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Quantitative analysis of risk influential factors of evacuation accidents for passenger ships

Zhongyuan Liu [1], Xinjian Wang [2*], Wenjie Cao [3], Jiashi Wang [4], Siming Fang [5], Sean Loughney [6]

Abstract: With the increasing use of passenger ships in passenger transport and tourism sighting, the risk of evacuation accidents is higher. To prevent such accidents and reduce casualties, a quantitative analysis method for identifying and evaluating risk influential factors (RIFs) of evacuation accidents is developed by integrating Complex Network (CN), Decision-Making Trial and Evaluation Laboratory (DEMATEL) and Interpretive Structural Modelling (ISM) methods. Firstly, 27 RIFs are identified by extracting accident casual chain from global emergency evacuation reports of large passenger ships, and a network model for evacuation accidents is constructed. Secondly, CN is used to conduct a topological analysis of these identified RIFs from a global perspective, and robustness analysis under different attack modes is used to validate the ranking of these RIFs. Finally, DEMATEL and ISM are used to establish a multi-layer structure model, 12 key RIFs are identified from causal relationship and structural perspective, and countermeasures are proposed to mitigate these RIFs. By identifying these key RIFs, this study aims to deepen the understanding of evacuation risk management, provide a theoretical basis for emergency decision-makers, optimize the evacuation process, and reduce casualties.

Keywords: Maritime safety; Emergency evacuation; Risk analysis; Machine learning; Complex network; DEMATEL, ISM

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1. Introduction

In recent decades, passenger ships have gained increasing popularity in maritime transport and tourism (Fang *et al.*, 2024b). Data from the Cruise Lines International Association indicates that from 1990 to 2021, the number of passengers on cruise ships worldwide increased at an average annual rate of 6.6% (Chiou *et al.*, 2021). Despite significant advances in structural design, operational practices, and navigational technology, modern passenger ships continue to experience accidents, resulting in substantial casualties and property damage (Valcalda *et al.*, 2023; Wan *et al.*, 2024b; Wang *et al.*, 2023b). For example, the MS Estonia accident in 1994 resulted in 823 deaths, with only 141 survivors, while the "Eastern Star" cruise ship capsized in the Yangtze River in 2015, causing 442 casualties (Wang *et al.*, 2021). According to Lloyd's Register, over 5% of global ship casualties between 2000 and 2020 were due to failures in timely and effective evacuation (Wang *et al.*, 2022). Therefore, analysing human evacuation from passenger ships during emergencies is crucial for ensuring passenger safety.

The emergency evacuation of passenger ships is a complex and dynamic process encompassing three main phases: assembly, ship abandonment, and search and rescue (International Maritime Organization, 2016; Wang *et al.*, 2023c). During this process, the captain must assess disaster risk, issue evacuation orders, coordinate response tasks, and transmit alarms and distress signals. Crew members are responsible for following instructions to guide passengers and operate life-saving equipment. Passengers need to respond quickly, wear life jackets, proceed to the assembly point, and board lifeboats or life rafts in an orderly manner (Fang *et al.*, 2022). Given the complexity of the evacuation process, the interconnectedness and mutual influence of the Risk Influential Factors (RIFs), passengers may not evacuate promptly, resulting in significant loss of life and property (Fang *et al.*, 2024a). Therefore, it is vital to conduct an in-depth study of those RIFs, accurately identify the key RIFs, and develop targeted strategies to comprehensively protect and prevent human casualties.

Currently, the analysis of accident RIFs has advanced from simple domino theory to complex linear theory (Cao *et al.*, 2023). However, some studies on causality still rely on chain structures (Ozaydin *et al.*, 2022; Wan *et al.*, 2024a). In reality, these RIFs influence each other, making it more appropriate to analyse them from a network structure perspective (Feng *et al.*, 2024b). Complex network (CN) theory uses graph theory to describe and analyse complex systems, offering a new perspective to explore the intrinsic connections and interaction mechanisms between RIFs in accidents (Alvarez *et al.*, 2021). This approach not only enhances the understanding of the interactions among RIFs in complex systems but also helps to reveal the causal chains behind accidents and potential risk propagation pathways. In the fields of safety science and risk management, CN has been used to analyse various systems, including transportation networks (Li and Pan, 2020), social networks (Zhang *et al.*, 2023) and biological networks (Xu *et al.*, 2021), etc. Particularly in the field of maritime safety, the application of the theory provides an important theoretical and practical basis for understanding and preventing collisions at sea (Feng *et al.*, 2024a; Shi *et al.*, 2024). However, there are relatively few studies focusing on evacuation accidents of passenger ships. There is potential room for further in-depth research to provide additional insights and understanding of the field.

In this study, after searching and analysing the evacuation accident reports of passenger ships from 1990 to 2023, the RIFs in the human evacuation from passenger ships are identified and a complex multi-layer network containing different RIFs is constructed. Based on the established multi-layer network, topological analysis is conducted from a global perspective, and robustness analysis under different attack modes is used to validate the ranking of these RIFs. In addition, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) and Interpretive Structural Modelling (ISM) methods are combined to identify the key RIFs from causal relationship and structural perspective, and targeted strategies and countermeasures are proposed. The results of this study can not only provide a theoretical basis for the safety management of passenger ships, but also have important practical significance for improving the maritime emergency response capability, reducing the probability of accidents, and ensuring the safety of passengers and crew members.

