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Risk Coupling Analysis of Metro Deep Foundation Pit Construction Based on Complex Networks

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Abstract: The exacerbation of safety risk levels in metro deep foundation pit construction is attributed to the interactive coupling of numerous risk factors. To comprehensively explore the underlying mechanisms of safety incidents, complex network theory is applied to analyze interactions among risk factors systemically. Initially, through the identification of safety risk factors, a risk factor system comprising six primary risk factors and 35 secondary risk factors is established. Subsequently, by utilizing coupling mechanism analysis and complex network theory, a coupling network model of safety risks in metro deep foundation pit construction with 42 nodes and 184 directed edges is constructed, with network topology indicators analysis revealing the evolutionary law of risk coupling. Finally, Python software is employed to simulate the network with single-node, random, and targeted immunization. Key risk factor nodes are identified using network efficiency measurement methods. The results indicate that all risk factors positively influence the connectivity of the coupling network, and the risk-coupling network presents small-world and scale-free characteristics. In comparison with different immunization strategies, targeted immunization is found to be more effective than random immunization, and prioritizing the control of risk factors with a high degree of centrality, such as "violation of operating regulations" and "inadequate safety supervision and hidden danger inspection", proves more effective in alleviating risk coupling, underscoring the importance of prioritizing control of key risk nodes in the network. These findings provide a scientific basis for risk management and optimization in metro deep foundation pit construction.

Keywords: metro deep foundation pit; risk management; risk coupling; complex network; immunization simulation

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1. Introduction

During the urban modernization process, the extensive construction of metro projects has effectively alleviated the pressure on ground transportation and urban spatial demands. Nevertheless, the complex and ever-changing construction environment, enormous excavation depth, diverse cross-functional operational procedures, extensive use of construction machinery and equipment, and complex construction management have made foundation pit construction a high-risk aspect of metro construction. During the construction process, the convergence of multiple risks often leads to accidents, resulting in severe casualties and property losses and posing significant challenges for construction workers and management personnel in terms of risk analysis and risk management. Therefore, it is necessary to adopt systematic scientific research methods to explore the mechanism of risk factors in metro deep foundation pit construction, which is important for the scientific prevention of safety accidents in metro deep foundation pits.

Due to the continuous development of subway transportation and the complex difficulties in metro deep foundation pit construction, research on the risks of subway deep excavation construction is currently extensive. In terms of risk factor identification, numerous studies analyze the causes of accidents from multidimensional perspectives. Zhang

et al. identified eight key risk factors for subway projects through questionnaire surveys, including the project management team, underground environment, and mechanical usage [1]. Hyun et al. categorized underground engineering risks into geological conditions, design, construction, and management factors using fault-tree analysis to analyze risks in tunnel construction [2]. Li et al. established safety risk assessment indicators for coastal area subway station excavation construction from four aspects: soil landslides, artesian water surges, bottom heave and support to fall [3]. Wang et al. conducted a risk assessment and analysis of subway deep excavation construction based on monitoring data from earthwork engineering, support and protection engineering and geological water level [4]. Meng et al. utilized the WBS-RBS method to obtain nine risk factors, including the selection of support systems and the design of enclosure structures [5]. In the aspect of risk analysis models, Zhou et al. developed a subway pit risk analysis model based on SVM and conducted risk prediction [6]. You et al. established an evaluation index system based on five factors: "people, management, technology, material, environment", proposing a subway station deep excavation risk assessment method based on G-COWA [7]. Jiang et al. proposed a pit risk evaluation model based on fuzzy evidence reasoning and TL-ANP [8]. Zhang et al. proposed a comprehensive analysis method for the dynamic risk of pit construction collapse based on FBN and FAHP [9]. Fu et al. used the Apriori algorithm to mine strong association rules between risks in metro deep foundation pit engineering, demonstrating that subway deep excavation engineering accidents are the result of strong interactions among safety risks of multiple stakeholders [10].

Research on the causes, analysis and risk management of engineering accidents under the perspective of multiple-factor coupling is emerging. Xiang et al. explored the risk-coupling mechanism of cross-regional mega projects using the system dynamics method and put forward the decoupling control method [11]. Zhou et al. analyzed the safety factors of tower crane construction in building engineering by integrating the SNA and N-K models [12]. Zhou et al. combined complex network and association rule mining as a new risk analysis method to reveal association rules between security risk monitoring types and risk coupling, improving the possibility of risks identified from abnormal monitoring combinations [13]. The risk factors of safety accidents in subway construction are complex and diverse. Wang et al. integrated the risk-coupling theory to analyze the interaction between risk factors and established a subway excavation construction risk assessment model based on the C-OWA operator and interaction matrix method [14]. Li et al. used the risk factor coupling coefficient to measure the degree of coupling between factors and establish a quantitative model for the safety risk system of large urban underground spaces [15]. Fang et al. used the four-module analysis approach to identify the key cause of metro collapse accident and its coupling risk effect and analyzed the evolution process of the accident [16]. Guo et al. utilized the N-K model to compute the risk-coupling value of complex geological and construction factors in tunnel construction, and their findings proved that the coupling risk of these components exceeded their individual effects [17]. Zhou et al. constructed a network model of subway construction accidents and explored the connections between 26 types of subway construction accidents [18]. Chen et al. established the risk factor network of underground engineering from the dimensions of management, environment, technology, and personnel elements, and the important risk factors were then identified by SNA analysis of each risk component's position and degree of interaction [19].

Many scholars have conducted valuable research on the coupling of safety risks and safety management in metro construction. However, the safety research of metro deep foundation pit construction tends to risk identification and evaluation [20–22]. In the study of risk coupling, reference [14] considered the coupling effect of risk factors in risk assessment, but the intricate interaction and coupling evolution mechanism between these risk factors have not been fully analyzed. The unsafe state and behavior of construction personnel, unsafe state of construction material and machinery, unfavorable environmental conditions, improper management, technological and methodological deficiencies, and other risk factors, collectively present a complex coupling state characterized by mutual influence and

interaction in the construction process of metro deep foundation pits. The network effects among risk factors have become increasingly apparent. Complex networks, as theoretical tools for studying various complex relationships in the real world, provide profound insights into risk analysis in fields such as transportation [23,24], construction [25–27], coal mines [28], and finance [29]. The essence of this lies in exploring the relationship between network structures and functions, providing a theoretical foundation and methodological support for the analysis of safety risk coupling in metro deep foundation pit construction. Therefore, this paper proposes a method for analyzing the coupling of safety risks in metro deep foundation pit construction based on the theory of complex networks. On the basis of risk factor identification and coupling mechanism analysis of metro deep foundation pit construction, a complex network model of risk coupling is established. Through analysis of network structure characteristics, the roles and importance of risk factors in the coupling network are revealed. Using immune simulation analysis to identify critical risk factors and risk reduction strategies, we provide valuable insights for risk management in metro deep foundation pit construction.

