carbon monoxide and carbon dioxide resulting from fire. Zhang et al. proposed a systematic hybrid approach combining safe evacuation time, numerical simulation, and multi-attribute analysis to assess fire risk. Lin et al. constructed a fire emergency response model for subway passengers using fire dynamics, while evaluating crowd behavior and the evacuation process during subway fire. While physics-based methods integrated with crowd evacuation models can compute casualty risk, they exhibit high sensitivity to different scenarios and are difficult to adapt to the heterogeneity inherent in complex spatial structures, such as subway .

The second method employs the Analytic Hierarchy Process (AHP) to construct safety evaluation indicators,

often integrated with fuzzy logic to handle uncertainty. Chai et al. developed a hybrid multi-attribute approach combining fuzzy analytic networks, grey relational analysis, and cloud models to assess fire safety. Wang et al. systematically built a four-layer framework covering human, management, environment, and equipment factors in subway operation. Using AHP, they calculated weights for each indicator and applied a fuzzy evaluation to establish a computational procedure for subway fire risk. Yan et al. used interval-based AHP to determine indicators at all levels and incorporated passenger simulation into the fuzzy evaluation to enhance the objectivity of risk assessment. Ju et al. established a risk assessment model of a subway station by applying a combination based on game theory to compute indicator weights, mitigating the limitations and dependency of both subjective and objective aspects of different evaluation methods. Gao et al. introduced a fuzzy consistent matrix to develop an AHP model for evaluating fire risk in subway tunnels. Zhang et al. employed software such as TextRank and Word2vec to compute fuzzy word vectors. With the vectors, a bidirectional long short-term memory network was integrated with a self-attention mechanism to extract semantic features from safety hazard text. The self-attention mechanism was further applied to analyze the extracted semantic features, thereby enhancing the machine learning algorithm. While the method facilitates the integration of expert knowledge, they are limited by static weight allocation, difficulties in reflecting dynamic risk evolution, and insufficient capability for causal reasoning.

The third category focuses on probabilistic graphical models, which have been less commonly applied but have seen growing adoption in recent years, particularly BN, due to their strength in probabilistic reasoning. Researchers often integrate fault trees with BN to analyze failure chains in fire monitoring, prevention, and emergency response processes, or use event trees to predict the effectiveness of emergency measures. Luan et al. employed a modified Subjective Assessment Method to aggregate expert opinion for BN parameter learning and developed a risk assessment model built upon a KG. Wang et al. proposed a dynamic evacuation model that uses event tree analysis to represent subway fire scenarios and incorporates Bayesian theory for real-time probability update. Wu et al.

developed an integrated reasoning model combining BN and the Delphi method for rapid, dynamic assessment of fire evolution and consequence in subway stations. Bai et al. introduced a novel risk assessment integrating KG, a decision-making trial and evaluation laboratory, and BN to analyze fire incidents of natural gas pipelines in a data-driven manner, thereby minimizing reliance on expert knowledge. Bakhtiari et al. applied dynamic BN to accurately model interdependencies among internal factors in infrastructure and simulate failure propagation under fault scenarios. Zheng et al. utilized a GNN to convolutionally aggregate neighborhood information from a KG. They introduced a self-attention mechanism during the aggregation process, which integrates the acquired neighborhood information into the initial representation. The approach was used to predict interaction probabilities, ultimately establishing a recommendation. Su et al. proposed a three-layer cognitive model integrating data, knowledge, and decision-making, based on KG and GNN. By organizing diverse data sources and applying knowledge reasoning strategies, the model achieves a seamless transformation from data to knowledge. It further employs an attention mechanism to effectively capture complex relational dynamics and thus construct a knowledge-centric decision support system. However, traditional risk assessment predominantly relies on expert knowledge to define cognitive boundaries and construct networks. These approaches exhibit limitations in logical reasoning, fail to sufficiently capture implicit relationships among entities, and are unable to dynamically construct a BN tailored to subway fire incidents.

To address the aforementioned challenge, both Chinese codes of subway fire safety and global fire incident records are conducted the following research. First, accident data were screened as the primary source to construct a fire accident KG incorporating 6 risk tags. Through the analysis of regulatory documents and accident reports, a NLP technique was employed to extract causal nodes according to the fire tag classification, establishing a comprehensive KG database, tag categories, and feature matrix that systematically integrates fire accident causation. Subsequently, a three-layer GNN was utilized for node classification training. Through a systematic

process incorporating node embedding extraction, confidence computation, cluster partitioning, and comprehensive scoring for node selection, key risk nodes were automatically identified to construct the core causal chain of the BN. Finally, within the constructed BN framework, expert scoring organized via the Delphi method was applied to determine prior and conditional probabilities of risk nodes, establishing the integrated KG-GNN-BN reasoning model. The methodology resolves the limitation of traditional BN in adaptive evolution, achieving a fully data-driven pipeline encompassing structured extraction of regulatory semantics, node feature embedding learning, and optimization of probabilistic reasoning networks. Specifically designed for subway fire scenarios, it provides a quantitative analytical tool for dynamic prediction and accident retrospective analysis, thereby supporting fire risk management of the subway. Furthermore, the KG-GNN-BN model demonstrates versatile applicability. It enables not only general risk analysis based on historical subway fire accidents but also supports the construction of a customized KG for well-equipped subway stations. Leveraging the GNN-trained node classification, the model facilitates the assisted development of BN, thereby enabling precise dynamic prediction and retrospective analysis tailored to specific operational context.

Section 2 describes the methodology of the KG-GNN-BN integrated reasoning model. Section 3 constructs the KG-GNN-BN integrated reasoning model and determines node probabilities based on GNN deep machine learning. Section 4 conducts sensitivity analysis, risk simulation, and prevention strategy research using the BN. Section 5 summarizes the conclusions of the study.

2. Methodology

To achieve dynamic prediction and retrospective analysis of fire risks in subway stations, it is necessary to integrate both subjective and objective approaches to overcome the limitations of a single method. First, a subway fire KG is constructed to represent entities and relationships. Second, a GNN is applied to uncover latent

relationships among entities. Finally, node weights are optimized to automatically generate BN, which quantitatively handles uncertainties and enables dynamic probabilistic inference.

2.1 Knowledge graph

The concept of the KG can be traced back to early semantic network research. By representing structured semantics and supporting reasoning, KG reduces semantic gaps and enhances accuracy and clarity in information search. With the rise of big data and cognitive computing, KG has become a fundamental infrastructure for artificial intelligence. Its core structure consists of different types of nodes and semantic relations, explicitly expressing conceptual support and reasoning. Based on coverage, KG can be divided into open-domain (*e.g.*, Wikidata) and specific-domain (*e.g.*, biomedical KG). Open-domain KG covers diverse knowledge such as history, science, and culture, while specific-domain KG captures specialized knowledge, such as diseases, drugs, and genes in biomedicine, for application in research, diagnosis, and healthcare.

KG construction typically involves multiple types of knowledge extraction, cross-source entity matching, and continuous updates in graph databases. Data scale and modality diversity significantly influence the choice of methods. In decision support and question answering, GNN-based deep learning excels in handling large-scale, varied data. The effectiveness of combining KG with GNN has been widely demonstrated.

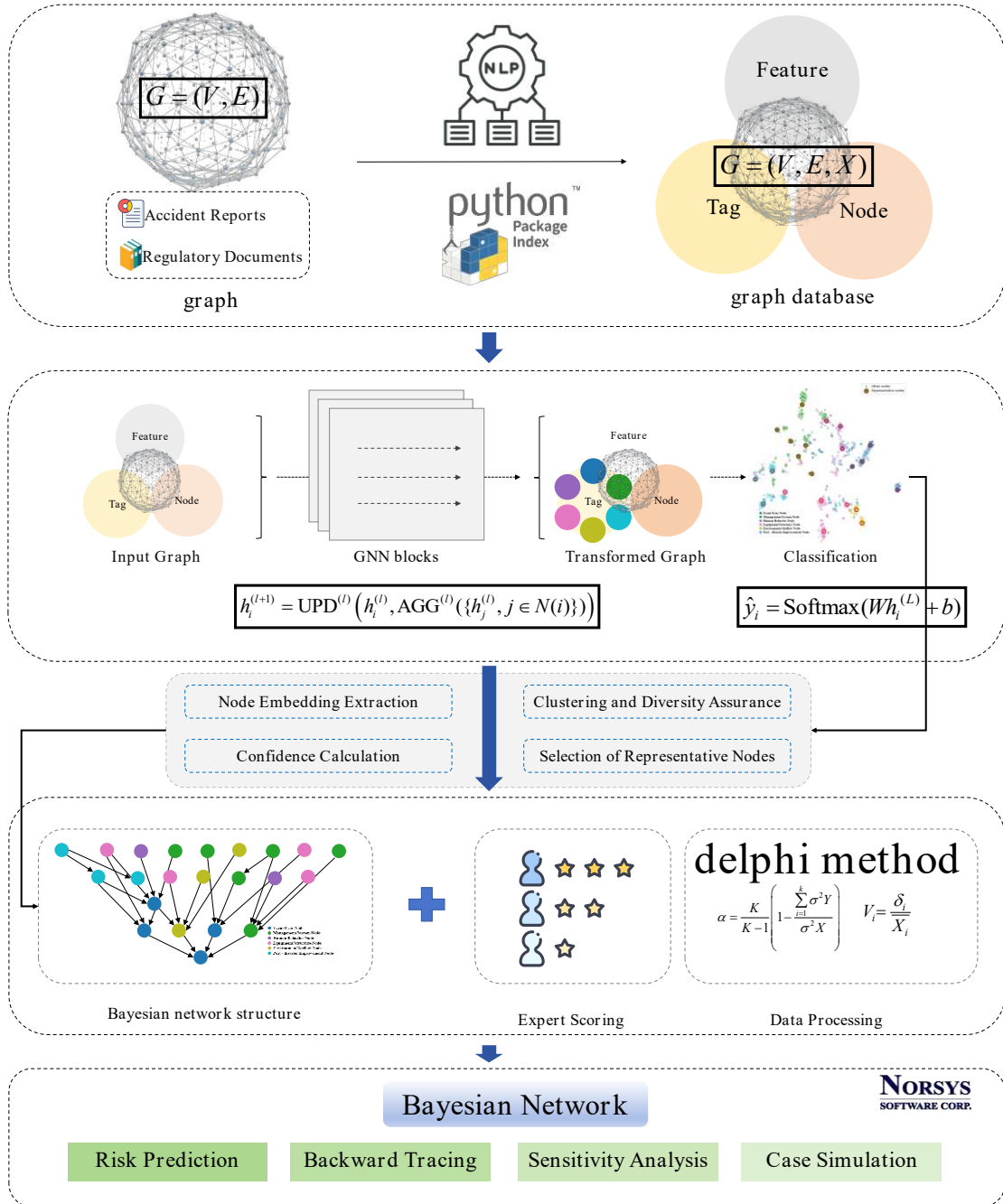
The proposed KG-GNN-BN integrated inference model comprises four key stages: KG construction, GNN training, representative node selection, and BN transformation. The overall training process is illustrated in **Fig.1**. Subway fire incident reports and regulatory documents are collected, and a subway fire accident KG is established using natural language processing techniques. The KG serves as input to the GNN model for node embedding and feature learning. After obtaining the node embedding extraction and confidence calculation, clustering analysis is performed to automatically select representative nodes that capture the global structure and critical risk factors through a comprehensive scoring process. Based on the embedding extraction of representative nodes, the model

integrates expert knowledge and historical cases to achieve an automatic transformation from the KG to the BN.