2. Literature review

2.1 The research on emergency evacuation from passenger ships

Emergency evacuation accidents have a significant impact on the safety of passenger ships and property, prompting extensive research into this critical issue. Wang *et al.* (2020) developed a logistic regression model to investigate passengers' likely evacuation behaviour during emergencies on passenger ships. Zhang *et al.* (2022) employed Pathfinder software to create a two-layer simulation model and set up four evacuation scenarios based on International Maritime Organization (IMO) guidelines. Fang *et al.* (2024b) developed a novel two-layer social force model (2LR-SFM) to enhance human evacuation efficiency on rolling ships. Most of those studies have concentrated on analysing human behaviour and simulating the evacuation process, often overlooking the effects of different RIFs during emergencies.

In recent years, with the in-depth exploration and summarization of evacuation-related studies, an increasing number of researchers have focused on RIFs affecting emergency evacuation (Wang *et al.*, 2021). These RIFs include human factors (Arshad *et al.*, 2022), environmental factors (Cotfas *et al.*, 2023) and various other factors, etc. By analysing RIFs in accidents more thoroughly, evacuation efficiency can be significantly improved. Regarding human factors, Wang *et al.* (2022) used FDS+EVAC evacuation simulation software to analyse how different passenger compositions, such as age and gender, as well as passengers' familiarity with the ship, influence the efficiency of human evacuation. In terms of environmental factors, Nevalainen *et al.* (2015) examined data from three reported passenger ship evacuation accidents to assess passengers' perceptions and behaviours in response to environmental conditions during emergencies. Concerning other factors, Fang *et al.* (2023) employed orthogonal experiments to investigate the effects of inclination angle, staircase availability, and evacuee priority on evacuation time and efficiency. It can be concluded from the literatures that researchers have primarily focused on the impact of individual factors in the evacuation process, overlooking potential interactions between them. This oversight limits the comprehensiveness of the analyses.

An analysis of existing literature reveals that studies on the RIFs affecting passenger ship evacuation accidents primarily focus on evacuation time and efficiency. These studies often overlook the detailed exploration of the abandonment and rescue phases. Therefore, this study not only considers the risk factors across different stages of an accident but also covers various aspects including human, ship, environment, and management.

2.2 The research on analysis methods of complex systems

Regarding the analysis of complex systems, CN theory is a widely used method that provides deep insights into the structure and topological features of these systems. This approach facilitates a more profound understanding of their internal dynamics and offers researchers a new perspective to explore and analyse such complexities. It has been extensively applied in various safety-related fields, enhancing the ability to assess and manage risks effectively. For example, in the context of hazardous materials transportation, Ren *et al.* (2023) analysed 792 accidents from 2017 to 2021 and constructed a cause-and-effect network of dangerous goods transportation accidents using a high-order network.

By applying the weighted k-core decomposition method, the network was divided into three layers, and 16 key causal factors were identified. In rail transportation, Zhou *et al.* (2015) constructed a directed-weighted accident causal network by extracting event chains from UK railway accident reports and analysed the network topology to identify key causal factors of railway accidents. In terms of marine transportation, Ma *et al.* (2022) used CN theory to construct a directed network model determining the coupling relationship between the hazardous causes of ship grounding accidents by analysing the network's topology. According to the above research, CN theory has proven to be an effective method for studying accident evolution in complex systems. While this method can analyse the interaction between RIFs during the occurrence of accidents, it cannot deeply analyse these RIFs from the perspective of causality.

Recently, the DEMATEL method has gained significant attention for its ability to analyse causal relationships in complex systems. It can examine the logical relationships between RIFs in each dimension of a complex system and construct an influence matrix to identify the causal relationships between RIFs and the degree of influence of each RIF in the system. For example, Xing *et al.* (2023) combined the Grey Relational Analysis (GRA) and DEMATEL methods to analyse the causal relationships between 21 RIFs affecting the quality of large offshore structures' lifting. However, in complex systems, simply considering the causal relationship between RIFs is often insufficient to identify and determine the coupling between different RIFs; the hierarchical structure of different RIFs must also be considered. In this regard, ISM can decompose the RIFs in a complex system into a well-organized, multi-layer hierarchical structure that shows the interactions and hierarchical relationships between RIFs. Liu *et al.* (2023) used the DEMATEL, ISM and cross influence matrix multiplication methods to analyse the RIFs of unsafe acts of construction workers. They constructed a hierarchy of RIFs, pinpointed the fundamental and direct factors, and proved this method is effective in identifying critical RIFs in complex systems.