Building upon the existing research and a comprehensive literature review, Section 2 introduces the research materials and methods and puts forward the application framework of complex network theory and the risk-coupling analysis process. Section 3 explores the construction of the risk-coupling network model and analyzes its topological features. Section 4 uses the simulation method to evaluate the importance of network nodes. Finally, Section 5 presents pertinent conclusions and suggests future research directions.

2. Materials and Methods

2.1. Identification of Risk Factors

Based on the "4M1E" system safety theory and Wuli–Shili–Renli (WSR) system approach [30], along with references to safety risk management practices and related studies in metro deep foundation pit construction, a detailed analysis of safety risk factors in metro deep foundation pit construction is conducted from six aspects, as shown in Table 1. The risk factors are divided into six core attributes: personnel, machinery, material, management, environment, and technology. Primary risk factors are high-level and macro risk factors that serve as the basis for overall risk analysis. Secondary risk indicators are then further subdivided based on the primary risk factors and represent more specific risk factors. This analysis is intended to support the subsequent research on the safety risk-coupling network model in metro deep foundation pit construction. The six factors of "personnel", "machinery", "material", "management", "environmental" and "technical" risk factors are represented by the combination of letters "a", "b", "c", "d", "e", "f" and serial numbers, respectively.

Table 1. Safety risk factors of metro deep foundation pit construction.

Risk	Primary Risk Factor	Secondary Risk Factor	Typical Accident Cases
Safety risk of metro deep founda-tion pit constr-uction (R)	Personnel risk factors (a)	Poor awareness of personnel security (a_1)	Falling accident on Guangzhou Metro Line 2
		Insufficient professional skills (a_2)	Collapse accident on Beijing Metro Line 5
		Poor communication and adaptability (a_3)	Collapse accident on Shenzhen Metro Line 1
		Poor physical or mental health (a_4)	The other accident on Shenzhen Metro Line 8
		Violation of operating regulations (a_5)	Object strike accident on Nanjing Metro Line 1
	Machinery risk factors (b)	Inadequate equipment maintenance (b_1)	Mechanical injury accident on Qingdao Metro Line 3
		Equipment failure (b_2)	Lifting injury accident on Nanjing Metro Line 3
		Unreasonable equipment selection (b_3)	Lifting injury accident on Guangzhou Metro Line 4
		Unreasonable arrangement of mechanical work (b_4)	Lifting injury accident on Nanjing Metro Line 10
		Insufficient safety protection measures for mechanical equipment (b_5)	Lifting injury accident on Beijing Metro Line 3

Table 1. *Cont.*

Risk	Primary Risk Factor	Secondary Risk Factor	Typical Accident Cases
Safety risk of metro deep founda-tion pit constr-uction (R)	Material risk factors (c)	Improper management of material storage, transportation and use (c_1)	Collapse accident on Hangzhou Metro line 9
		Substandard concrete strength (c_2)	Collapse accident on Hangzhou Metro Line 4
		Insufficient stress in steel support (c_3)	Collapse accident on Singapore metro
		Inadequate strength of anchor rod (c_4)	Collapse accident on Nanchang Metro Line 1
		Unqualified quality of retaining wall materials (c_5)	Collapse accident on Qingdao Metro Line 1
		Improper control of material processing quality (c_6)	Object strike accident on Shanghai Metro Line 7
	Management risk factors (d)	Inadequate safety education and training (d_1)	Collapse accident on Hefei Metro Line 6
		Incomplete rules and regulations (d_2)	Collapse accident on Changsha Metro Line 4
		Insufficient safety investment (d_3)	Collapse accident on Xuzhou Metro Line 3
		Inadequate safety supervision and hidden danger inspection (d_4)	Object strike Accident on Shanghai Metro Line 7
		Inadequate safety briefing (d_5)	Collapse accident on Shenzhen Metro Line 13
		Unreasonable construction organization and schedule arrangement (d_6)	Collapse accident on Hangzhou Metro Line 1
	Environmental risk factors (e)	Poor geological and hydrological conditions (e_1)	Collapse accident on Guangzhou Metro Line 3
		Harsh weather or natural disasters (e_2)	Collapse accident on Hangzhou Metro Line 4
		Complicated underground pipeline laying (e_3)	Collapse accident on Beijing Metro Line 4
		Closing to large high-rise buildings (e_4)	Collapse accident on Harbin Metro
		Complicated peripheral traffic (e_5)	Collapse accident on Beijing Metro Line 4
		Harsh operating environment (e_6)	Electric shock accident on Wuhan Metro Line 4.
	Technical risk factors (f)	Unspecified or deviation of geological and hydrological survey (f_1)	Collapse accident on Hangzhou Metro Line 1
		Improper design and construction scheme (f_2)	Collapse accident on Singapore metro
		Improper earthwork excavation (f_3)	Collapse accident on Shanghai Metro Line 8
		Improper construction method of retaining structure (f_4)	Collapse accident on Changsha Metro Line 4
		Error in setting and demolishing supports (f_5)	Collapse accident on Shenzhen Metro Line 1
		Insufficient monitoring of foundation pit (f_6)	Collapse accident on Qingdao Metro Line 3
		Untimely dewatering and drainage (f_7)	Collapse accident on Shanghai Metro Line 4.

2.2. Theory and Methods

2.2.1. Analysis of Risk Coupling Mechanism

The significance of analyzing the risk-coupling mechanism lies in uncovering the interactions and influences among various risk factors at a theoretical level, thereby understanding how these factors collectively contribute to increasing or decreasing systemic risk. Coupling refers to the phenomenon in which two or more elements interact with each other, forming a dynamic relationship of mutual coordination and promotion. In the process of safety risk spreading of metro deep foundation pit, diverse risk factors exert an influence and interact, which ultimately alters the flow and nature of safety risks, that is, produces a coupling effect. Safety accidents manifest as a consequence of this coupling effect of safety risks, and Figure 1 illustrates this coupling mechanism.

If a certain risk occurs, the safety system makes the risk factors unable to pass through the six sub-defense systems through self-adjustment, and the state of "zero coupling" for the risk factors is present. Under these circumstances, the risk factors are isolated from each other and act independently. When the continuously intensified risk factors rush through the sub-defense system, the safety system relies on its ability of self-adaptability, self-organization and self-adjustment to slow down and weaken the risk-coupling process, so that its coupling degree and influence cannot further exceed the partial risk-coupling threshold, at this time, risk factors are in a "weak coupling" state. The interaction intensity of risk factors after partial coupling is constantly improved under the action of oscillation coupling, which leads to a sharp increase in risk, or a sudden change to a new risk factor, which evolves into a "strong coupling" risk state. Under the strong coupling, the risk factors break through the comprehensive defense system, which destroys and renders

useless the safety system, consequently culminating in risk accidents. The risks that are not effectively disposed of will enter a new round of risk coupling.