Fig.1 GNN-KG-BN structure

2.2 Graph neural network

GNNs are deep learning algorithms designed for non-Euclidean graph-structured data. The core idea is to



iteratively learn node and edge features and capture complex topological dependencies. GNNs perform well in

node classification, link prediction, and graph-level tasks, and have been applied in domains such as social networks, chemistry, and transportation.

The training and prediction process typically includes four steps: Step 1: Define the graph structure.

In graph theory, a graph is typically represented as $G=(V,E)$. V denotes the set of nodes (*i.e.*, vertices) and E represents the set of edges. In the open-source PyTorch deep learning framework, the graph structure is further extended to incorporate a node feature matrix. The data structure is represented as $G=(V,E,X)$, where $X \in \mathbb{R}^{|V| \times d}$ is the node feature matrix, and d represents the feature dimension. **Fig.2** illustrates the mapping process from graph representation to the data structure of PyTorch.

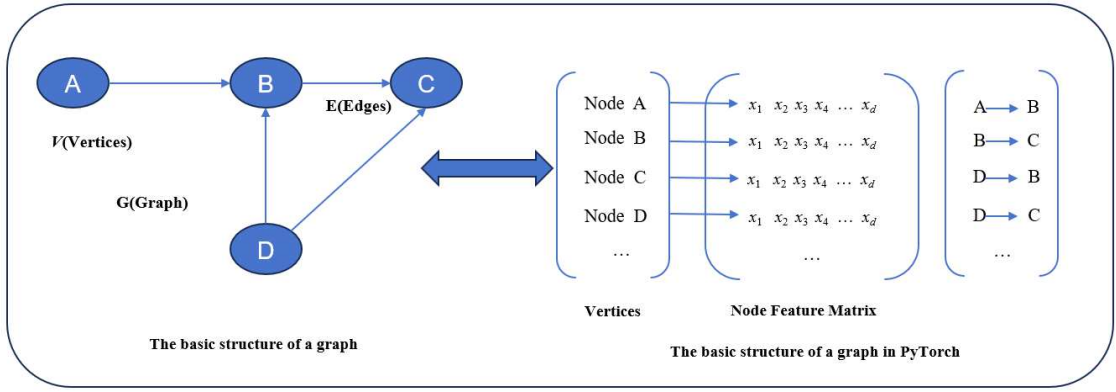


Fig.2 Graph Components and Data Structure in PyTorch

Step 2: Design the message-passing function.

Taking the topological relationship and features of graph nodes as input variables, for each node $v_i \in V$, the features of its neighboring nodes $N(v_i)$, denoted as $h_j^{(l)}$, are accumulated by an aggregation function (*i.e.*, AGG). Then, through an update function (*i.e.*, UPD), the hidden feature $h_i^{(l)}$ of the node i at the l^{th} layer of the GNN is iteratively updated by **Eq.(1)**:

$$h_i^{(l+1)} = \text{UPD}^{(l)} \left(h_i^{(l)}, \text{AGG}^{(l)}(\{h_j^{(l)}, j \in N(v_i)\}) \right) \quad (1)$$

where, l denotes a specific layer of the GNN within the range $1 \leq l \leq L$, L is the predefined total number of

GNN layers, $h_i^{(l)}$ is the hidden state vector of node i at layer l ; $h_j^{(l)}$ denotes the hidden state of neighbor node j at layer l .

Step 3: Iterate through multiple layers.

As shown in **Eq. (1)**, the multi-layer message-passing function is executed iteratively, progressively expanding the receptive field of each node. The hidden features $h_i^{(L)}$ are the output nodes at the final layer L , corresponding to the predefined node tags.

Step 4: Generate prediction and optimization.

Using the output of the hidden features $h_i^{(L)}$ as input from Step 3, a node tag classification is constructed. The model parameters are optimized by a loss function. The predicted node tag $\hat{y}_i$ is given by Equation (2):

$$\hat{y}_i = \text{Softmax}(Wh_i^{(L)} + b) \quad (2)$$

where, Softmax is the activation function in the output layer for classification, converting the hidden states of nodes in the last GNN layer into a normalized probability distribution to predict node tags. W and b are the trainable model parameters.

The representational capacity of a GNN is determined by the AGG, the UPD, and the number of network layers L . Through a multi-layer message-passing mechanism, it extracts high-order hidden features from both node attributes and topological relationships, thereby constructing a predictive model for node classification.

2.3 Bayesian network

BN is a probabilistic graphical model for quantifying uncertainty. It consists of parent, intermediate, and child nodes linked by directed edges that represent causal dependencies, as illustrated in **Fig.3**.

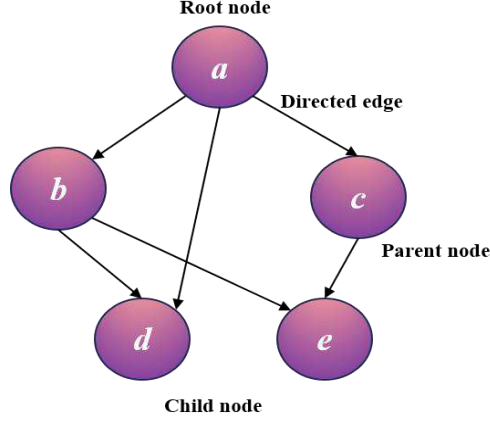


Fig.3 Schematic diagram of a chain structure in a BN

The mathematical foundation lies in Bayes' theorem, with the joint probability given by **Eq.(3)**:

$$P(a,b,c) = P(c|a,b) \cdot P(b|a) \cdot P(a) \quad (3)$$

where, node a has no parent and its probability is $P(a)$; node b has a parent a ; and node c has parents a and b , with conditional probabilities $P(b|a)$ and $P(c|a,b)$, respectively.

When new evidence becomes available, Bayes' theorem can update posterior probabilities. For example, given the states of nodes b and c , the posterior probability of the target node a can be updated by **Eq.(4)**:

$$P(a|b,c) = \frac{P(a) \cdot P(b|a) \cdot P(c|a,b)}{\sum_a [P(a) \cdot P(b|a) \cdot P(c|a,b)]} \quad (4)$$

The numerator represents the joint probability of a , b , and c , while the denominator denotes the marginal probability of b and c , obtained by summing over all possible states of node a .

2.4 Application of the KG-GNN-BN integrated theory in subway fire analysis

Traditional BN construction relies heavily on expert knowledge, requiring manual definition of nodes and causal structures, which introduces subjectivity and limits adaptability to complex dynamic systems. To overcome this shortcoming, a data-driven KG-GNN-BN framework is proposed to enable automatic conversion of a domain-specific KG into an optimized BN.

As shown in **Fig.4**, the framework includes three phases: (i) knowledge input, (ii) auto-conversion and

optimization, and (iii) probabilistic reasoning and application. The workflow consists of four steps: node embedding, confidence estimation, clustering, and node selection.

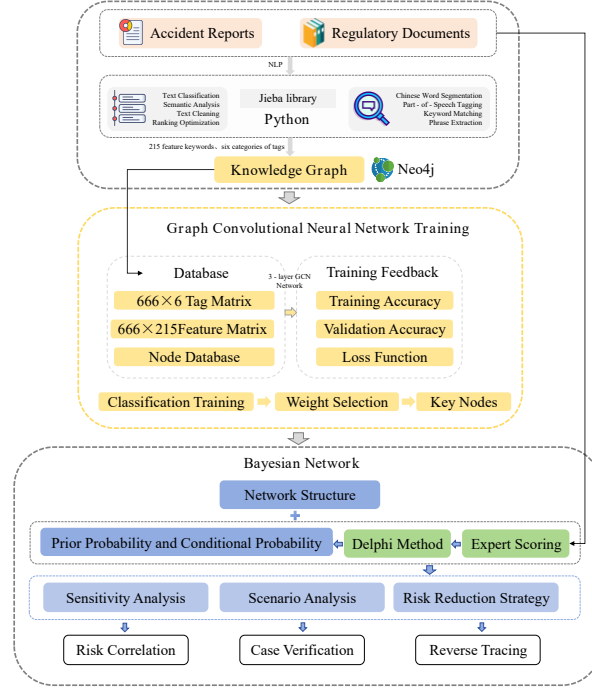


Fig.4 Framework of the KG-GNN-BN model

Node embedding is generated by a GNN, which encodes both structural and attribute features. Through iterative aggregation, high-dimensional features are mapped into low-dimensional vectors while preserving topological and semantic information. The propagation rule is given by **Eq.(5)**:

$$h_i^{(l+1)} = \sigma \left(\sum_{j \in N(v_i)} \frac{1}{\sqrt{\hat{d}_i \hat{d}_j}} W^{(l)} h_j^{(l)} \right) \quad (5)$$

where, $h_j^{(l)}$ denotes the hidden state of node i at layer l ; $j \in N(v_i)$ represents the set of neighboring nodes of i ; $\hat{d}_i$ and $\hat{d}_j$ are the connection degrees of nodes i and j , respectively; $W^{(l)}$ is a learnable weight matrix at layer l ; $\sigma(\cdot)$ is the activation function (*e.g.*, ReLU).

During the confidence computation, the final output vector $z_i \in y^C$ is first obtained by the GNN. The vector is then normalized into a probability distribution via the function Softmax, which quantifies the reliability of the node classification, as shown in **Eq.(6)**:

$$P_i(c) = \frac{\exp(z_{i,c})}{\sum_{c=1}^C \exp(z_{i,c})} \quad (6)$$

where, C is the total number of tags; c is the tag indices; $P_i(c)$ represents the probability that node i belongs to tag c ; $z_{i,c}$ denotes the score of node i for tag c .

The maximum probability is taken as the confidence score of the node i : $\text{Conf}(i) = \max P_i(c)$. A higher value indicates greater reliability of the tag classification for the node i .

Clustering is employed to ensure the diversity of node representation and avoid feature coverage bias. The K-means algorithm is used to partition the node embedding vectors into K clusters with distinct features. In this study, $K = 6$, consistent with the number of tags C . The clustering objective is to minimize the sum of squared distances between nodes and their corresponding cluster centroids, as given by **Eq.(7)**:

$$\min \sum_{i=1}^n \sum_{k=1}^K r_{ik} \text{dist}(h_i, \mu_{k(i)})^2 \quad (7)$$

where, K denotes the number of clusters; $\mu_{k(i)}$ represents the centroid of the k^{th} cluster; r_{ik} is an indicator variable equal to 1.0 if the node i belongs to cluster k ; and 0.0 otherwise; $\text{dist}(\cdot)$ denotes the cosine distance.