2.3 The research gaps and contributions

Compared to traditional risk analysis methods, the aforementioned approaches have unique advantages and have been applied in various fields. However, using these methods separately to analyse passenger ship evacuation accidents can result in partial findings. For example, relying solely on CN theory for robustness analysis might neglect the causal and hierarchical relationships between factors, thereby compromising the accuracy of the findings. This limitation can be effectively addressed by combining the DEMATEL and ISM methods with CN analysis. To enhance the safety of passenger evacuation processes more effectively, this study leverages the attributes of complex networks combined with robustness analysis and integrates the DEMATEL and ISM methods. This comprehensive approach allows for an in-depth investigation of the causal and hierarchical relationships among RIFs in passenger ship evacuation accidents and aids in identifying key RIFs. Consequently, this study makes the following significant contributions to the field by providing a more nuanced understanding of the complex dynamics involved in evacuation processes, ultimately leading to more targeted and effective safety measures.

(1) For the first time, this study analyses the entire process of passenger ship evacuation, covering human, ship, environment, and management factors from a complex system perspective.

(2) This study combines the DEMATEL and ISM methods with CN analysis to innovatively identify and analyse key RIFs and their interrelationships in passenger ship evacuation accidents.

(3) By constructing the direct influence matrix and calculating the reachability matrix, the hierarchical structure and causal relationships between the factors are clarified, providing a new method for screening key RIFs.

3. Materials and methods

To study the evolution of RIFs during passenger ship evacuation, this study develops a two-stage risk analysis model, as shown in Fig. 1. In the first stage, evacuation accident reports of passenger ships are analysed to extract the corresponding causal chains, identify the RIFs in the evacuation process, and construct an RIFs set. Then, in the second stage, two aspects of risk analysis are carried out. Firstly, a topological analysis of the passenger ship evacuation accident network is conducted, followed by robustness analysis using different topological characteristics. Secondly, risk analysis is performed using the DEMATEL and ISM methods from the perspectives of causality and hierarchical structure. Finally, the results of both analyses are combined to identify the critical RIFs and propose relevant countermeasures.

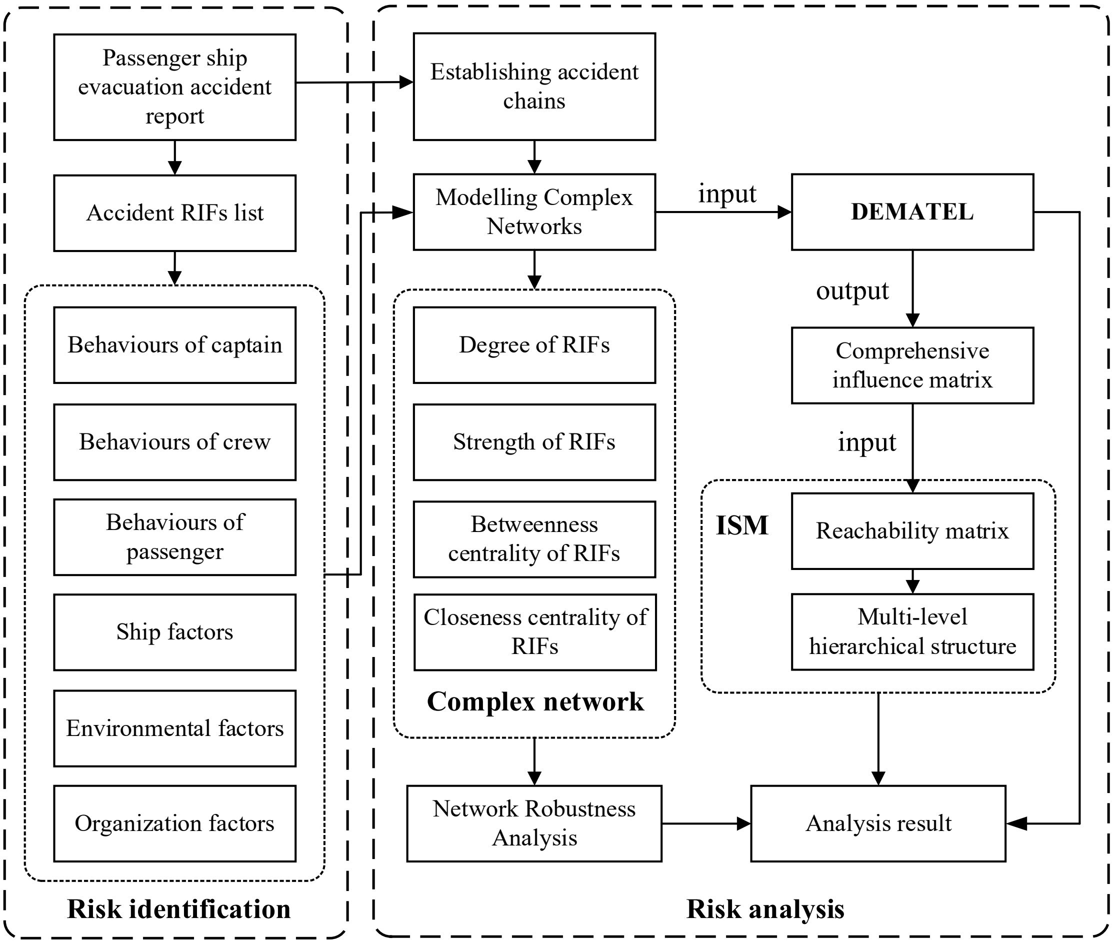


Fig. 1 The method framework of this study.