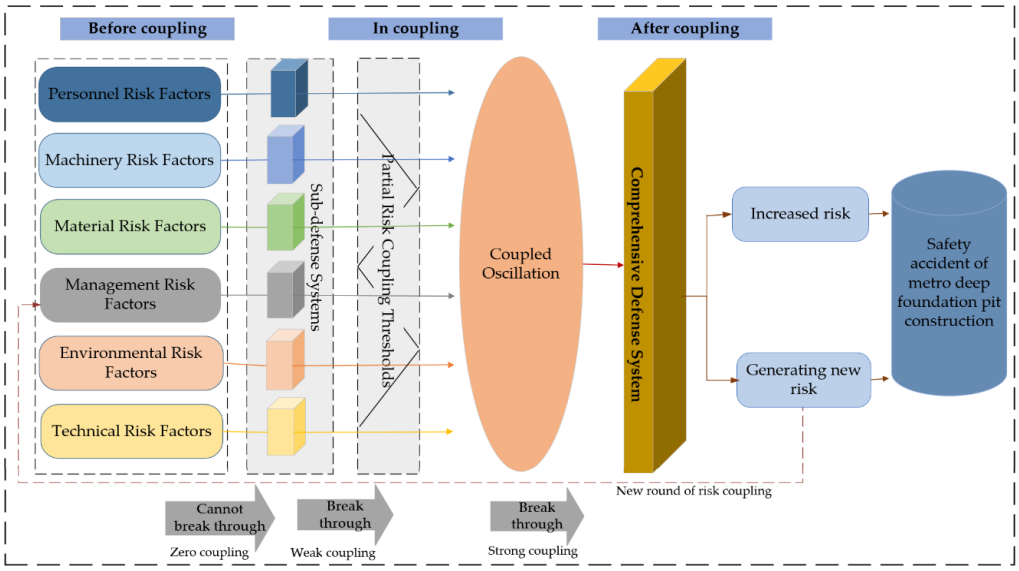


Figure 1. Analysis of risk-coupling mechanism.

The coupling relationships of safety risk factors in metro deep foundation pit construction are intricate and complex. Different factors within the same category interact and influence each other. For instance, within the material risk factor category, inadequate maintenance of mechanical equipment can lead to equipment failure. Likewise, complex interactions exist among different types of safety risk factors, such as those involving environmental conditions, personnel behavior, and mechanical factors. Based on the types of factors involved in risk coupling, an analysis of the risk-coupling scenarios in the construction of metro deep foundation pits is conducted. This includes an analysis of homogeneous coupling relationships under the same primary risk factors and heterogeneous coupling relationships based on different primary risk factors, as illustrated in Figure 2.

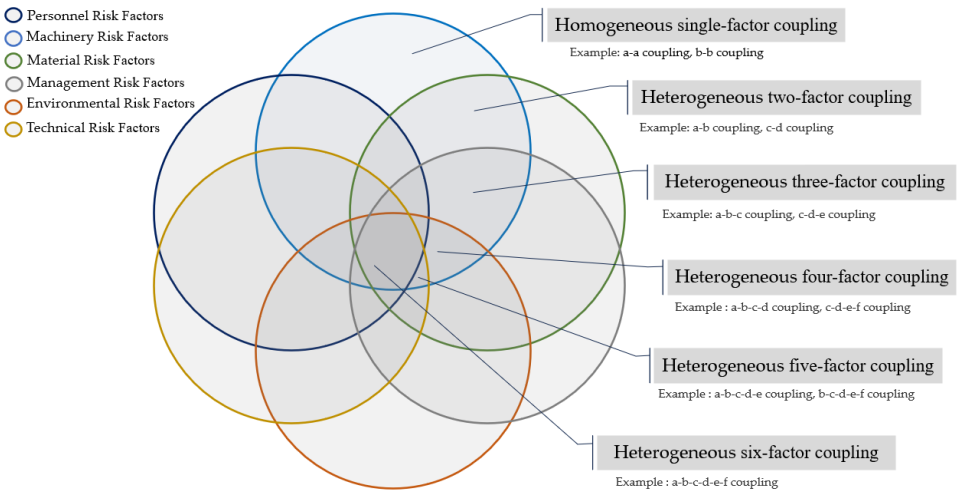


Figure 2. Analysis of risk-coupling scenario.

2.2.2. Overview of Complex Network Theory

The complex network is a graph theory-based mathematical theory that consists of nodes and relationships as fundamental elements, exhibiting high complexity. They possess some or all properties such as self-organization, self-similarity, attractor, small-world, and

scale-free [31]. The complex network can be used to abstract, model, and analyze complex systems. Metro foundation pit construction involves numerous and interconnected risk factors. Therefore, it is possible to abstract these risk factors into a complex network system. Utilizing complex network theory, an in-depth analysis of the risk factors can be conducted to reveal the coupling relationships between risk factors. The topology indicators of complex network models describe various network features from different perspectives within the complex network. They can aid in identifying and quantifying the interactions between risk factors in metro foundation pit construction, revealing the evolutionary patterns of risk coupling. The main topology indicators analyzed in this study are as follows:

(1) Degree centrality: It refers to the number of all nodes that are adjacent to a particular node, reflecting the direct influence of that node. For a directed network, the degree is the sum of the in-degree and out-degree.

$$k_i = \sum_{j=1}^{N} a_{ji} + \sum_{i=1}^{N} a_{ij} \tag{1}$$

(2) Degree distribution: It refers to the proportion of nodes in the network with a degree value of k, reflecting the distribution of nodes in the entire network.

$$P(k) = \frac{n(k)}{\sum_{j=1}^{\infty} n(j)} \tag{2}$$

(3) Clustering coefficient: It refers to the proportion of other nodes closely connected to a node that also have mutual connections, used to measure the degree of aggregation between nodes in a network.

$$C_i = \frac{2E_i}{k_i(k_i - 1)} \tag{3}$$

(4) Betweenness centrality: It refers to the proportion of shortest paths through node a in the network, used to measure the ability of a single node to control relationships between other pairs of nodes.

$$B_a = \sum_{i,j \in N, i \neq j} \frac{n_{ij}(a)}{n_{ij}} \tag{4}$$

(5) Eigenvector centrality: It is used to measure the importance of nodes in the network, considering not only the number of connections with other nodes but also the number of connections of the other nodes that the node connects to.

$$EC_i = \lambda^{-1} \sum_{j=1}^{n} a_{ij} x_j \tag{5}$$

(6) Average path length: It refers to the average distance between all pairs of nodes in the network, reflecting the speed and efficiency of information propagation among nodes in the network.

$$L = \frac{1}{N(N-1)} \sum_{i,j \in N, i \neq j} d_{ij} \tag{6}$$

(7) Network density: It is a parameter that measures the ratio of the actual number of existing edges in a network to the potential number of edges, reflecting the closeness of the network.

$$d = \frac{l}{N(N-1)} \tag{7}$$

(8) Network diameter: It refers to the maximum distance between any two nodes in the network, reflecting the scalability of the network.

$$D = \max_{1 \le i \le j \le N} d_{ij} \tag{8}$$

where, k_i represents the total degree of node i, a_{ji} represents the number of edges from other nodes to node i, a_{ij} represents the number of edges from node i to other nodes, N represents the total number of network nodes, C_i represents the clustering coefficient, E_i the actual number of edges between k_i nodes, B_a represents the betweenness centrality, n_{ij} represents the number of shortest paths from node i to node j, $n_{ij}(a)$ represents the number of paths passing through node a between nodes i and j, EC_i represents the eigenvector centrality, λ represents a constant, x_j represents the eigenvector corresponding to the eigenvalue λ^{-1} of the adjacency matrix, L represents the average path length, d_{ij} represents the shortest path between nodes i and j, D represents the network diameter, and d represents the network density.