During the comprehensive scoring phase, multi-criteria optimization is achieved by integrating confidence and intra-cluster representativeness. The scoring formula is defined by **Eq.(8)**:

$$\text{Score}(i) = \alpha \cdot \text{Conf}(i) + (1 - \alpha) \cdot \left(1 - \frac{\text{dist}(h_i, \mu_{k(i)})}{\max_j \text{dist}(h_j, \mu_{k(j)})}\right) \quad (8)$$

where, α is a weighting coefficient, $\text{Conf}(\cdot)$ denotes the classification confidence of node i , $\text{dist}(h_i, \mu_{k(i)})$ represents the distance from node i to its cluster center, $\max_j \text{dist}(h_j, \mu_{k(j)})$ is the maximum distance from any node to its respective cluster center.

Nodes are selected from each cluster based on the scores, resulting in 22 representative nodes to meet the multi-criteria optimization objective. Through the automated process, a structurally optimized BN is obtained. Delphi method is then incorporated to integrate expert knowledge and complete the parametric learning of the conditional

probabilities, ultimately forming the integrated KG-GNN-BN reasoning model depicted in the aforementioned **Fig.4** combined with prior knowledge and driven by monitoring data, the approach enhances the objectivity and discovery capability of the BN model.

3. Applying KG and GNN for constructing BN

Construction of the KG-GNN-BN model initiates with NPL techniques extracting nodes, tags, relationships, and feature information from unstructured accident data and fire safety regulations. Subsequently, a subway fire knowledge graph incorporating tag information is established. The process further develops into a fire incident knowledge repository containing complete tags and features. The knowledge database then supports GNN classification training of nodes, where the machine learning procedure integrates node embedding extraction, confidence computation, and a clustering algorithm to automatically select nodes with high comprehensive scores. The selected nodes form the primary framework of BN. This methodology implements the complete workflow from KG to BN conversion through GNN training, which utilizes actual subway fire incident data throughout the process.

3.1 GNN Training based on knowledge graph

Data collection for subway fire incidents employed a web crawler, literature review, and regulatory documentation analysis, compiling 166 fire accident records from the years 1958 to 2025. To improve GNN training precision, 16 major accidents with clear causal relationships and complete information, such as the London underground fire in 1987, Daegu subway arson case in 2003, and New York subway terrorist attack fire in 2020, were selected as core training samples. The constructed KG ontology framework appears in **Fig.5**. The node database contains 666 accident nodes and the connecting edges. The feature database consists of a 6×215 dimensional matrix with 6 categories of tags and 215 features, serving as crucial data for GNN training. The tag database also employs a matrix representation, structured as a 6×666 dimensional matrix.

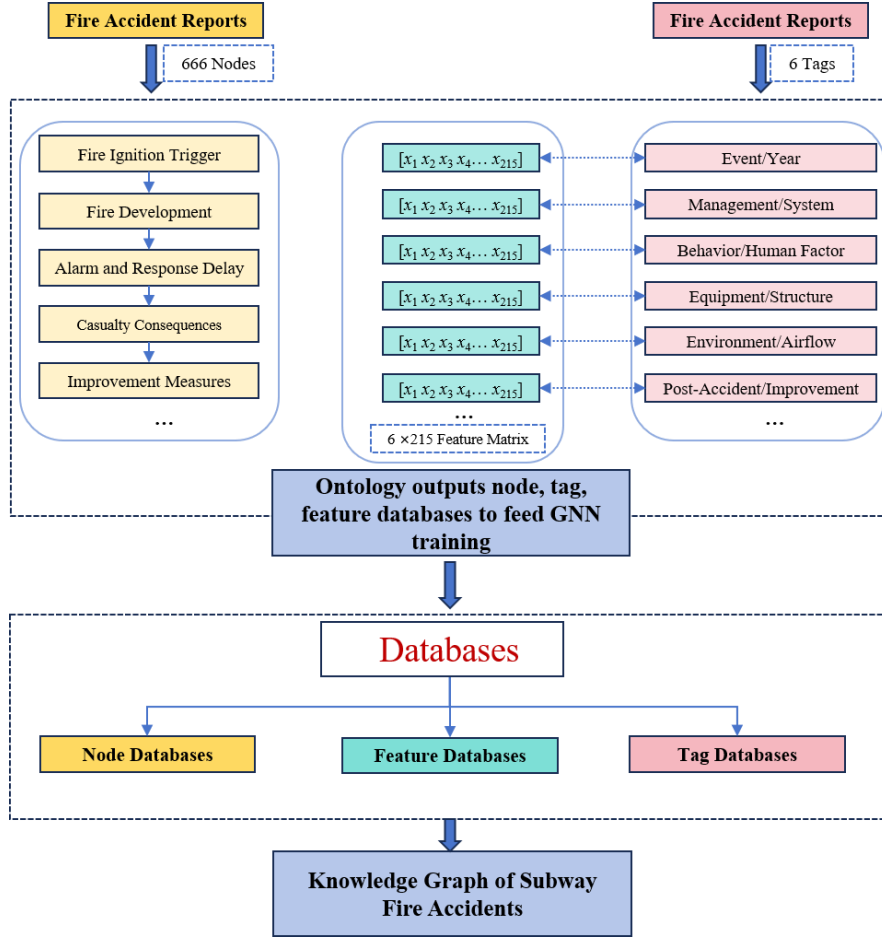


Fig.5 Ontology of the subway fire incident knowledge base

As shown in **Fig.6**, the constructed KG of subway station fire incidents encompasses 16 representative accident cases along with the associated tags and characteristic factors. The nodes are interconnected through relational edges, forming a complete semantic network. Taking the London subway station fire in 1987 as an example, the KG representation of the nodes and the corresponding tags is displayed on the right, illustrating the full information covered by 6 categories of tags. Similarly, each node of other incidents also contains its corresponding tag information.

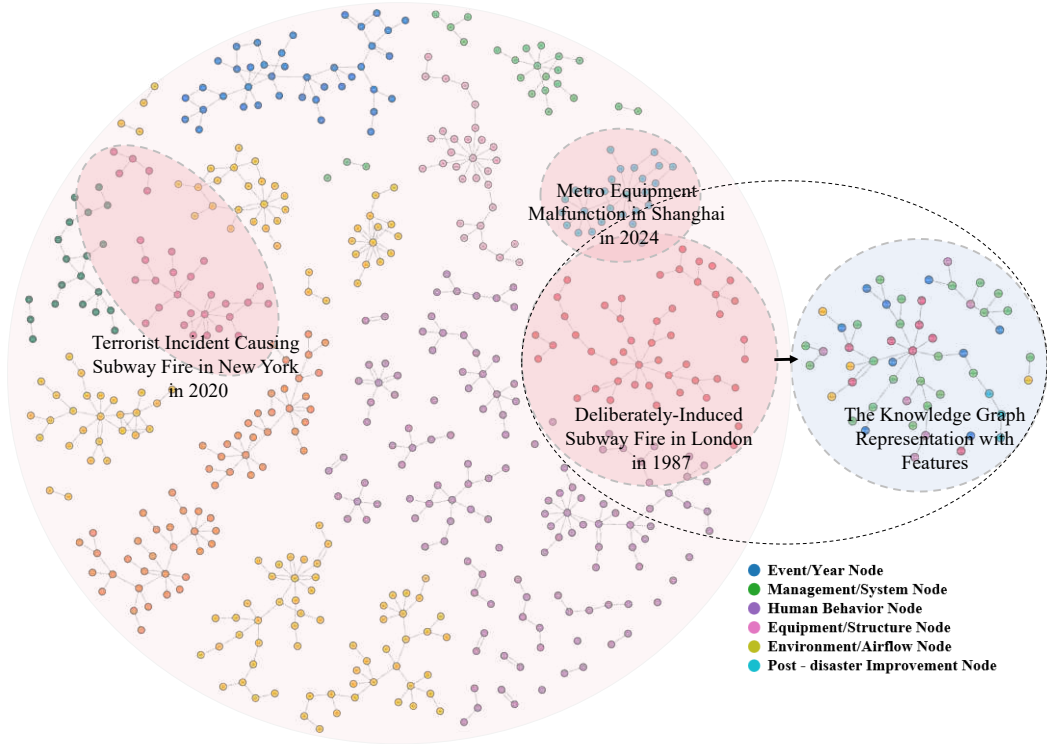


Fig.6 KG of subway station fire accident

In summary, based on GNN learning, key risk nodes are identified, and the weights are calculated. Nodes of **Fig.6** with clear classification and high confidence levels are prioritized as critical variable nodes in the BN. The process provides an objective, data-driven topological foundation for the automated construction of the BN.

3.2 Development of the integrated KG-GNN-BN reasoning model

Using the natural language processing tool Jieba, semantic parsing, keyword extraction, and entity-relationship identification were performed on accident reports and regulatory documents. The Neo4j graph database was utilized to achieve structured storage and visualization of the KG, constructing a foundational topology that incorporates entity association and causal logic. Based on the constructed subway fire incident KG, the process further transforms the KG into a BN.

To achieve the mapping from the KG to a BN, in-depth processing of the KG is conducted by a GNN. Through node feature learning and weight calculation, key risk nodes are screened, potential causal chains are optimized, and precise topological support is provided for the construction of the BN. It ultimately enables dynamic prediction

of subway fire risks and inverse analysis of accidents.

The GNN training employs knowledge graph data from **Table 1**, containing a dataset composed of 16 subway fire incidents spanning 1958-2025 and two fire safety codes. The dataset adopts a matrix representation, constructing a knowledge graph with 666 nodes and 931 edges, along with a 6×215 feature matrix and a 666×6 tag matrix.

Table 1 Overview of GNN Training Data for Subway Fire Incidents

Item	Description
Dataset	16 detailed subway fire incident records, 2 regulatory documents.
Knowledge Graph Structure	666 nodes, 931 edges.
Tag Categories	Event/Year, Management System, Human Behavior, Equipment/Structure, Environment/Airflow, Aftermath/Improvement.
Feature Matrix Basis	Keywords extracted from 2 regulatory documents using the NLP tool Jieba.
Feature Matrix Dimension	6×215 (6 tag categories, 215 features in total).

The GNN model employs a three-layer GNN architecture, supplemented with residual connections and batch normalization to mitigate gradient vanishing issues in deep network training and accelerate convergence. The input layer has a dimension of 215, corresponding to the 215 keywords in the feature matrix. The hidden layer dimension is set to 64, with ReLU activation introducing non-linearity, and the output layer corresponds to the 6 tag categories. During the training process, the 666 nodes were randomly split into 70% for training, 15% for validation, and 15% for testing purposes. The loss function is cross-entropy loss, optimized with the Adam algorithm combined with a cosine annealing learning rate scheduler to enhance the generalization ability of the model.

Over 500 training epochs, **Fig.7** illustrates the trend in training and validation accuracy. The input consists of the 215-dimensional features of the 666 nodes, and the output is the node tags. The horizontal axis represents the number of epochs, and the vertical axis shows accuracy (i.e., ranging from 0 to 1.0). As training progressed, the training accuracy increased steadily from an initial low value, approaching 1.0 by epoch 500, indicating excellent fitting performance on the subway fire incident data. The validation accuracy also improved consistently, eventually stabilizing around 0.9, demonstrating strong generalization capability to unseen data and good

adaptability to subway fire features across different scenarios.