3.1 RIFs identification of passenger ship evacuation accidents

The causes of passenger ship evacuation accidents primarily stem from unsafe acts, unsafe conditions, and management deficiencies (Wang *et al.*, 2023c). These factors collectively increase the risk of inappropriate responses during emergencies. In analysing passenger ship evacuation accidents, this study identifies RIFs that cover personnel behaviour, internal ship conditions, external environment, and management. Due to the uncertainty and suddenness of personnel behaviour during evacuation, it is a complex factor that must be considered. This includes the decisions and actions of crew and passengers during emergencies. Personnel's decisions and actions significantly impact the outcome of catastrophic events. For example, the timing and method of evacuation directly affect the final result. To more accurately analyse the impact of personnel behaviour, this study categorizes the specific behaviours of different groups: the captain, whose decisions are crucial for the evacuation process; the crew, whose performance in executing evacuation orders and assisting passengers is key; and the passengers, whose speed of response and cooperation in receiving and following instructions affect evacuation efficiency. Additionally, internal ship conditions, including the design and functionality of equipment and maintenance status, impact safety performance during emergencies. External environmental factors, such as weather and sea conditions, are uncontrollable and can increase the difficulty and risk of evacuation. Management factors are equally important, as establishing and implementing effective safety procedures and emergency drills is fundamental to preventing accidents and improving emergency response capabilities. In summary, the main risk categories for passenger ship evacuation include captain behaviour, crew behaviour, passenger behaviour, ship factors, environmental factors, and management factors (Wang *et al.*, 2023c).

Based on the official websites of the Global Integrated Shipping Information System, the Marine Accident Investigation Bureau, and several national maritime administrations, 200 passenger ship accident reports resulting in casualties between 1990 and 2023 were collected. Since this study focuses on the RIFs associated with human evacuation actions in these reports, aiming to analyse those with complete information records of the entire evacuation process. However, most of the small and medium-sized passenger ship accidents did not involve evacuation processes or had limited information on them. Consequently, after screening for detailed human evacuation data, 36 completed casualty accident reports were retained. The types of passenger ship accidents include sinking, flooding, fire, contact, and collision. This study extracted RIFs from these 36 accident reports based on relevant literature (Fang *et al.*, 2024c; Fang *et al.*, 2023; Wang *et al.*, 2023c) and expert judgement, the list of these RIFs is shown in Table 1.

Table 1 RIFs of passenger ship evacuation accident.

Node category	Node code	Node description	Node category	Node code	Node description
Behaviours of captain	M1	Insufficient risk assessment of the accident	Ship factors	S1	The spread of hazards on board
	M2	Poor assembly/evacuation decision		S2	Hull design defect
	M3	The captain's improper handling of the emergency		S3	Failure of emergency response system
	M4	Inadequate safety awareness of captain		S4	Power/manoeuvring equipment failure
Behaviours of crew	C1	Lack communication and crowd management skills	Environmental factors	E1	Rough sea state
	C2	Inadequate safety awareness of crew		E2	Poor visibility
	C3	Improper emergency response to accident		E3	Night environment
	C4	Improper binding/fastening of cargo	Management factors	O1	Inadequate shore-based decision support
	C5	Ship manipulation error		O2	Inadequate company safety

					management
Behaviours of passenger	P1	Return behaviours		O3	Inadequate ship safety management
	P2	Limited mobility		O4	Poor search and rescue response by neighbouring country/vessel
	P3	Competitive behaviour		O5	Lack of communication with neighbouring country/vessel
	P4	Panic/herd behaviour	Accident result	A	Casualties and injuries to personnel
	P5	No/wrongly wearing life-saving equipment			

3.2 RIFs network model based on Complex network

3.2.1 Construction of evacuation accident RIFs network

CN is a special kind of network structure, it's structure can be represented by a $n \bullet n$ adjacency matrix A, as shown in Eqs. (1), (2) and (3):

$$A = \begin{array}{c} \\ n_1 \\ n_2 \\ \vdots \\ n_i \\ \vdots \\ n_n \end{array} \begin{array}{c} \begin{array}{cccccc} n_1 & n_2 & \cdots & n_j & \cdots & n_n \end{array} \\ \begin{bmatrix} 0 & a_{12} & \cdots & a_{1j} & \cdots & a_{1n} \\ a_{21} & 0 & \cdots & a_{2j} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots & \cdots & \vdots \\ a_{i1} & a_{i2} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & \vdots & \cdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nj} & \cdots & a_{nn} \end{bmatrix} \end{array} \tag{1}$$

$$A_{ij} = g_{ij} \bullet w_{ij} \tag{2}$$

$$g_{ij} = \begin{cases} 1, i \Rightarrow j & \text{connection exists} \\ 0, i \Rightarrow j & \text{no connection exists} \end{cases} \tag{3}$$

where n is the number of the nodes, A_{ij} represents the connection status from node n_i to node n_j; w_{ij} is the weight of the edge from node n_i to node n_j (i.e., number of connections from i to j); g_{ij} indicates whether there is a connection from node n_i to node n_j, if there is a connection, it is 1, and otherwise it is 0.