2.2.3. Overview of Immunization Theory for Complex Networks

In the coupled network of risk factors in subway foundation pit engineering, the positions and importance of various risk factors differ. Identifying and evaluating key nodes are crucial to ensuring project safety and reducing risks. When studying the importance evaluation of nodes in complex networks, the evaluation method based on network topology indicators quantifies the importance of nodes from different angles by calculating various centrality indicators in the network. Additionally, the analysis method based on network vulnerability and robustness focuses on the network's performance when facing attacks or failures, evaluating the stability and efficiency changes of the network by simulating the removal of specific nodes to assess the importance of nodes. This paper proposes a comprehensive evaluation framework by combining these two methods, using the design of immunization strategies to compare the impact of removing important nodes on network efficiency under various parameter indicators, simulating the risk reduction effect to identify and evaluate key nodes in the network.

The study mainly adopts the following two immunization strategies: (1) random immunization, which involves randomly selecting network nodes for immunization; (2) targeted immunization, which entails purposefully extracting important nodes from the network for immunization. Based on the ranking of node importance using network indicators, targeted immunization strategies can be subdivided into four types: degree centrality, betweenness centrality, clustering coefficient, and eigenvector centrality immunization strategies. Network efficiency is used as the evaluation parameter to quantify the effectiveness of different immunization strategies.

$$E = \frac{1}{N(N-1)} \sum_{i \ne j} \frac{1}{d_{ij}} \tag{9}$$

where, E represents the network efficiency, which describes the ease of establishing connections between any two nodes in the network, reflecting the magnitude of network connectivity.

2.3. The Analytical Framework

Based on complex network theory, safety risk-coupling analysis of metro deep foundation pit projects is conducted. The analysis process mainly includes establishing a risk factor coupling network model, analyzing network feature indicators, and conducting immunization simulation analysis. The specific steps are shown in Figure 3.

(1) By identifying the risk factors and analyzing the coupling relationship, a risk-coupling network model is established and a visual risk-coupling network topology structure diagram is generated.

(2) The risk-coupling law from the overall and individual perspectives is revealed by quantitatively calculating the topology indicators of the network model.
(3) Based on the immunization theory of complex networks, the effects of different immunization factors and immunization sequences are evaluated through the dynamic changes of network efficiency, and the key risk factors are identified.

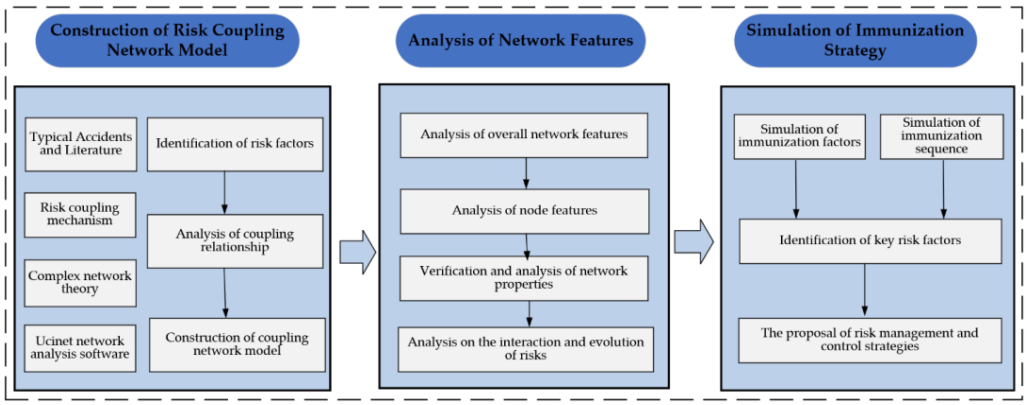


Figure 3. Flow chart of risk-coupling analysis of metro deep foundation pit construction.

3. Network Model of Risk Coupling in Metro Deep Foundation Pit Construction

3.1. Construction of the Risk Coupling Network Model

Through the analysis of the coupled relationship of safety risk factors in metro deep foundation pit construction, a network topology structure diagram is utilized to understand the coupling relationship of risk factors and a visual network model is constructed (Figure 4). The specific construction steps are delineated as follows:

(1) Based on the list of risk factors of metro deep foundation pit construction, the risk-coupling evolution relationship is sorted out.
(2) Constructing the adjacency matrix of the complex network, which provides a structured depiction of the interactions between the various risk factors.
(3) Establishing a visual risk-coupling network model by using Ucinet6.0 software. In this model, the names of risk factors are replaced with concise risk factor codes, and the presence of an influence relationship between any two risk factors is indicated by a connection edge.

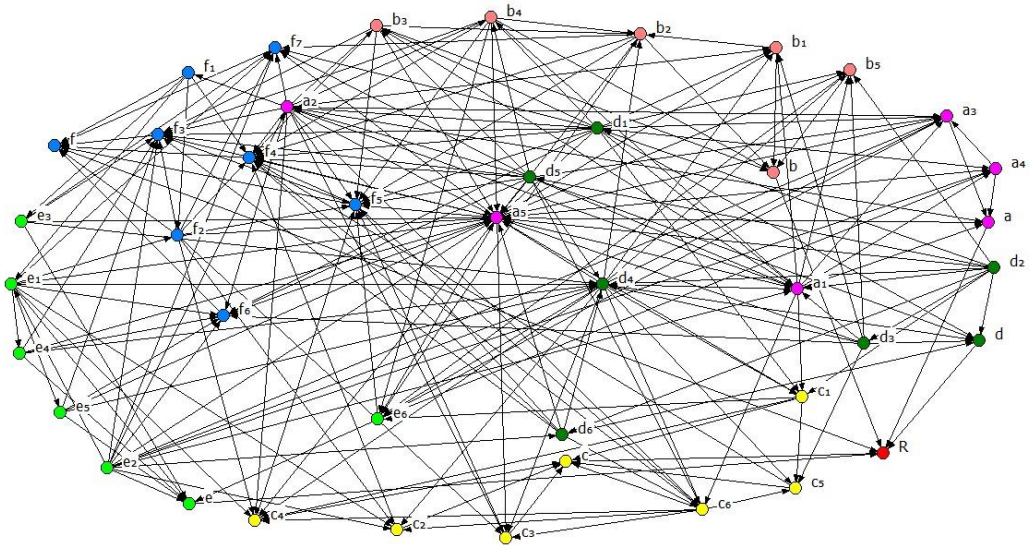


Figure 4. Coupling network model of metro deep foundation pit construction.