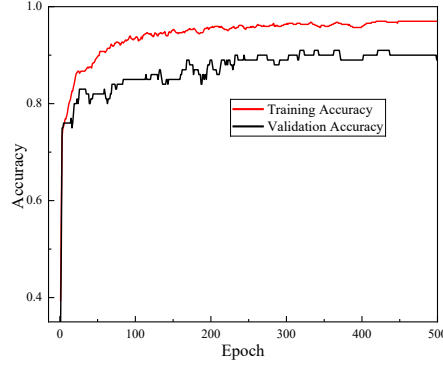


Fig. 7 Training and Validation Accuracy Trends of the GNN Model

Fig.8 shows the cross-entropy loss values during training and validation of the GNN model. The horizontal axis represents the number of epochs, and the vertical axis indicates the value of the cross-entropy loss function. N is the number of samples in the batch, $C = 6$ is the total number of tag classes, y_{ic} denotes the one-hot encoded truth tag, and p_{ic} represents the predicted probability distribution. Both the training and validation loss values decrease rapidly in the initial phase and gradually approach zero in later epochs. The descending trend reflects continuous optimization and enhanced stability of the GNN model during the training process.

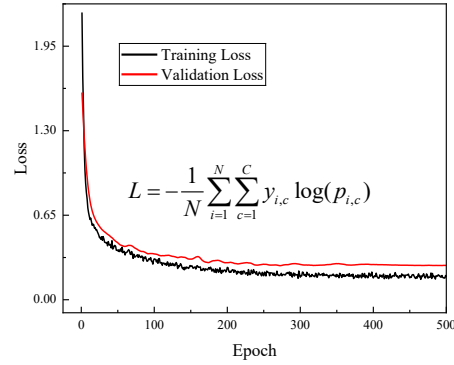


Fig.8 Training and validation loss trends of the GNN model

For the 666 nodes in the subway fire incident and regulatory document KG, the distribution of actual node classification tags closely aligns with the predicted tags, indicating a balanced predictive capability of the GNN model for node classification. **Fig.9** presents the comparative histogram of KG node classification labels from the GNN model.

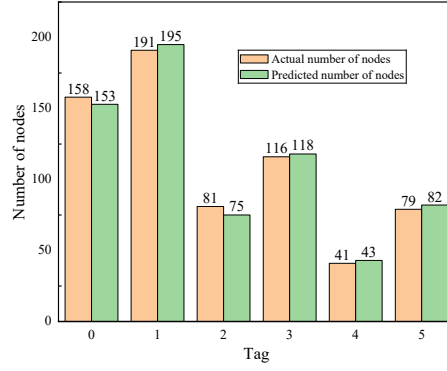


Fig. 9 Comparison of actual and predicted tags for KG nodes

Fig. 10 presents a heatmap of the confusion matrix for the 6 tag categories, providing an in-depth analysis of the GNN model accuracy in predicting node classification tags across the 666-node dataset of subway fire incidents and regulatory documents.

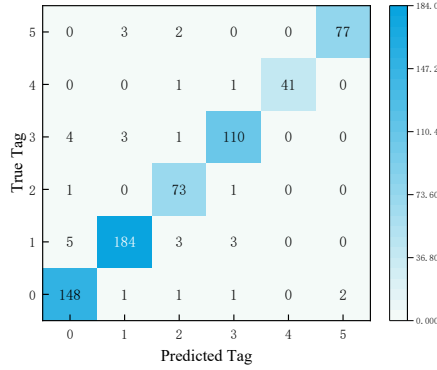


Fig. 10. Confusion matrix heatmap of node classification prediction

The heatmap indicates that the GNN model achieves a high number of correct predictions for several tag categories. For instance, when the true tag is category 0, 148 samples are accurately predicted as tag 0. Similarly, for the true tag category 1, the number of correct predictions reaches 184. The same pattern holds for other tag categories, demonstrating the strong discriminative capability of the GNN model in classification.

The GNN node classification training incorporates algorithms for node embedding extraction, confidence computation, and cluster-based filtering. These methods automatically select nodes with high comprehensive scores to form the primary framework of the BN. The distribution of selected nodes is shown in the accompanying **Fig.11**. The number of selected nodes can be modified by adjusting the weight coefficients in the comprehensive scoring system.

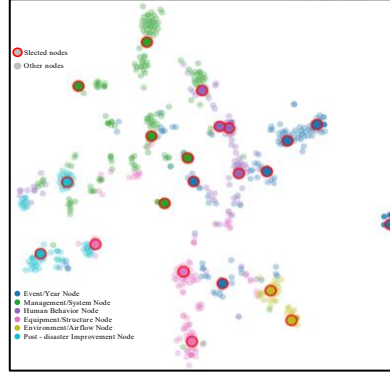


Fig. 11 Distribution of Automatically Selected Representative Nodes

Through preliminary experiments, the final selection was determined using scoring thresholds and cluster center representativeness analysis to maintain model interpretability while adequately capturing primary causal pathways of subway fire risks, preventing model overfitting or degraded reasoning efficiency. From the 6 clusters, the highest-scoring nodes from each cluster were chosen, resulting in 22 nodes that optimally cover all 6 labels while demonstrating superior performance in confidence, intra-cluster representativeness, and structural diversity. The selection preserves critical risk characteristics. The process for selecting the 22 representative nodes was as follows. First, the 666 nodes were partitioned into $k=6$ clusters using the K-means algorithm, ensuring coverage across all risk categories. Second, within each cluster, nodes were ranked in descending order based on the comprehensive score of Equation (8), which integrates classification confidence and intra-cluster distance. Finally, the top n nodes were selected from each cluster. The value of n varied per cluster to ensure a balanced representation from all risk categories while keeping the total number of nodes manageable for both BN construction and expert evaluation.

3.3 BN probability parameterization

To automatically select nodes that exhibit feature representativeness, prediction reliability, and coverage diversity based on the graph database, a multi-criteria fusion framework was adopted to ensure optimization across the dimensions. The approach ultimately forms a hybrid probabilistic model characterized by data-driven and semantically-enhanced reasoning. The integrated structure of the KG-GNN-BN network is illustrated in **Fig.12**.

The BN comprises 22 nodes. Each node has 2 to 3 states: Low, Medium, and High risk. The probability for each state indicates its likelihood of occurrence. It shows the distribution of all nodes across the 6 main risk Tags.

To determine the prior and conditional probabilities of the BN, the Delphi method was introduced to incorporate expert knowledge and statistical data. Seventeen experts in subway fire safety were invited to evaluate probability parameters based on historical accident cases and regulatory requirements. A questionnaire survey comprising 27 core questions was conducted, and probability parameters were refined through aggregated analysis of expert feedback. The coefficient of variation V_i was used to assess the dispersion of expert opinion, calculated as:

$$V_i = \frac{\delta_i}{\overline{X_i}} \quad (9)$$

where δ_i is the standard deviation of the i^{th} question, and $\overline{X_i}$ is its mean value. A smaller V_i indicates a higher degree of consensus among experts. Meanwhile, Cronbach's alpha coefficient α was used to evaluate overall consistency:

$$\alpha = \frac{K}{K-1} \left(1 - \frac{\sum_{i=1}^k \sigma^2 Y}{\sigma^2 X} \right) \quad (10)$$

where, K is the number of questions, $\sigma^2 X$ is the total variance of all items, and $\sigma^2 Y$ is the single variance.

When $\alpha > 0.8$, the expert opinions are considered to have high consistency, and the mean values are adopted as the final probability parameters, providing a quantitative foundation for probabilistic reasoning in the BN.

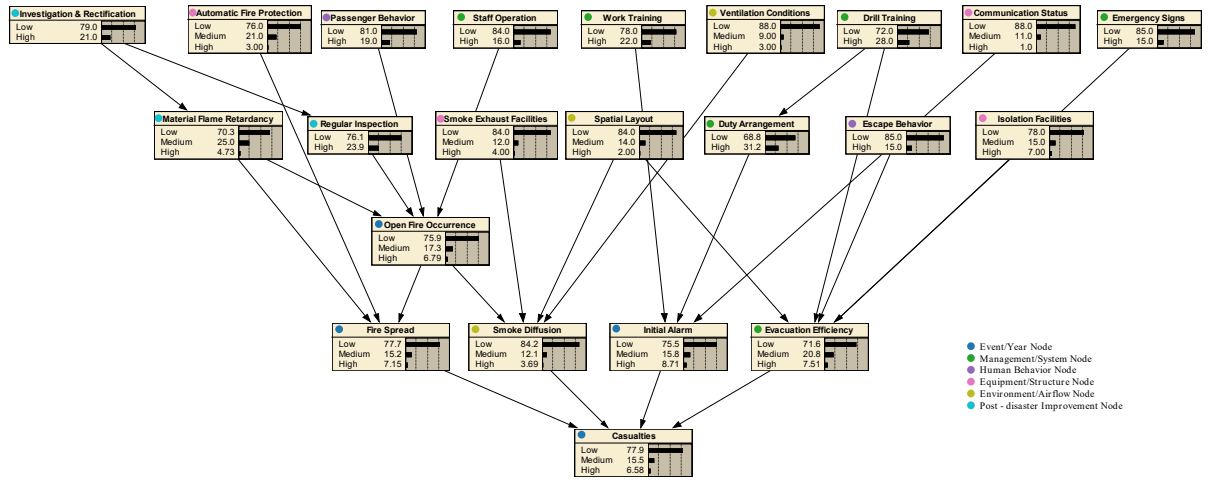


Fig. 12. Network Structure of GNN-KG-BN

4. BN-Based risk analysis

The established KG-GNN-BN reasoning model enables quantitative assessment and dynamic simulation of fire risk in subway stations. Sensitivity analysis first identifies critical risk nodes and quantifies the impact on outcomes such as casualties. A multi-scenario simulation framework then examines different state combinations through BN-based dynamic probability reasoning. Typical real accident cases validate the model accuracy and practicality in identifying key causal nodes and risk evolution paths. Finally, retrospective analysis from four critical nodes clarifies the risk transmission mechanism, establishes the core prevention chain, and proposes targeted, hierarchical risk mitigation strategies.

4.1 Sensitivity analysis

Sensitivity analysis quantifies inter-node relationships and evaluates the degree to which target nodes are influenced by others. Using software Netica, single-factor sensitivity analysis computes a value for each node. A higher value indicates greater criticality of the node in risk evolution.

4.1.1 Sensitivity analysis of key causes for fire accidents

Sensitivity analysis was first conducted on the 'Casualties' node, with results presented in Fig.13. The 'Initial Alarm' node shows the highest sensitivity coefficient of 2.05, identifying it as the core driver of subway fire

casualties. The enclosed, elongated nature of subway space causes rapid smoke diffusion and sharp visibility reduction after fire ignition. Timely initial alarm activation directly determines the initiation speed of emergency response. A one-minute delay can multiply fire expansion within confined areas. Furthermore, high passenger density and limited evacuation routes mean even brief delays can close the critical escape window.

The ‘Evacuation Efficiency’ node demonstrates a sensitivity coefficient of 1.9, forming dual critical constraints in both temporal and spatial dimensions with the ‘Initial Alarm’ node. Although the ‘Fire Spread’ and ‘Smoke Diffusion’ nodes show lower sensitivity coefficients than the former two, they exhibit significant amplification effects in the subway environment. Under confined ventilation, fire spread velocity reaches 2-3 times that in open space, while horizontal smoke diffusion speed attains 0.5-1.0m/s in tunnels, easily forming smoke blockades that obstruct evacuation passages. Nodes including ‘Duty Arrangement’, ‘Open Fire Occurrence’, and ‘Material Flame Retardancy’ show sensitivity coefficients merely 1/5 to 1/10 of core nodes. However, these nodes can amplify fire risks through coupling effects with highly sensitive nodes.