This study focuses on analysing passenger ship evacuation accidents using CN theory to understand and prevent these accidents better by examining their RIFs. Firstly, RIFs are extracted from each accident report and used to establish causal chains based on the specific steps and stages of the accident. Secondly, these RIFs are converted into nodes to form a multi-layered influence matrix. Each element in the matrix represents a causal relationship from one RIF to another. If there is a single causal relationship from the column node to the row node, the corresponding matrix element is marked as 1; if this relationship appears twice, it is marked as 2, and so on. Based on the node influence matrix, a network reflecting the accident process is drawn, as shown in Fig. 2. Finally, 36 accident reports are combined into a comprehensive accident network using the accident chain combination process, generating a corresponding node influence matrix. This influence matrix is then visualized in Python, forming the RIF evolution relationship network model shown in Fig. 3. In the accident network model, due to the integration of numerous causal chains, similar causal relationships frequently occur. Thus, the frequency of the same connecting edges is used as weights assigned to the corresponding elements of the accident influence matrix. Subsequent analysis using DEMATEL and ISM methods will be based on this to calculate the hierarchical causal relationships among the RIFs.

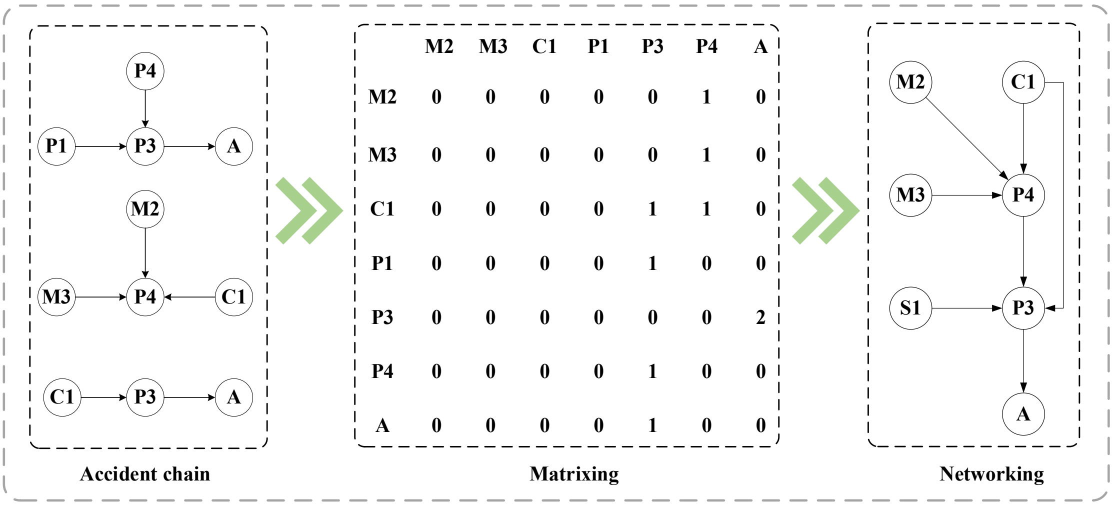


Fig. 2 The fusion process of accident chain.

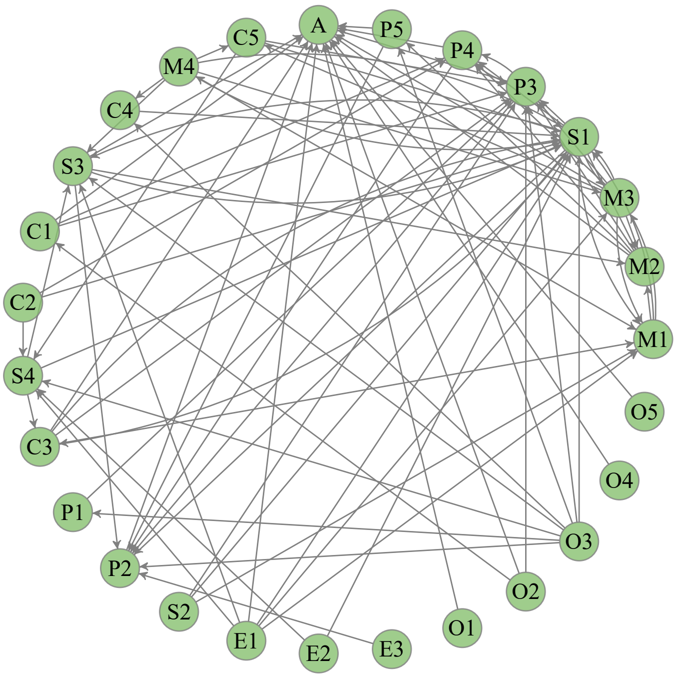


Fig. 3 The RIFs network model for passenger ship evacuation accidents.