In the network, the risk factor is abstracted as a node, and the interaction between factors is abstracted as an edge. The direction of the edge represents the direction of influence transmission. In terms of the composition and quantity of factors involved, the risk-coupled network includes 42 risk factor nodes, forming a risk connection relationship with 184 directed edges, systematically reflecting the coupling effect among risk factors in metro deep foundation pit construction.

3.2. Analysis of the Topological Features of Risk-Coupling Networks

3.2.1. Analysis of Overall Network Features

In the analysis of network topology indicators, the selection of network size, network density, average path length, and network diameter is used to analyze the degree of closeness of the influence relationship among risk factors from the overall network perspective.

(1) Network size and network density

Network size refers to the specific number of risk factor nodes in the network, while network density can be used to measure the degree of interconnection among different risk factors in the risk network. The metro deep foundation pit construction safety risk-coupled network contains 42 nodes and 184 directed edges, with an overall network density of 0.155. This indicates a relatively low probability of direct causal relationships among risk factors in metro deep foundation pit construction, suggesting limited interaction between risk factors. The evolutionary path of risk in the network may be relatively fixed, suggesting that the purpose of reducing risks can be achieved by identifying and isolating specific risk factors.

(2) Average path length and network diameter

In the metro deep foundation pit construction safety risk-coupled network, the average path length between each node of risk factors is 2.061, indicating that the risk factors in the network can influence each other through an average of 2.061 paths. Cases where the path length is 1 or 2 occurred 184 and 256 times, respectively, accounting for 15.5% and 21.5% of the total occurrences. The network diameter is 6, meaning that the risk factor node in the network requires a maximum of 6 steps to lead to an incident. This indicates that the risk-coupled network has high reachability, bringing systemic risks to metro deep foundation pit construction.

3.2.2. Analysis of Node Features

Choosing the degree centrality, clustering coefficient, betweenness centrality, and eigenvector centrality as node feature indicators for analysis can help identify key risk factors and their roles in the network. This can also aid in further revealing the laws of risk evolution. The occurrence of accidents is closely related to the coupling interaction between risk factors; therefore, an analysis is conducted on the 35 risk factor nodes that have risk-coupling relationships.

(1) Degree centrality

Degree centrality is mainly used to reflect the direct correlation of risk factors in the network and can somewhat indicate the importance of risk factors in the network. The calculation results are shown in Figure 5.

According to the calculation results and the 80/20 principle, we selected the top seven factors as important factors for analysis, including a_5, d_4, a_2, a_1, d_1, f_5 and d_5. These nodes have relationships with more nodes, making them more susceptible to the influence of other factors or causing the appearance of other factors, leading to the successive increase in unsafe factors in metro deep excavation construction. The targeted control of these risk factor nodes can effectively reduce the connectivity of the risk evolutionary chain. In directed networks, it is determined by the joint action of out-degree centrality and in-degree centrality. The value of out-degree centrality reflects the ability of a risk factor to induce

other risks in the security system. In the calculation results of out-degree, risk factors such as d_4, d_1, a_2, and e_2 ranked higher. In the practice of safety management, unfavorable conditions related to personnel, management, and environmental factors play a role as risk disseminators or influencers within the risk-coupling network, which can easily lead to the sequential occurrence of other risk factors. Conversely, in-degree reflects the extent to which a risk factor is influenced by other factors within the safety system. In the calculation results of in-degree, risk factors such as a_5, f_3, f_4 and f_5 ranked higher. From the safety management practice, unsafe behaviors of construction workers, and improper operation of construction technology are more susceptible to other risk factors, thereby playing a role in risk aggregation and increasing the possibility of accidents.

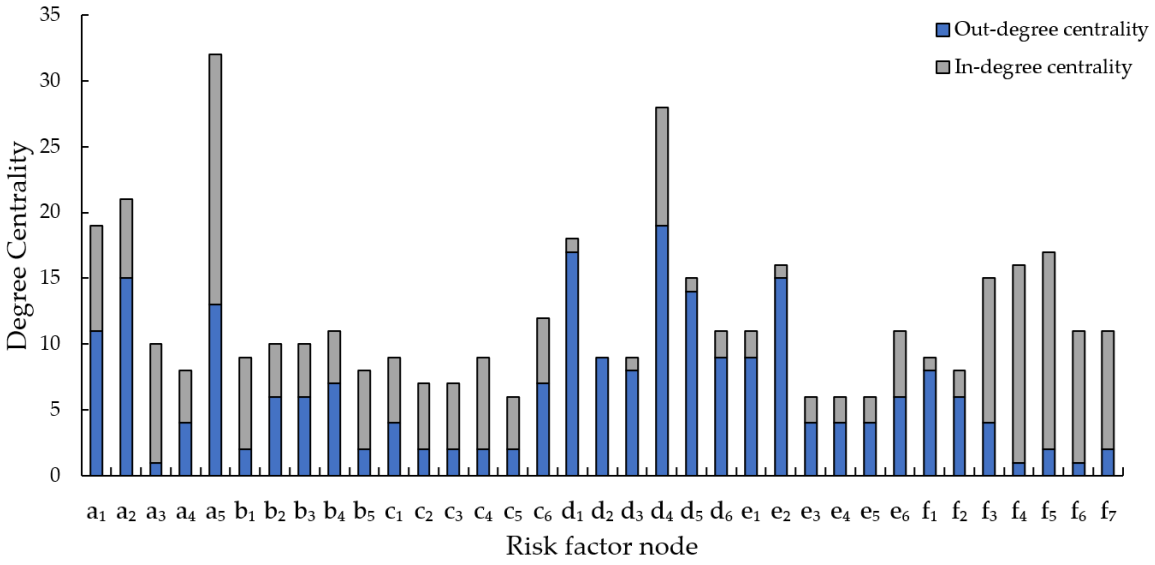


Figure 5. Distribution diagram of degree centrality.

(2) Betweenness centrality

Betweenness centrality reveals the role of risk factors in risk communication and reflects the control degree of risk factors on risk transmission in the network. The calculation results are shown in Figure 6.