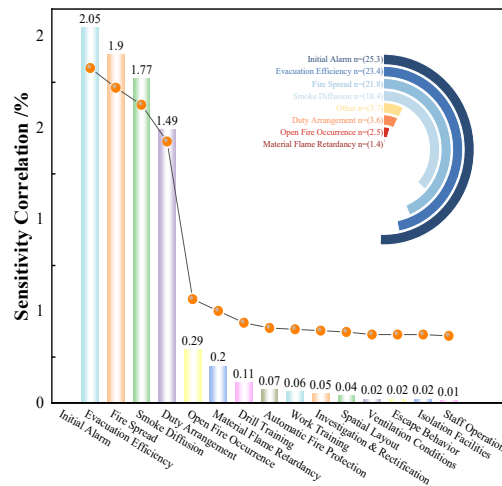


Fig. 13 Sensitivity analysis of casualties

Historical incidents, particularly the 1987 London Underground fire and 2003 Daegu subway arson case, validated the dominant roles of initial alarm and evacuation efficiency in an enclosed subway environment,

demonstrating strong alignment with the time-sensitive, space-constrained, and consequence-serious characteristics of subway fires.

4.1.2 Sensitivity analysis of key parent nodes

To reveal the critical causal chain of intermediate nodes in subway fires, sensitivity analysis was conducted on four key nodes: ‘Fire Spread’, ‘Smoke Diffusion’, ‘Initial Alarm’, and ‘Evacuation Efficiency’, with results shown in **Fig. 14**. The analysis indicates that ‘Fire Spread’ is mainly influenced by ‘Material Flame Retardancy’ at 3.72%, with a sensitivity 1.5 times that of ‘Automatic Fire Protection’. ‘Smoke Diffusion’ is primarily governed by ‘Open Fire Occurrence’ at 4.77%, showing 6 times the sensitivity of ‘Ventilation Conditions’. ‘Initial Alarm’ is predominantly affected by ‘Duty Arrangement’ at 9.17%, significantly exceeding the influence of ‘Communication Status’ at 0.4%. ‘Evacuation Efficiency’ is co-determined by factors including ‘Drill Training’ and ‘Spatial Layout’.

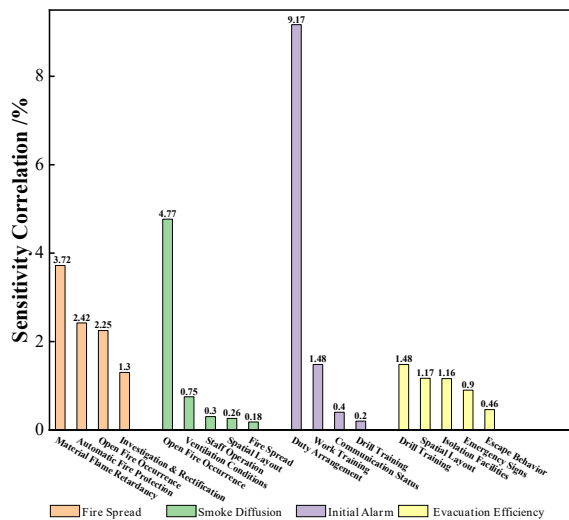


Fig. 14 Sensitivity analysis of four key nodes in the BN

The 2020 New York subway arson case exemplified these patterns. A passenger carried an open flame to ignite a train, with fire spreading throughout the vehicle within 90 seconds. The use of combustible materials, including polyethylene seats and rubber flooring, resulted in a fire growth rate approximately double that of a standard compartment. The ventilation failure to switch modes promptly allowed rapid smoke diffusion through the enclosed tunnel, causing 1 fatality and 17 injuries. During the incident, delayed response by duty staff postponed

the initial alarm by approximately 3 minutes. Insufficient passenger training and unclear escape routes caused significant evacuation obstacles. The accident chain demonstrates strong consistency with the highly sensitive nodes identified by the model.

4.2 Scenario analysis

BN core capability resides in dynamic consequence prediction through evidence input. By constructing multiple typical scenarios, it quantifies accident probabilities and impact scopes under varying risk combinations.

4.2.1 Composite risk scenario simulation

To quantify the impact of the combined risk of ‘Passenger Behavior’ and ‘Open Fire Occurrence’ on ‘Casualties’ probability during normal operation, a BN scenario was constructed where these factors couple to trigger a fire incident. Four fire scenarios were designed by applying extreme state assumptions to four key nodes: ‘Fire Spread’, ‘Smoke Diffusion’, ‘Initial Alarm’, and ‘Evacuation Efficiency’, while maintaining other nodes at normal states, to study probability variation in the ‘Casualties’ node. Taking the ‘Fire Spread’ node as an example, **Table 2** presents the state configuration along with other relevant nodes, with ‘Fire Spread’ serving as the dominant node in fire incident development.

Table 2 Node State Configuration of the BN under Fire Spread Scenarios

Bayesian nodes	Setup of Bayesian nodes (%)
Other nodes	Normal state
Passenger behavior	High = 100
Material flame retardancy	Low = 100
Ventilation	Low = 100
Open flame occurrence	High = 100
Fire spread	Low = 100% / Medium = 100% / High = 100%

Fig.15 displays the corresponding state probabilities of the ‘Casualties’ node under the extreme assumption of the ‘Fire Spread’ node being in the High state. The updated Bayesian network shows that Low, Medium, and High

represent node failure states. For instance, ‘Passenger Behavior’ (i.e., High=100%) indicates a 100% probability of the node being in a high-failure state, meaning malicious behavior is assumed to occur with certainty in this scenario. Similarly, ‘Fire Spread’ (i.e., High=100%) signifies a 100% probability of a high-failure state for fire spread, indicating fire propagation is assumed to occur with certainty.

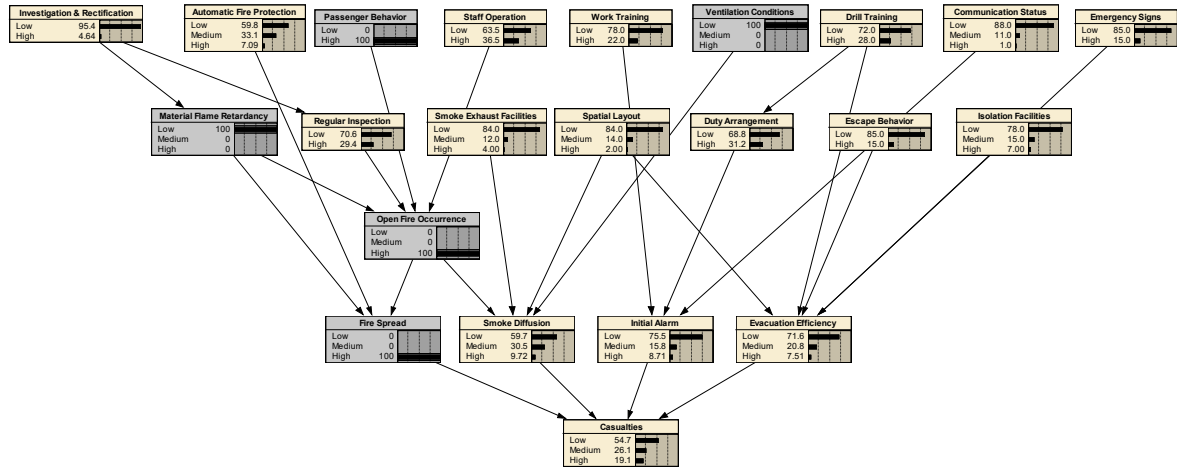


Fig. 15 Updated BN for the fire spread node state (i.e., High=100%) scenario

In scenarios where the spread of the fire dominates the occurrence of a fire incident, the probability of human casualties varies depending on the situation, as shown in **Table 3**.

Table 3 Casualty Probability under Different Fire Spread Scenarios

State Classification (%)	Low (%)	Medium (%)	High (%)
Original state	77.9	15.5	6.58
Low=100	77.6	15.7	6.76
Medium=100	73.4	17.9	8.68
High=100	54.7	26.1	19.1

When the ‘Fire Spread’ node state is set to Low=100%, indicating a low-failure state with no fire propagation, the ‘Casualties’ node shows a probability distribution of 77.6% for Low, 15.7% for Medium, and 6.76% for High. Compared to the baseline state, the Low probability slightly decreases while Medium and High probabilities exhibit minor increases, demonstrating minimal impact on casualty probability when fire spread is completely suppressed. When the ‘Fire Spread’ node is set to High=100%, representing a high-failure state with full fire

propagation, the 'Casualties' node distribution shifts to 54.7% for Low, while Medium and High probabilities rise to 26.1% and 19.1%, respectively. It indicates that intensive fire spread dramatically elevates casualty risks, establishing it as a critical factor in causing severe casualty consequences.

Fig.16 summarizes the simulation results of four fire scenarios, each dominated by one of four key nodes: 'Fire Spread', 'Smoke Diffusion', 'Initial Alarm', and 'Evacuation Efficiency', analyzing probability variation in the 'Casualties' node under different states. Across all four fire scenarios, the 'Casualties' node consistently shows decreasing Low probability and increasing High probability, indicating continuous contraction of the safety margin and escalation of consequence as fire conditions deteriorate. The 'Smoke Diffusion' node exerts the most significant impact on 'Casualties'. When its state transitions from Low to High, the Low probability of 'Casualties' drops from 77.8% to 47.7%, while the High probability rises from 6.6% to 24.1%. This largest variation demonstrates the most explosive escalation of casualties. The 'Fire Spread' node shows secondary influence. When fire develops from the initial stage to full propagation, the Low probability of 'Casualties' decreases from 77.6% to 54.7%, with High probability increasing from 6.76% to 19.1%, indicating that accelerated fire growth directly intensifies fatality risk. The 'Initial Alarm' node primarily affects the temporal aspect. Delayed alarm response increases High casualty probability by approximately 13%, confirming alarm response time as the critical constraint determining escape window availability. The 'Evacuation Efficiency' node reflects spatial constraint. When its state transitions from Low to High, indicating a deterioration in evacuation performance, the Low probability of the 'Casualties' node decreases by approximately 20% while the High probability increases to 20%. It demonstrates that reduced evacuation speed and passage obstruction significantly expand the casualty scope.