3.2.2 Topological analysis based on Complex network

Node degree can be defined as the number of edges connected to a specific RIF. However, the meaning of degree varies in different types of networks (Jiang *et al.*, 2024). In directed networks, node degree can be classified into in degree and out degree considering the direction of these edges. In degree refers to the number of edges ending at the node and originating from other nodes. Out degree refers to the number of edges starting from the node and ending at other nodes (Wang *et al.*, 2023a). When considering the weight of each edge, node weighted degree is also known as node strength. According to the node degree, node strength can also be classified into in strength and out strength. Betweenness centrality of a node measures the extent to which the node acts as an intermediary in the shortest paths between other nodes in the network. Specifically, it is the ratio of the number of shortest paths passing through the node to the total number of shortest paths between all other pairs of nodes. Closeness centrality measures how close a node is to all other nodes in the network. It is the reciprocal of the sum of the shortest path distances from the node to all other nodes in the network (Feng *et al.*, 2024a).

In a CN, in degree and in strength reflect the degree to which the RIFs are affected, while out degree and out strength reflect the degree to which a RIF affects other RIFs. Total degree and total strength indicate the centrality of RIFs within the whole complex system. Higher centrality means a greater effect of the RIFs on the complex system. Betweenness centrality and closeness centrality measure the pivotal role of nodes in the transmission of information within the complex system. The greater the pivotal role, the more central the factors are in the network. Therefore, this study primarily analyses the topological characteristics of the network in terms of node degree and node strength, as well as betweenness centrality and closeness centrality.

3.3 RIFs causal analysis model based on DEMATEL

The DEMATEL method uses graph theory and matrix tools to address complex issues where relationships are not obvious, identifying direct and indirect relationships between factors (Kuzu, 2021). Compared to the topological features of CN, DEMATEL can confirm the interdependencies between RIFs and reflect the relative relationships between RIFs. The basic steps of DEMATEL are as follows:

Step 1: Construct the direct influence matrix Z, as shown in Eq. (4).

$$Z = \begin{array}{c} \\ v_1 \\ v_2 \\ \vdots \\ v_i \\ \vdots \\ v_n \end{array} \begin{array}{c} \begin{array}{cccccc} v_1 & v_2 & \cdots & v_j & \cdots & v_n \end{array} \\ \begin{bmatrix} 0 & e_{12} & \cdots & e_{1j} & \cdots & e_{1n} \\ e_{21} & 0 & \cdots & e_{2j} & \cdots & e_{2n} \\ \vdots & \vdots & \ddots & \vdots & \cdots & \vdots \\ e_{i1} & e_{i2} & \cdots & e_{ij} & \cdots & e_{in} \\ \vdots & \vdots & \cdots & \vdots & \ddots & \vdots \\ e_{n1} & e_{n2} & \cdots & e_{nj} & \cdots & e_{nn} \end{bmatrix} \end{array} \tag{4}$$

where v_n is the n^{th} node of the CN, $e_{ij}\begin{cases} 0, & v_{ij} \text{ no connection exists} \\ \neq 0, & v_{ij} \text{ connection exists} \end{cases} \left(i = 1, 2\cdots n, j = 1, 2\cdots n\right)$.

Step 2: Construct a normalised influence matrix E, as shown in Eq. (5).

$$E = \frac{1}{\max\limits_{1 \le i \le n} \sum_{j=1}^{n} e_{ij}} Z \tag{5}$$

Step 3: Construct a comprehensive influence matrix T, as shown in Eq. (6).

$$T = E(1-E)^{-1} \tag{6}$$

Step 4: Calculate the values of influence degree, influenced degree, centrality degree, and cause degree of the node, as shown in Eqs. (7), (8), (9) and (10):

$$r_i = \sum_{j=1}^{n} T_{ij} \tag{7}$$

$$c_j = \sum_{i=1}^{n} T_{ij} \tag{8}$$

$$FI = r_i + c_j \tag{9}$$

$$EI = r_i - c_j \tag{10}$$

where the influence degree r_i represents the overall influence of RIF i on the other RIFs; influenced degree c_j indicates the overall effect of other RIFs on RIF j; FI is the centrality degree, indicating the importance of RIF i in the overall system; EI is the cause degree, indicates the causal relationship associated with the RIF i.

3.4 RIFs structural analysis model based on ISM

ISM method was firstly proposed by Warfield (1973), which constructs a clear and intuitive hierarchical structural model by block decomposition and hierarchical division of a complex system, sorting out the interrelationships among the factors of the system. The construction steps of the ISM are as follows:

Step 1: Construct the overall influence matrix Q, as shown in Eq. (11):

$$Q = T + I \quad (Q = [q_{\mathrm{ij}}]_{n \times n}) \tag{11}$$

where I is the unit matrix.

Step 2: To simplify the system hierarchy, a threshold value need to be introduced. In this study, the sum of the mean and standard deviation of the RIFs of the overall influence matrix is used as the threshold. Construct reachable matrix K, as shown in Eq. (12):

$$K_{ij} = \begin{cases} 1 & q_{ij} \geq \lambda \\ 0 & q_{ij} < \lambda \end{cases} \qquad (i, j = 1, 2, 3, \cdots, n) \tag{12}$$

where λ is a threshold value used to determine whether there is a direct influence relationship between two RIFs.