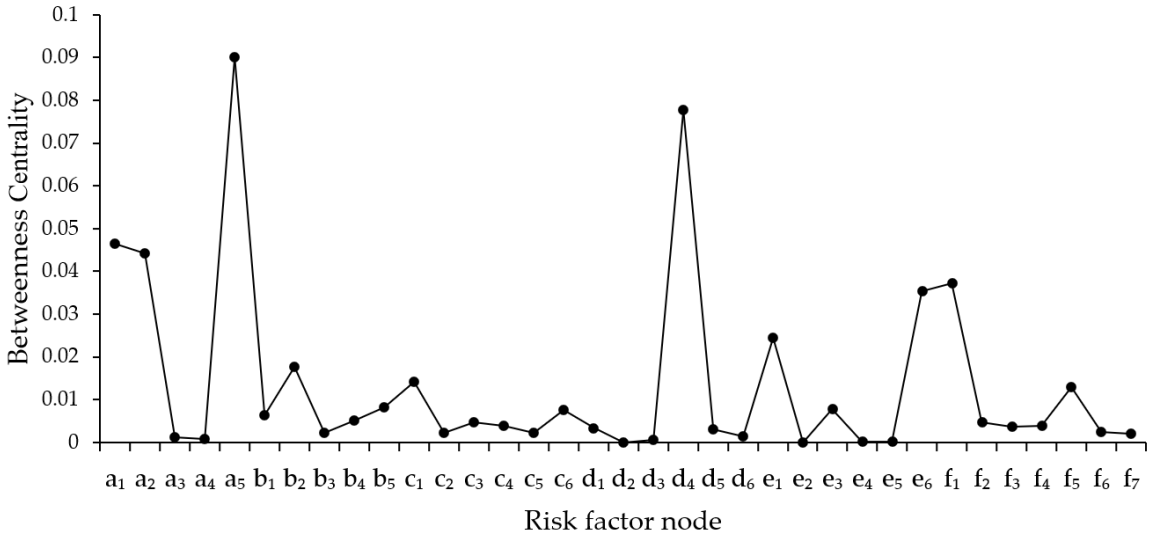


Figure 6. Distribution diagram of betweenness centrality.

The calculation results of betweenness centrality reveal that risk factors such as a_5, d_4, a_1, a_2, f_1, e_6 and e_1 have higher rankings, with values of 0.090, 0.078, 0.046, 0.044, 0.037, 0.035 and 0.024, respectively. These risk factors frequently appear on the shortest path between nodes, serving as critical nodes for numerous risk evolution trajectories and exerting significant influence as intermediaries on risk propagation. Additionally, the value of betweenness centrality of d_2 and e_2 is 0, indicating that they do not serve as intermediate nodes for risk propagation. Effectively controlling the occurrence of such risk factors with high betweenness centrality can lengthen the risk transmission path, thereby reducing the risk transmission rate and avoiding safety accidents.

(3) Eigenvector centrality

Eigenvector centrality simultaneously considers the number and importance of adjacent nodes connected to the risk factor node to determine its status and influence in the risk network. The calculation results are shown in Figure 7.

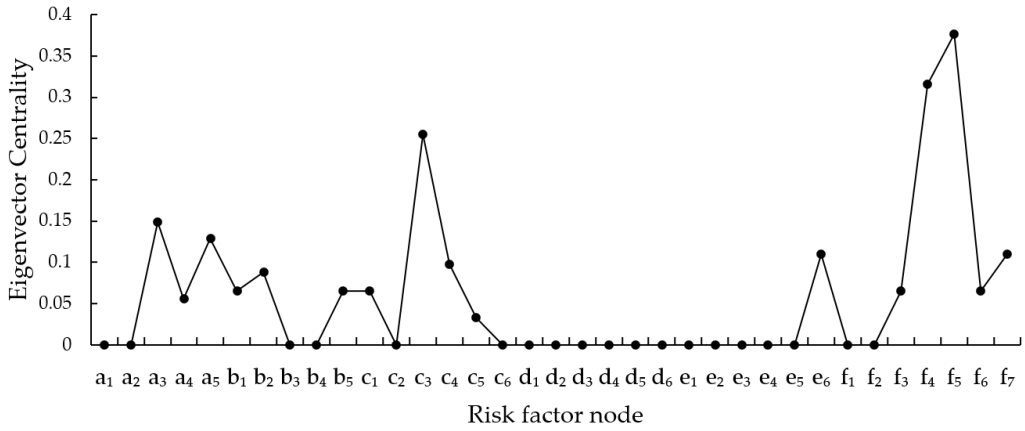


Figure 7. Distribution diagram of eigenvector centrality.

The eigenvector centrality values of f_5, f_4, c_3, a_3, a_5, e_6, and f_7 are relatively high, which are 0.471, 0.376, 0.316, 0.149, 0.129, 0.110 and 0.109, respectively, indicating that these risk factors are more closely related to other important risk factors in the network. Controlling these risk factors can reduce the correlation and transmission of important risk factors. Furthermore, it is observed that the eigenvector centrality of management and environmental factors tends to be relatively low. From the perspective of safety management practices, these risk factors are considered root causes of accidents, with their impact on risk incidents typically being indirect and accumulating over the long term.

(4) Clustering coefficient

The clustering coefficient can reflect the local clustering around a risk node in the network. The distribution of clustering coefficients for various risk factors is shown in Figure 8.

In the calculation results of the clustering coefficient of risk factors, the clustering coefficient values of a_4, a_3, b_3, d_2 b_4, b_5, and c_3 are relatively high, which are 0.333, 0.300, 0.300, 0.282, 0.268 and 0.259, respectively, indicating that the connections with other factors adjacent to these risk factors are also very tight. If these risk factors with high clustering coefficients are not controlled, it can easily lead to changes in the states of adjacent other risk factors, resulting in cascading effects and causing safety accidents.

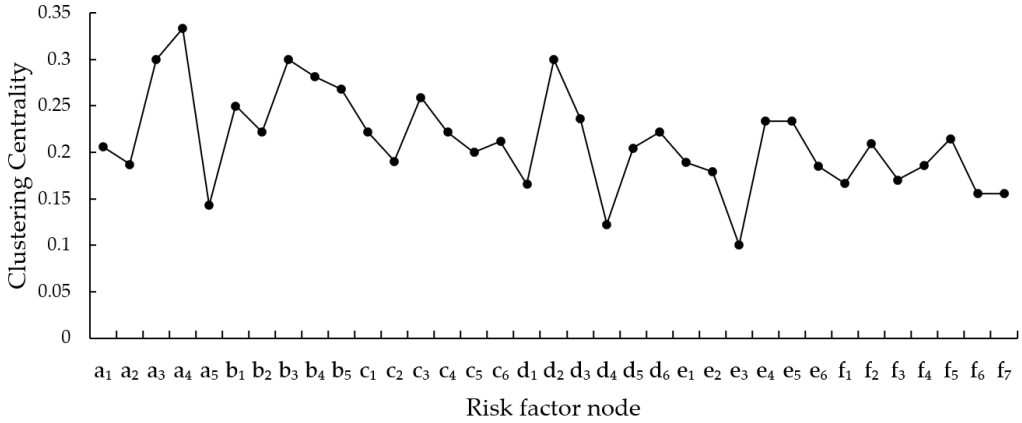


Figure 8. Distribution diagram of clustering coefficient.

3.3. Verification and Analysis of Network Model Properties

(1) Small-world property

The small-world index of the risk-coupled network for subway deep foundation pit construction established in this study is 1.444, with an average clustering coefficient of 0.240 and an average path length of 2.061. These results comply with the characteristics of a small-world network with a high clustering coefficient and short average path length. This implies that most risk factors may not be directly connected to each other, but most risk factors can lead to the occurrence of another factor through a short path. This indicates that the coupling and evolution efficiency of risk factors in the metro deep foundation pit construction risk-coupling network are high. The interactions of multiple risk factors increase the likelihood of accidents, posing challenges to the prevention and control of accidents in subway deep foundation pits.