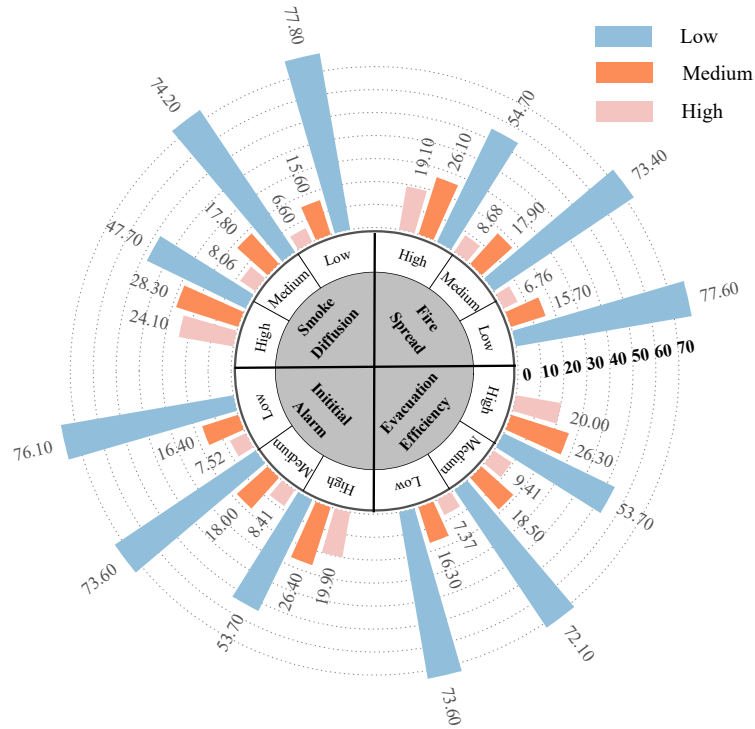


Fig. 16. Comparison of human casualty probability in complex risk scenarios

The Medium states across all 4 scenario nodes exhibit a consistent pattern of gentle decrease in Low probability and modest increase in High probability. For instance, when the ‘Smoke Diffusion’ node is in Medium state, the ‘Casualties’ node shows merely a 4.2% decrease in Low probability and a 1.92% increase in High probability. This indicates the transitional nature of Medium state influence, while High states represent the critical juncture for risk mutation. In summary, the High state of ‘Smoke Diffusion’ demonstrates the most significant impact on casualties, followed by the High state of ‘Fire Spread’. Both Low and Medium states exhibit relatively gradual influence, closer to ‘gradual change’ rather than ‘abrupt mutation’. The conclusion indicates that fire prevention strategies should prioritize controlling high-intensity smoke diffusion. Meanwhile, ‘Initial Alarm’ and “Evacuation Efficiency” represent critical defensive lines in temporal and spatial dimensions, respectively. When alarm delays or evacuation obstacles combine with coupling effects of fire spread and smoke diffusion, they form a composite risk chain leading to high casualties.

4.2.2 Verification with real accident cases

Through causal chain construction based on BN nodes, the 2003 Daegu subway arson case in Korea was used as a validation scenario to examine the model consistency with actual incidents. A passenger with deliberate arson initiated the fire, which propagated rapidly through the flammable cabin interior. Combined with smoke exhaust failure, delayed emergency response, and chaotic evacuation routes, the incident resulted in 192 fatalities.

The accident exhibited multiple overlapping risk scenarios, including malicious passenger behavior, low material flame resistance, failed smoke exhaust, delayed initial alarm, and disordered evacuation. Each critical failure encompassing material flammability, smoke management, alarm response, and evacuation organization corresponded directly to core nodes within the model. The nodes operated in high-risk states during the actual incident. Table 4 presents the configuration of BN node states for the Daegu subway fire, demonstrating the correspondence with the actual incident.

Table 4 Configuration of BN Node States Corresponding to the Daegu Subway Fire Incident

Bayesian Nodes	Setup of Bayesian Nodes (%)	Content of Real Accident
Other Nodes	Normal State	No special abnormal situation.
Passenger Behavior	High=100	Intentional arson occurs, and malicious behavior by passengers happens.
Material Flame Retardancy	Low=100	The interior of the carriage is flammable, and the flame retardancy is insufficient.
Smoke Exhaust	Low=100	The smoke exhaust system fails and cannot discharge smoke in time.
Initial Alarm	Low=100	Emergency response is delayed, and alarm disposal is lagging.
Evacuation Efficiency	Low=100	Evacuation routes are chaotic, and personnel escape in disorder.
Open Fire Occurrence	High=100	Arson causes a fire, and an open fire occurs.
Fire Spread	High=100	The fire spreads rapidly with the deterioration of flammable interior, and the fire gets out of control.

Fig.17 displays the BN node states according to the aforementioned disaster incident. Critical deficiencies identified in the accident, including insufficient material flame resistance, delayed initial alarm response,

malfunctioning smoke exhaust system, and disordered personnel evacuation, have been correspondingly assigned to the respective nodes.

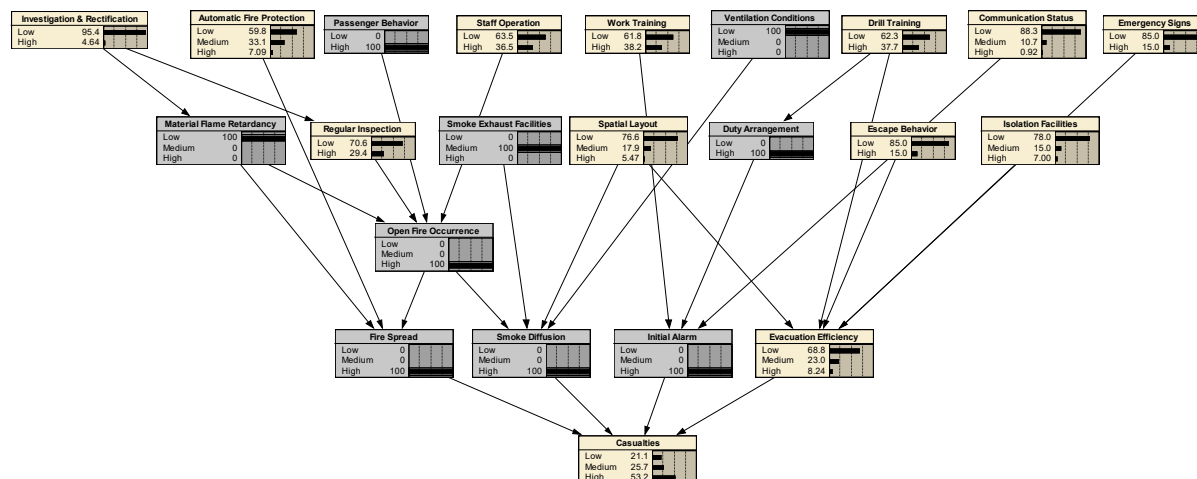


Fig. 17. BN causal association diagram of the Daegu subway fire incident in Korea

Case analysis demonstrates that under the coupling effects of core parent nodes ‘Fire Spread’, ‘Smoke Diffusion’, and delayed ‘Initial Alarm’, the Low state probability of the ‘Casualties’ node decreases from the baseline 77.9% to 21.1%, representing a 54 percentage point reduction. Simultaneously, the High state probability increases from 6.58% to 53.2%, a 46.62 percentage point rise, with Medium and High casualty risks collectively exceeding half of the total probability distribution.

In the Daegu subway incident in Korea, ‘Smoke Exhaust Facilities’ failure directly caused rapid toxic smoke propagation, becoming the primary factor hindering escape and exacerbating suffocation casualties. The empirical evidence fundamentally aligns with the conclusions. Both quantitative BN analysis and the actual Daegu subway arson case confirm that when ‘Smoke Diffusion’ reaches a High state condition specifically during ‘Smoke Exhaust Facilities’ failure with rapid smoke accumulation, its impact on ‘Casualties’ becomes most pronounced.

Although synergistic effects from ‘Fire Spread’, delayed ‘Initial Alarm’, and inefficient ‘Evacuation Efficiency’ further amplify risk, uncontrolled ‘Smoke Diffusion’ typically serves as the decisive factor in mass casualty events. Consequently, for fire prevention in confined spaces like subways, prioritizing enhanced ‘Smoke Exhaust Facilities’

reliability and controlling ‘Smoke Diffusion’ velocity represent crucial measures for reducing extreme casualty risk.

4.3 Reverse traceability and risk reduction strategies

The completed KG-GNN-BN integrated reasoning model supports comprehensive risk quantification through three analytical dimensions: sensitivity quantification, scenario simulation, and retrospective analysis. The systematic methodology identifies critical nodes and causal chains in subway fire risk evolution, forming the basis for targeted risk mitigation strategies.

4.3.1 Reverse tracing of key nodes and quantitative analysis of risk

Retrospective analysis compares variation (*i.e.*, risk increments) between baseline state (*i.e.*, normal operation) and incident state (*i.e.*, disaster scenario) to examine critical risk nodes across four core dimensions: ‘Casualties’, ‘Evacuation Efficiency’, ‘Smoke Diffusion’, and ‘Open Fire Occurrence’, revealing failure propagation patterns and quantitative characteristics in the accident chain. **Fig.18(a)** demonstrates that ‘Initial Alarm’, ‘Evacuation Efficiency’, and ‘Fire Spread’ constitute core risk sources in the retrospective analysis of the ‘Casualties’ node, with variation reaching 15.29%, 13.39%, and 13.07%, respectively, forming the primary risk transmission chain. Secondary factors include ‘Duty Arrangement’ (*i.e.*, 8.6%) and ‘Smoke Diffusion’ (*i.e.*, 8.1%), while nodes such as ‘Work Training’ show variation below 3.5%, representing a minor contributor.

The highest variation value of the ‘Initial Alarm’ node underscores its critical role as the initiation point of risk response. Functional delays in the node during an incident directly compromise the emergency response window and amplify subsequent risk. The ‘Evacuation Efficiency’ node ranks second; combined with confined space and limited escape routes in the subway, its risk elevation directly correlates with evacuation success rate, representing the core spatial constraint factor. The ‘Fire Spread’ node shows comparable variation to the former two, with its risk transmission directly linked to fire compartment integrity and material flame retardancy. Loss of control in

the node during an incident accelerates disaster escalation.

Hence, risk prevention for the "Casualties" node should focus on the primary chain of ‘Initial Alarm’, ‘Evacuation Efficiency’, and ‘Fire Spread’, prioritizing functional stability of the chain nodes.

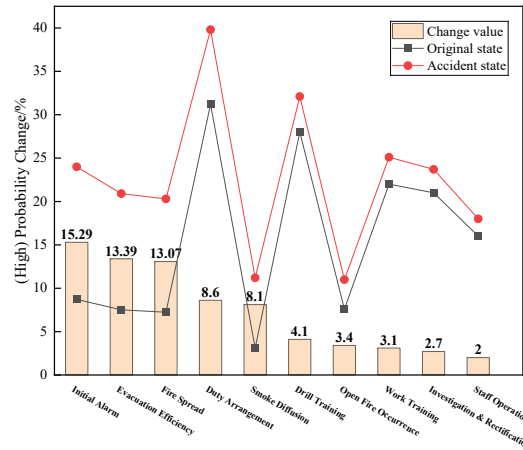


Fig.18(a) Reverse tracing of the risk node for human casualties and analysis of probability change

Fig.18(b) presents the retrospective analysis of the ‘Evacuation Efficiency’ node, showing risk variation and probability characteristics under baseline and incident states for nodes including ‘Drill Training’ and ‘Escape Behavior’.