Step 3: According to the reachability matrix K, in the set U composed of all RIFs, calculate the reachable set $R(u_i)$, the prior set $S(u_i)$, and the common set Y to classify the different layers. As shown in Eq. (13):

$$\begin{cases} R(u_i) = \left\{ u_j \mid u_j \in U, k_{ij} = 1 \right\}, \\ S(u_i) = \left\{ u_j \mid u_j \in U, k_{ji} = 1 \right\}, \\ Y = \left\{ u_j \mid R(u_j) \cap S(u_j) = R(u_j) \right\} \end{cases} \tag{13}$$

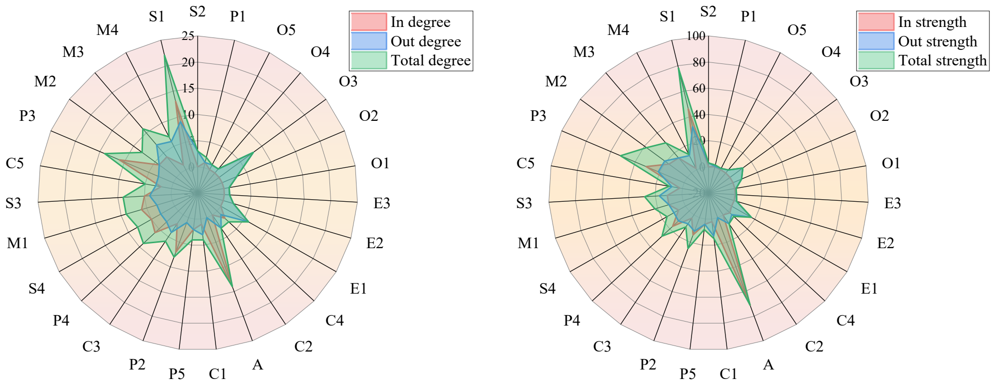
4. Results and discussion

4.1 The analysis results of complex network

In this section, an in-depth analysis of the evacuation accident RIFs network is conducted based on Complex Networks. Firstly, the degree and strength of the nodes are discussed to reveal the importance of each RIF in the network. Secondly, an analysis of betweenness centrality and closeness centrality is carried out to further explore the roles of RIFs in the process of risk propagation. Finally, robustness analysis is used as a manner for selecting critical RIFs to analyse risk control measures. Through these analyses, the multidimensional characteristics and mechanisms of RIFs in the evacuation accident RIFs network are comprehensively demonstrated.

(1) Node degree and strength

The node degree and strength of the RIFs network can be calculated using the Complex network theory, and the result is shown in Fig. 4.



(a) Degree distribution (b) Strength distribution

Fig. 4 The degree of RIFs.

As shown in Fig. 4(a), most of the RIFs in the network have high degree values. Among them, the RIFs with the largest total degree values are S1 (The spread of hazards on board), followed by P3 (Competitive behaviour) and A (Casualties and injuries to personnel), etc., which interact with most of the other RIFs. There are two RIFs with the smallest total degree values, O4 (Poor search and rescue response by neighbouring country/vessel) and O5 (Lack of communication with neighbouring country/vessel), each of which has only one connection point. This indicates that very few countries do not respond immediately to rescue in the event of an accident. The RIFs with higher in degree are A (Casualties and injuries to personnel), S1 (The spread of hazards on board), and P3 (Competitive behaviour), all of which have degree values of 11 or higher, indicating that they directly receive information delivered by nearly half of the RIFs in the network. The RIFs with higher out degree are S1 (The spread of hazards on board), O3 (Inadequate ship safety management), and M3 (The captain's improper handling of the emergency), all with values of 7 or higher, indicating that they can send information directly to many RIFs in the network.

Node strength indicates the probability of interaction between RIFs in the network. As can be seen in Fig. 4(b), the distribution trends of node degree and node strength are approximately the same, although they may differ for some nodes. In terms of node total strength, the RIFs with higher strength include S1 (The spread of hazards on board), A (Casualties and injuries to personnel), and P3 (Competitive behaviour), and so on. These RIFs are almost the same as those with greater total degree, but their order differs, suggesting that RIFs with similar degree values can have a significant difference in the probability of interacting with other RIFs. Regarding node in strength, the in degree of M3 (The captain's improper handling of the emergency) is smaller than that of P2 (Limited mobility). However, the in strength of M3 is larger than that of P2, indicating that although M3 can directly receive information from fewer RIFs, it has a greater probability of receiving the information. In terms of node out strength, P3 (Competitive behaviour) has a smaller out degree than M2 (Poor assembly/evacuation decision). Still, P3 has a greater out strength than M2, suggesting that although fewer RIFs can directly receive the information conveyed by P3, there is a higher probability that its information will be received directly.

(2) Node betweenness centrality and closeness centrality

The node betweenness centrality and closeness centrality of the RIFs network can also be calculated using the CN theory, and the result is shown in Fig. 5.