(2) Scale-free property

In the metro deep foundation pit construction risk-coupled network, fewer risk factor nodes have a higher degree of centrality, while the majority of risk factor nodes have a lower degree of centrality. By using cumulative degree distribution to assess whether the metro deep foundation pit construction risk-coupling network exhibits scale-free property, it is found that the cumulative degree distribution follows a power-law distribution with a power exponent of -1.3455, indicating scale-free network features. The scale-free property enables the network to have higher robustness against random attacks but higher vulnerability to targeted attacks. This provides a clear direction for the decoupling of safety risks in metro deep foundation pit construction, which involves prioritizing the control of critical risk factors and disconnecting risk-coupling pathways.

4. Immunization Simulation Analysis

4.1. Analysis of Simulation Strategies

Considering the network features of the coupling relationships of risk factors, immunization simulation provides a systematic method for analyzing and managing risks. Implementing immunization strategies prevents the risk factor nodes in the network from propagating and triggering coupling reactions. The network efficiency is used as the evaluation standard for immune effectiveness, and Python3.12 software is used for simulation modeling. The immunization strategies consider both the immunization factors and the immunization sequence, as shown in Table 2.

Table 2. Analysis of simulation strategies.

Strategy	Ranking Indicator	Interpretation
Single-node immunization	Only consider nodes.	Individually remove risk factor nodes one at a time
Targeted immunization	Degree centrality	Remove risk factor nodes continuously in the order of degree centrality
	Betweenness centrality	Remove risk factor nodes continuously in the order of betweenness centrality
	Eigenvector centrality	Remove risk factor nodes continuously in the order of eigenvector centrality
	Clustering coefficient	Remove risk factor nodes continuously in the order of clustering coefficient
Random immunization	Random order	Remove risk factor nodes continuously in random order

4.2. Simulation Analysis of Single-Node Immunization

The importance of different risk factor nodes varies in the network, therefore, different immunization factors have different effects on the efficiency of the risk-coupling network model. Figure 9 illustrates the changes in network efficiency after the removal of each risk factor node.

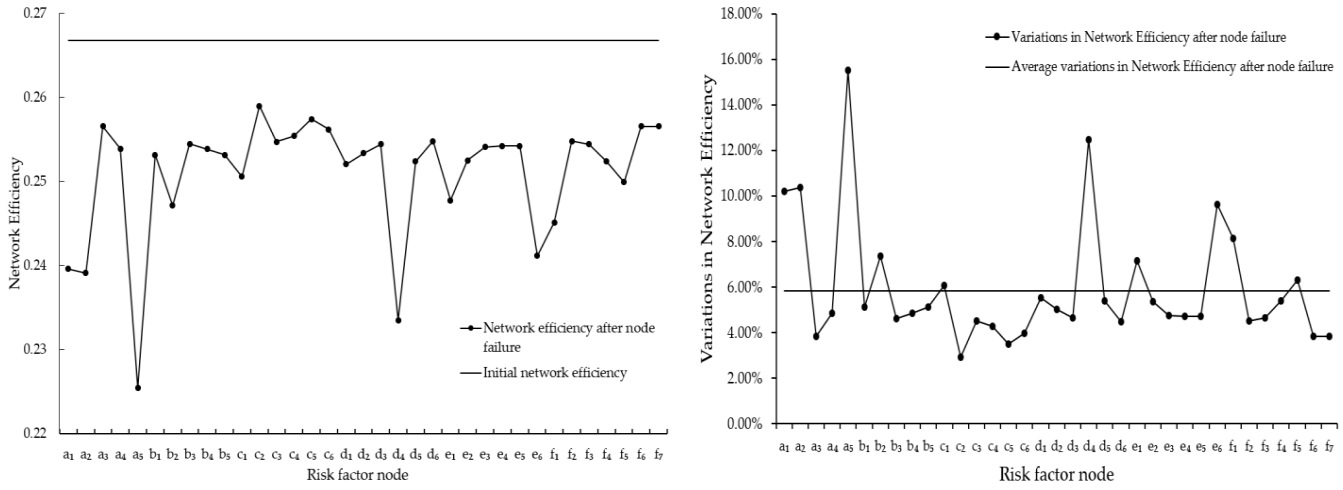


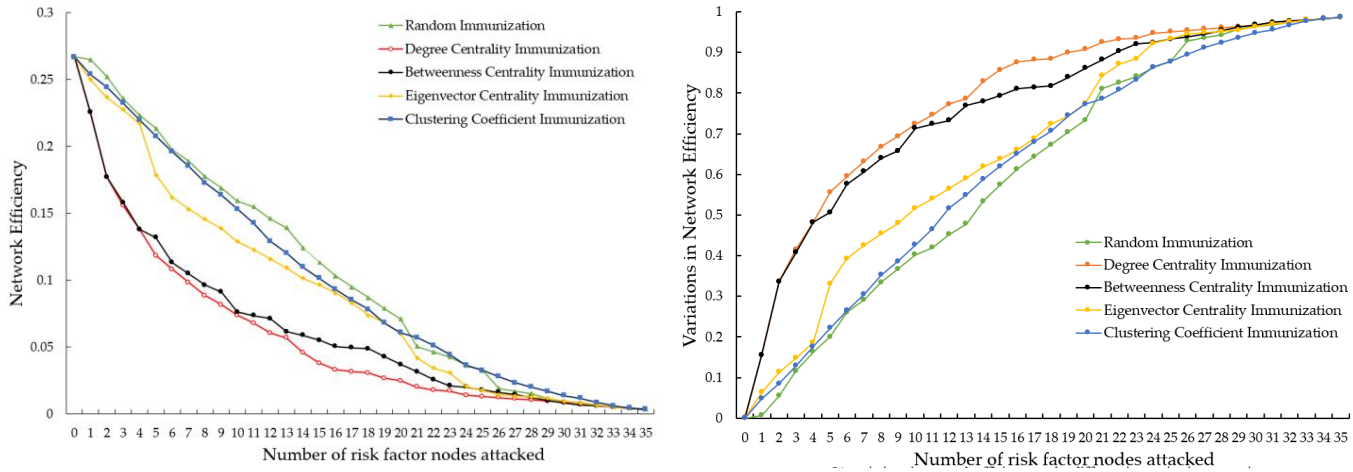
Figure 9. Network efficiency after failure of single node. (**a**) Comparison of network efficiency before and after node failure; (**b**) Variations in network efficiency after node failure.

The overall network efficiency decreases after the failure of each risk factor, indicating that all risk factors play a positive role in the connectivity and information dissemination of the risk-coupling network of metro deep foundation pit construction. The risk propagation paths in the network lengthen after the failure of risk factors. Specifically, the impact of the failures of a_5, d_4, a_2, a_1, e_6, f_1, b_2, e_1, f_5, and c_1 on network efficiency is particularly significant. Removing these risk factors individually results in respective network efficiency decreases of 15.53%, 12.49%, 10.39%, 10.21%, 9.62%, 8.14%, 7.38%, 7.15%, 6.33%, and 6.09%, all of which exceed the average decrease of 5.85%. Prioritizing the control of these risk factors can lead to the loss of multiple critical paths in the network, effectively reducing the probability of risk incidents and thereby enhancing the safety and stability of subway deep foundation pit projects.