In terms of variation, ‘Drill Training’ demonstrates the highest variation at 15.4%, serving as the primary driver of ‘Evacuation Efficiency’. ‘Escape Behavior’ follows with 8.5% variation. Subsequent nodes show progressively smaller contributions: ‘Isolation Facilities’ (i.e., 2.51%), ‘Duty Arrangement’ (i.e., 2.3%), ‘Emergency Signs’ (i.e., 1.5%), and ‘Spatial Layout’ (i.e., 0.87%). From the state probability perspective, ‘Drill Training’ shows a baseline probability around 28% that surges beyond 43% during incidents, indicating training deficiencies substantially amplify risk probability. ‘Escape Behavior’ increases from approximately 15% baseline to about 23% during incidents, demonstrating passenger behavior standardization significantly influences risk transmission.

The results establish ‘Drill Training’ as the core driving node whose effectiveness directly determines risk amplification. ‘Escape Behavior’ serves as an important correlated node where behavioral standardization affects risk transmission efficiency. Although ‘Isolation Facilities’ and ‘Duty Arrangement’ show lower variation, which

continuously influence the risk state within their respective dimensions. ‘Emergency Signs’ and ‘Spatial Layout’ exhibit relatively weaker impacts on risk.

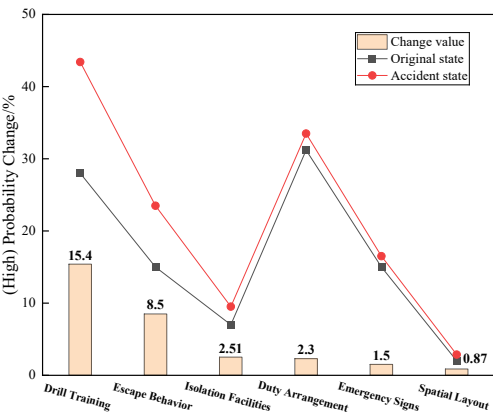


Fig.18(b) Reverse tracing of the evacuation efficiency risk node and analysis of probability variation

Fig.18(c) displays risk variation and state probability characteristics for nodes including ‘Open Fire Occurrence’. Regarding variation, ‘Open Fire Occurrence’ ranks highest at 11.7%, followed by ‘Staff Operation’ at 7.8%, with the remaining nodes showing progressively decreasing values.

In state probabilities, ‘Open Fire Occurrence’, ‘Staff Operation’, ‘Regular Inspection’, and ‘Fire Spread’ demonstrate significant increases from baseline to incident states, while ‘Investigation & Rectification’ maintains consistently high probabilities. ‘Material Flame Retardancy’ exhibits limited influence. The findings establish ‘Open Fire Occurrence’ as the core driving node, with ‘Staff Operation’ serving as an important correlated node. ‘Regular Inspection’ amplifies risk through a coupling effect, while ‘Material Flame Retardancy’ demonstrates a relatively weaker impact.

In a subway operational context, ‘Open Fire Occurrence’ corresponds to real-world hazards, including equipment short circuits and passenger violations involving open flames. Once ignition occurs, it directly causes a sharp escalation of ‘Smoke Diffusion’ risk. The prominent risk of ‘Staff Operation’ reflects practical issues in subway personnel training deficiencies and procedural non-compliance, where operational errors accelerate smoke diffusion. The consistently high incident-state probability of ‘Regular Inspection’ indicates inadequate

implementation of the inspection regime in subway maintenance, where latent equipment failures remain undetected, ultimately amplifying ‘Smoke Diffusion’ risk.

Overall analysis indicates that subways require strengthened open flame control, standardized staff operation, and rigorous inspection mechanisms to address core ‘Smoke Diffusion’ risk from an operational perspective.

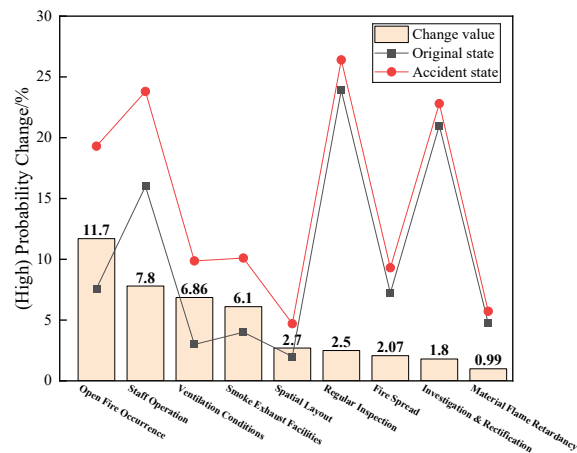


Fig .18(c) Reverse tracing of the risk node for flue gas dispersion and analysis of probability variation

Fig.18(d) presents risk variation and probability characteristics under baseline and incident states for nodes including ‘Passenger Behavior’ and ‘Staff Operation’.

State probability analysis reveals ‘Passenger Behavior’ increases from approximately 19% in the baseline state to over 37% during incidents, indicating passenger violations substantially amplify ‘Open Fire Occurrence’ risk. ‘Staff Operation’ rises from around 16% to about 32%, demonstrating staff operational standardization significantly influences ‘Open Fire Occurrence’ risk transmission. ‘Fire Spread’ shows probabilities of approximately 7% under baseline conditions and 18% during the incident, reflecting its risk coupling effect with ‘Open Fire Occurrence’. ‘Material Flame Retardancy’ increases from approximately 5% under baseline conditions to 14% during the incident, indicating that insufficient flame retardant performance indirectly promotes ‘Open Fire Occurrence’ risk escalation. ‘Investigation & Rectification’ maintains consistently high probabilities at approximately 21% in the baseline state and 30% during the incident, reflecting its continuous correlation with ‘Open Fire Occurrence’ risk across operational states. ‘Regular Inspection’ probabilities measure approximately

24% under baseline conditions and 32% during an incident, demonstrating that inspection deficiencies exacerbate potential ‘Open Fire Occurrence’ risk. ‘Smoke Diffusion’ maintains low probabilities across both scenarios, exhibiting limited direct impact on ‘Open Fire Occurrence’ risk.

Variation analysis identifies ‘Passenger Behavior’ with the highest variation, highlighting its core driving role in ‘Open Fire Occurrence’ risk. These findings establish passenger behavior management as the most critical intervention point for controlling fire ignition risks in the subway system.

Variation analysis identifies ‘Passenger Behavior’ with the highest value, confirming its core driving effect on ‘Open Fire Occurrence’ risk. The 2012 incident at Yonganli Station on Beijing Subway Line 1 exemplifies the pattern, where a passenger violated the smoking regulation, and improper disposal of an unextinguished cigarette butt into a distribution box directly ignited a fire, demonstrating how passenger misconduct serves as the primary trigger for ‘Open Fire Occurrence’.

State probability analysis further substantiates the relationship, showing ‘Passenger Behavior’ increases from approximately 19% under baseline conditions to over 37% during the incident. The 2025 case on Guangzhou Subway Line 3, where a passenger with a power bank suddenly emitted smoke, creating a fire risk, visually demonstrates the risk amplification effect of prohibited item carriage.

Similarly, ‘Staff Operation’ shows significant risk elevation from approximately 16% under baseline conditions to about 32% during the incident. The 2009 incident at the Caoyang Road construction site on Shanghai Rail Transit Line 11 illustrates the mechanism, where workers violated the welding procedure, causing an acetylene gas explosion resulting in 1 fatality and 6 injuries, confirming the critical impact of operational error on ‘Open Fire Occurrence’ risk.

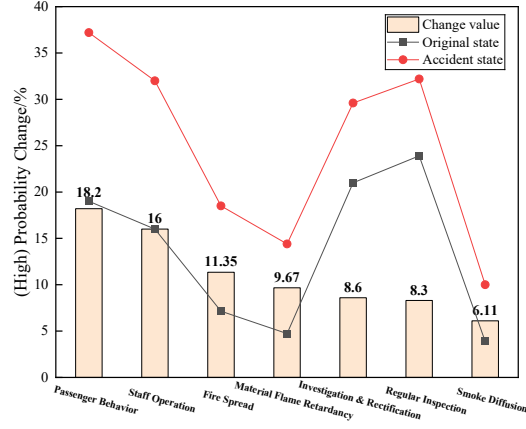


Fig .18(d). Reverse tracing of risk nodes associated with open flame and analysis of probability change

Integration of the evidence demonstrates that the coupling failure of personnel, facilities, and management factors forms the core pathway for subway fire risk transmission. Specifically, ‘Initial Alarm’, ‘Evacuation Efficiency’, ‘Smoke Diffusion’, and ‘Casualties’ form the dominant chain across temporal, spatial, and consequence dimensions. Alarm delays cause response lag, reduced evacuation efficiency creates congestion, and uncontrolled smoke diffusion dramatically amplifies casualties. Results demonstrate that ‘Initial Alarm’ and ‘Evacuation Efficiency’ serve as critical temporal control nodes, while ‘Smoke Diffusion’ acts as the core node for consequential amplification. Risk prevention should prioritize rapid alarm response, stable evacuation, and controlled smoke diffusion. It requires compressing response delays, enhancing drill training and smoke exhaust facility reliability, and establishing an efficient coordinated early warning and emergency system, with particular focus on preventing low-probability, high-consequence latent risks.

4.3.2 Risk reduction strategy

Analysis of sensitivity and retrospective tracing results for the ‘Casualties’ node enables data-driven risk prioritization. **Fig.19** compares retrospective difference values with normalized sensitivity across nodes, clarifying risk reduction priority and critical pathway.

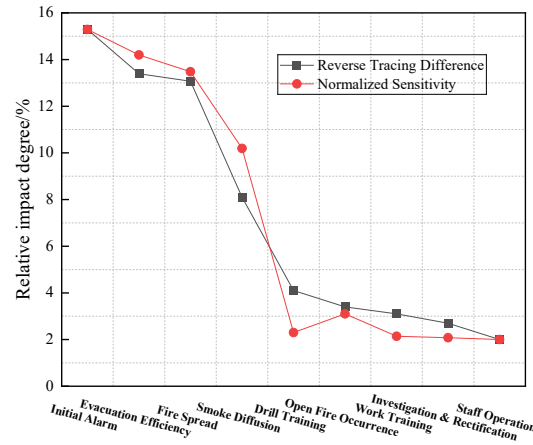


Fig.19. Comparison of node impact trends in the context of reverse tracing and normalization sensitivity

The ‘Initial Alarm’, ‘Evacuation Efficiency’, and ‘Fire Spread’ nodes show aligned high values in both metrics, with relative influence exceeding 12%. These form the risk transmission core chain, serving as both sensitivity amplifiers and retrospective causal factors. Specific mitigation measures include optimizing smoke temperature sensor algorithms to reduce alarm confirmation time while establishing standardized dispatch protocols. Additional measures involve quarterly clearance and updating of evacuation signage, monthly passenger drills with dynamic display guidance, semi-annual inspection of train electrical components, installation of an automatic fire suppression system, and quarterly testing of the fire compartmentation curtain.

The ‘Smoke Diffusion’ node connects upstream equipment, including ‘Smoke Exhaust Facilities’ and ‘Ventilation Conditions’, to downstream ‘Casualties’. Its normalized sensitivity around 10 percent exceeds retrospective difference around 8%. Meanwhile, ‘Drill Training’ shows the reverse pattern, with retrospective difference exceeding normalized sensitivity, indicating accumulated root causes from long-term training deficiencies. The ‘Open Fire Occurrence’ node exhibits balanced metrics as an ignition trigger. Several nodes, including ‘Work Training’, ‘Investigation & Rectification’, and ‘Staff Operation’ show low values in both dimensions, representing terminal support layers. Corresponding strategies involve establishing a training reinforcement mechanism, implementing source control for open flames, and optimizing procedures for terminal nodes to target weak links in the causal chain.