4.3. Simulation Analysis of Random and Targeted Immunization

In this study, targeted immunization selects degree centrality, betweenness centrality, eigenvector centrality, and clustering coefficient as ranking indicators. Random immuniza-

tion employs the "random choice" function in Python3.12 software to randomly determine the order of node removal. By utilizing Python programming, the dynamic changes in network efficiency under different immunization sequence strategies can be obtained, as shown in Figure 10.



(**a**) (**b**)

Figure 10. Dynamic changes in network efficiency under different immunization strategies. (**a**) Comparison of network efficiency under different immunization strategies; (**b**) Variations in network efficiency under different immunization strategies.

In different immunization strategies, removing the same number of risk factor nodes has significantly different effects on the efficiency of risk-coupling network of metro deep foundation pit construction, highlighting the importance of immunization strategy selection.

(1) Comparing targeted immunization and random immunization strategies, the random immunization strategy performs worse than the targeted immunization strategy. After removing 7 risk factor nodes, the network efficiency under random immunization and four targeted immunization strategies decreased by 0.291, 0.632, 0.607, 0.426, and 0.305, respectively. After further removal of 15 risk factor nodes, the network efficiency decreased by 0.574, 0.857, 0.794, 0.638, and 0.620, respectively. This indicates that the risk-coupling network has a strong vulnerability to targeted immunization, and targeted immunization strategies perform better in improving risk management efficiency. The targeted immunization strategy can effectively slow down the evolution of risk network coupling by selectively removing nodes with higher associated feature indicator values, which is a more effective means of risk management.

(2) During the implementation of targeted immunization strategies, a nonlinear characteristic is observed in the decrease in network efficiency. With an increase in the number of attacked nodes, the initial decrease in network efficiency is significant, followed by a gradual slowdown. This phenomenon can be attributed to the fact that in the early stages of an attack, the removal of risk factor nodes with high associated feature indicator values, which play crucial roles in the network, can prolong or even cut off risk evolution paths, causing substantial disruption to the network's risk-coupling effects. In the later stages of the attack, the remaining nodes generally have lower feature indicator values, and their removal has a limited impact on the overall connectivity of the network, leading to a slowing down in the decreasing trend of network efficiency. This underscores that controlling critical causal factors is more effective for safety management in metro deep foundation pits.

(3) Among the four targeted immunization strategies, the degree centrality immunization strategy performs the best, while the clustering coefficient immunization strategy shows the lowest effectiveness, but all are superior to random immunization. Given

the superior effectiveness of the degree centrality immunity strategy, concentrating resources on attacking the key nodes a_5, d_4, a_2, a_1, d_1, f_5, and d_5 can effectively impede the risk-coupling effects and prevent risk incidents. In the practice of safety risk management in metro deep foundation pit construction, emphasis should be placed on identifying and evaluating key risk factors to achieve optimal resource allocation and maximize risk control effectiveness.

5. Conclusions

Based on the risk identification and coupling mechanism analysis of metro deep foundation pit construction, this research used the risk factor analysis approach that integrates complex network theory and immunization theory methods to analyze safety risk factors in metro deep foundation pit construction, leading to the following conclusions:

(1) Based on complex network theory, a quantitative analysis of the characteristic indicators of the risk-coupling network in metro deep foundation pit construction was conducted using Ucinet6.0 software. The risk factor coupling network presents typical scale-free and small-world network properties. The nodes with higher degree, such as a_5, are connected with more nodes. The nodes with large clustering coefficients, such as a_4 have a strong local clustering effect. The nodes with large betweenness centrality play a significant intermediary role in risk propagation. The nodes with large eigenvector centrality are closely associated with other key risk factors.

(2) Analysis of immunization strategies: Compared with different immunization factors, the failures of nodes like a_5 and d_4 have the most significant impact on risk coupling. Compared with different immunization sequences, targeted immunization is superior to random immunization, and degree centrality immunization has the best implementation effect. Prior control of key risk factors corresponding to degree centrality can effectively delay the risk-coupling effect, providing a theoretical basis for the formulation of risk-decoupling strategies.

(3) Based on the above analysis, the following recommendations are proposed for the safe production construction and risk management of metro deep foundation pit projects: (1) Standardize safety behavior, strictly adhering to standard construction practices, and enhancing the level of employee competence are the primary tasks of safety management; (2) Strengthen the daily maintenance and inspection of construction machinery and equipment, to enhance the safety and operational efficiency of construction machinery and equipment; (3) Enhance the management of construction materials in storage, transportation, processing, and utilization to ensure the safety and reliability of engineering structures; (4) Strengthen safety education and training, implement safety briefings, safety supervision, and hazard inspections, establish standardized, comprehensive, and procedural management mechanisms to provide guarantees for safety management work; (5) Enhance the monitoring and early warning of risks related to the natural environment and work environment to mitigate the impact of environmental factors on the safety of metro deep foundation pit construction; and (6) Strengthen geological and hydrological surveys, and implement strict control over the design and construction processes of metro excavation shoring.

While the current research provides valuable insights, it has some limitations. The analysis of accident data is not exhaustive, and the risk analysis process does not account for the varying strengths of risk–influence relationships. Consequently, this study may not fully encapsulate the complete laws of risk-coupling evolution in metro deep foundation pit construction. To enhance the contribution of the study to the safety management of metro deep foundation pits, future research should focus on the following directions: (1) Conducting more comprehensive data analysis, incorporating more comprehensive risk factors, and constructing weighted network models to more accurately reflect the levels of influence and coupling effects among risk factors. (2) Utilizing machine learning techniques to automatically identify risk associations based on a substantial accumulation of accident data to refine the analysis.

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Nomenclature

Abbreviation	
WBS-RBS	Work breakdown structure-risk breakdown structure
SVM	Support vector machine
G-COWA	Gray cluster analysis-combination ordered weighted averaging
TL-ANP	Two-tuple linguistic analytic network process
FBN	Fuzzy Bayesian network
FAHP	Fuzzy analytic hierarchy process
SNA	Social network analysis
C-OWA	Combination ordered weighted averaging
WSR	Wuli-Shili-Renli
Notation	
k_i	Degree centrality
a_{ji}	Number of edges from other nodes to node i
a_{ij}	Number of edges from node i to other nodes
N	Total number of network nodes
C_i	Clustering coefficient
E_i	Actual number of edges between k_i nodes
B_a	Betweenness centrality
n_{ij}	Number of shortest paths from node i to node j
$n_{ij}(a)$	Number of paths passing through node a between nodes i and j
EC_i	Eigenvector centrality
λ	Constant
x_j	Eigenvector corresponding to the eigenvalue λ^{-1} of the adjacency matrix
L	Average path length
d_{ij}	Shortest path between nodes i and j
D	Network diameter
d	Network density
E	Network efficiency

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