5. Discussion

To address the challenge of insufficient semantic understanding, weak causal reasoning capability, and poor dynamic adaptability in subway fire risk assessment, the study proposes an integrated KG-GNN-BN reasoning model combining KG, GNN, and BN methodologies. The model effectively combines knowledge-driven and data-driven advantages: the knowledge graph enables structured representation of fire causation knowledge, the graph neural network facilitates deep mining of implicit relationships between nodes, and the BN supports dynamic reasoning and retrospective analysis of uncertain events. Results demonstrate the model's effectiveness in identifying critical risk chains involving 'Initial Alarm', 'Evacuation Efficiency', 'Smoke Diffusion', and 'Casualties', while revealing the transmission of multi-factor coupling in subway fires. Regarding the model mechanism, the incorporation of GNN significantly enhances node feature representation, demonstrating high stability and generalization performance in node classification and key risk identification. Nevertheless, the current research exhibits several limitations. The KG maintains a constrained scale, with data sources principally drawn from web crawlers, literature reviews, and subway regulatory documentation. A significant deficiency exists in a comprehensive dataset from specific subway projects, compounded by insufficient real-time operational data. Consequently, at the perceptual level, the absence of real-time dynamic monitoring capabilities for equipment status, personnel behavior, and environmental parameters impedes the enhancement of intelligent maintenance efficiency.

6. Conclusion

As densely populated and enclosed public transport facilities, metro systems are a core priority for fire prevention and control. Targeting the existing methods for metro fire risk assessment, this study constructed an integrated KG-GNN-BN reasoning model and conducted fire risk analysis for metro stations. The main research outcomes are as follows:

(1) Based on historical metro fire incidents and metro fire protection codes, natural language processing technology was used to extract fire characteristic keywords and define six categories of accident risk labels. Feature and label attributes were embedded into the node-edge-node topological structure of the knowledge graph. A metro fire knowledge graph database with 666 nodes, 215-dimensional features, and six types of risk labels was eventually established.

(2) Relying on the knowledge graph database, we performed GNN node classification training with a three-layer GCN. Weighting algorithms such as confidence calculation and K-means clustering were incorporated into the well-trained GNN model. An automatic selection method for BN nodes based on KG-GNN was proposed, which addresses the subjectivity of traditional manual screening of BN nodes.

(3) In the KG-GNN-BN integrated model, the baseline probability of severe casualties in metro fires is 6.58%. Probabilistic reasoning indicates that under the combined scenario of malicious passenger behaviors, smoke exhaust system failure, delayed alarm response, and other coupled risks, the probability of severe casualties surges to 53.2%. The probability variation values of initial alarm, evacuation efficiency, and fire spread all exceed 13%; those of duty arrangement and smoke diffusion are approximately 8%, while the values of other auxiliary nodes are below 3.5%. This work quantifies the impacts and coupling effects of risk factors, providing solid data support for metro fire prevention and control.

References

- [1] Wu, J., Hu, Z., Chen, J., Li, Z., 2018. Risk assessment of underground subway stations to fire disasters using Bayesian network. *Sustainability*, 10(10), 3810.
- [2] Ministry of Transport of the People's Republic of China. Monthly operational data report of urban rail transit in February 2025 [EB/OL]. Beijing: Ministry of Transport of the People's Republic of China, 2025-03-10. Available:
- [3] Kırılangoğlu C, Coşkun G, Yalçınkaya O, et al. An Integrated Spatio-Temporal Risk Assessment Model for Fire

- Dynamics and Evacuation in Subway Tunnels[J]. *Fire*, 2026, 9(9): 381.
- [4] Lin X, Song S, Zhai H, et al. Using catastrophe theory to analyze subway fire accidents[J]. *International Journal of System Assurance Engineering and Management*, 2020, 11(1): 223-235.
- [5] Yan W, Wang J, Jiang J. Subway fire cause analysis model based on system dynamics: A preliminary model framework[J]. *Procedia Engineering*, 2016, 135: 431-438.
- [6] Li, X., Zhang, L., Shang, B., Fang, X., Tao, Y., Ma, Y., & Tu, J. (2025). Study on full-scale experimental and numerical investigation of fire-induced smoke control in an underground Double-Island Subway Station. *International Communications in Heat and Mass Transfer*, 163, 108697.
- [7] Xu, D., Li, Y., Du, T., Zhong, H., Huang, Y., Li, L., & Xiangling, D. (2024). Investigating the influence of outdoor temperature variations on fire-induced smoke behavior in an atrium-type underground metro station using hybrid ventilation systems. *Energy*, 287, 129570.
- [8] Teodosiu, C. I., & Kubinyecz, V. F. (2022). Numerical study on the impact of platform screen doors in a subway station with a train on fire. *Applied Sciences*, 12(16), 8296.
- [9] Wu J, Hu Z, Chen J, et al. Risk assessment of underground subway stations to fire disasters using Bayesian network[J]. *Sustainability*, 2018, 10(10): 3810.
- [10] Lin, X., Chen, S., Ji, B., Fan, H., Pan, Z., & Zhai, H. (2024). Research on a subway fire evacuation model based on system dynamics. *International Journal of System Assurance Engineering and Management*, 15(11), 5196-5205.
- [11] Chai, N., Zhou, W., Chen, Z., Lodewijks, G., & Zhao, Y. (2024). Multi-attribute fire safety evaluation of subway stations based on FANP-FGRA-Cloud model. *Tunnelling and Underground Space Technology*, 144, 105526.
- [12] Sajid Z, Yang Y, You P, et al. An explorative methodology to assess the risk of fire and human fatalities in a subway station using fire dynamics simulator (FDS)[J]. *Fire*, 2022, 5(3): 69.
- [13] Yan, Z., & Wang, Y. (2021). Developing a subway fire risk assessment model based on analysis theory. *Mathematical*

- Problems in Engineering, 2021(1), 5549952.
- [14] Ju, W., Wu, J., Kang, Q., Jiang, J., & Xing, Z. (2022). Fire Risk Assessment of Subway Stations Based on Combination Weighting of Game Theory and TOPSIS Method. *Sustainability*, 14(12), 7275.
- [15] Gao, J. P., Xu, Z. S., Liu, D. L., & Cao, H. H. (2014). Application of the model based on fuzzy consistent matrix and AHP in the assessment of fire risk of subway tunnel. *Procedia Engineering*, 71, 591-596.
- [16] Zhang L, Wu X, Liu M, et al. Discovering worst fire scenarios in subway stations: A simulation approach[J]. *Automation in construction*, 2019, 99: 183-196.
- [17] Wang, J., Yan, W., Xu, H., Zhi, Y., Wang, Z., & Jiang, J. (2018). Investigation of the probability of a safe evacuation to succeed in subway fire emergencies based on Bayesian theory. *KSCE Journal of Civil Engineering*, 22(3), 877-886.
- [18] Wu, J., Hu, Z., Chen, J., & Li, Z. (2018). Risk Assessment of Underground Subway Stations to Fire Disasters Using Bayesian Network. *Sustainability*, 10(10), 3810.
- [19] Bai, Y., Wu, J., Ren, Q., Jiang, Y., & Cai, J. (2023). A BN-based risk assessment model of natural gas pipelines integrating knowledge graph and DEMATEL. *Process Safety and Environmental Protection*, 171, 640-654.
- [20] Bakhtiari, S., Najafi, M. R., Goda, K., & Peerhossaini, H. (2025). A dynamic Bayesian network approach to characterize multi-hazard risks and resilience in interconnected critical infrastructures. *Reliability Engineering & System Safety*, 257, 110815.
- [21] Zheng, Q., Guo, T., Ding, G., Zhang, H., Zhang, K., 2025. Manufacturing service recommendation method based on knowledge graph and graph convolutional network. *Advanced Engineering Informatics*, 68, 103599.
- [22] Su, C., Jiang, Q., Han, Y., Wang, T., He, Q., 2025. Knowledge graph-driven decision support for manufacturing process: A graph neural network-based knowledge reasoning approach. *Advanced Engineering Informatics*, 64, 103098.
- [23] Jeon G, Hong W. Characteristic features of the behavior and perception of evacuees from the Daegu subway fire and safety measures in an underground fire[J]. *Journal of Asian Architecture and Building Engineering*, 2009, 8(2): 415-422.

- [24] Sowa, J. F., 1984. Conceptual structures: information processing in mind and machine. Addison-Wesley Longman Publishing Co., Inc..
- [25] Nickel, M., Murphy, K., Tresp, V., Gabrilovich, E., 2015. A review of relational machine learning for knowledge graphs. *Proceedings of the IEEE*, 104(1), 11-33.
- [26] Paulheim, H., 2017. Knowledge graph refinement: A survey of approaches and evaluation methods. *Semantic Web*, 8(3), 489-508.
- [27] Srinivasan, S. B. T., Ozaki, M., Nishida, Y., Oono, M., Yamanaka, T., 2023. Situation-aware system based on knowledge graphs derived from R-Map analysis of accident situational big data. *Procedia Computer Science*, 220, 436-445.
- [28] Ji, S., Pan, S., Cambria, E., Marttinen, P., Yu, P. S., 2021. A survey on knowledge graphs: Representation, acquisition, and applications. *IEEE Transactions on Neural Networks and Learning Systems*, 33(2), 494-514.
- [29] Tiddi, I., Schlobach, S., 2022. Knowledge graphs as tools for explainable machine learning: A survey. *Artificial Intelligence*, 302, 103627.
- [30] Santos, A., Colaço, A. R., Nielsen, A. B., Niu, L., Strauss, M., Geyer, P. E., Mann, M., 2022. A knowledge graph to interpret clinical proteomics data. *Nature Biotechnology*, 40(5), 692-702.
- [31] Scarselli, F., Gori, M., Tsoi, A. C., Hagenbuchner, M., Monfardini, G., 2008. The graph neural network model. *IEEE Transactions on Neural Networks*, 20(1), 61-80.
- [32] Zhou, J., Cui, G., Hu, S., Zhang, Z., Yang, C., Liu, Z., Sun, M., 2020. Graph neural networks: A review of methods and applications. *AI Open*, 1, 57-81.
- [33] Kipf, T. N., 2016. Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907*.
- [34] Gilmer, J., Schoenholz, S. S., Riley, P. F., Vinyals, O., Dahl, G. E., 2017. Neural message passing for quantum chemistry. In *International Conference on Machine Learning* (pp. 1263-1272). PMLR.
- [35] Wu, Z., Pan, S., Chen, F., Long, G., Zhang, C., Yu, P. S., 2020. A comprehensive survey on graph neural networks. *IEEE*

Transactions on Neural Networks and Learning Systems, 32(1), 4-24.

- [36] Pearl, J., 1985. Bayesian networks: A model of self-activated memory for evidential reasoning. In Proceedings of the Annual Meeting of the Cognitive Science Society (Vol. 7, pp. 329-334).