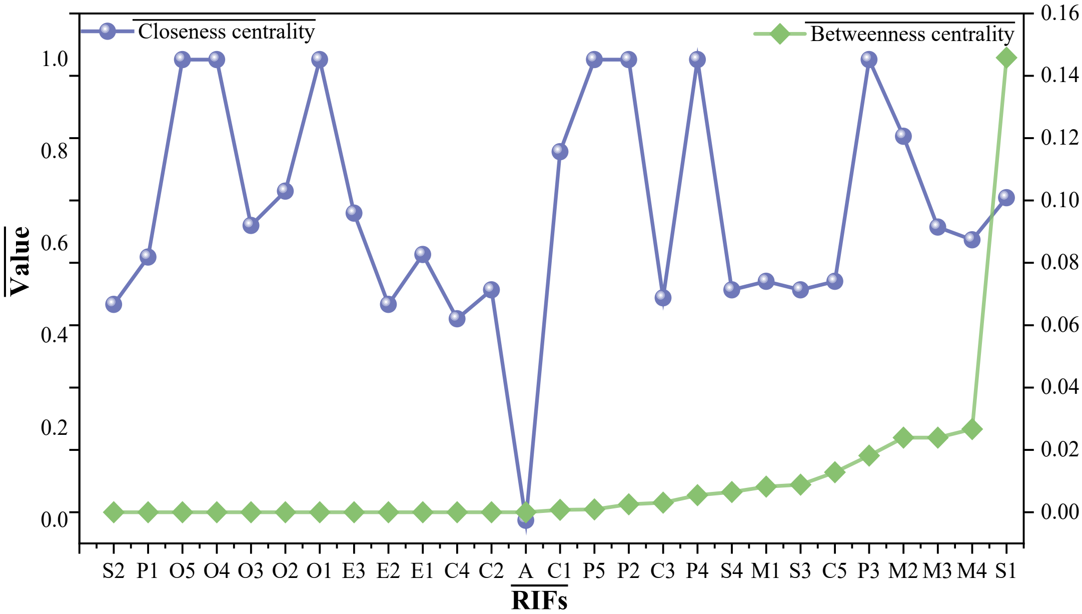


Fig. 5 Distribution of nodal betweenness centrality and closeness centrality.

It can be seen from Fig. 5, the betweenness centrality of S1 (The spread of hazards on board) is the largest. This indicates that this RIF plays the most crucial role in information transfer. When the state of this RIF changes, the efficiency of information transfer in the network will also change substantially, affecting the network's stability. In the evacuation process, S1 (The spread of hazards on board) serves as a bridge connecting various RIFs, which increases the probability the occurrence of RIFs such as M2 (Poor assembly/evacuation decision) and P3 (Competitive behaviour). This also accelerates information transmission within RIFs, potentially leading to casualty events.

Additionally, from Fig. 5, it can be observed that RIFs with greater closeness centrality include P3 (Competitive behaviour), P4 (Panic/herd behaviour) and P2 (Limited mobility), etc. This means that these RIFs have a short distance to other RIFs, are at the centre of the network and the information transmitted reaches the other RIFs quickly. However, P3 (Competitive behaviour), P4 (Panic/herd behaviour), and P2 (Limited mobility) belong to passenger behaviour. Taking P3 as an example, once competitive behaviour such as insubordination and jumping into the sea occurs during evacuation, then the probability of casualties increases significantly.

(3) Robustness analysis

Network robustness is the ability of a network to maintain its basic functional and structural integrity in the event of a breach. In the RIFs network of passenger ship evacuation accidents, the destruction of key nodes can reduce the stability of the network, thereby controlling or slowing down the spread of accidents. This study analyses the changing trend of network robustness by simulating attack on key nodes, providing decision support to reduce the probability of passenger ship evacuation accidents.

In the RIFs network of passenger ship evacuation accidents, the factors affecting the network's robustness come from various aspects. Consequently, attack strategies for these RIFs involve both random and deliberate attacks. Random attacks utilize a Monte Carlo simulation approach, while deliberate attack strategies focus on high-importance nodes. The top 10 nodes in terms of importance within the RIFs network are shown in Table 2.

Table 2 Ranking of network feature parameters.

Total degree			Total strength			Betweenness centrality			Closeness centrality		
Sort	Node	Value	Sort	Node	Value	Sort	Node	Value	Sort	Node	Value
1	S1	22	1	S1	78	1	S1	0.1458	1	P3	1.0000
2	P3	14	2	A	71	2	M4	0.0267	2	P4	1.0000
3	A	14	3	P3	52	3	M3	0.0239	3	P2	1.0000
4	M3	11	4	M2	38	4	M2	0.0239	4	P5	1.0000
5	M1	9	5	M3	30	5	P3	0.0182	5	O4	1.0000
6	P4	9	6	P4	28	6	C5	0.0129	6	01	1.0000
7	S3	9	7	S3	28	7	S3	0.0089	7	05	1.0000
8	M2	8	8	P2	25	8	M1	0.0082	8	M2	0.8333
9	S4	8	9	M1	22	9	S4	0.0065	9	C1	0.8001
10	P2	8	10	E1	17	10	P4	0.0055	10	O2	0.7143

The change in network robustness under the two attack strategies is illustrated in Fig. 6. As shown in Fig. 6, regardless of whether the attacks are random or deliberate, the network's robustness decreases gradually as the number of attacked nodes increases. It is found that deliberate attacks compromise the network's stability more rapidly than random attacks, particularly when targeting nodes with high total degree, total strength, and betweenness centrality. This indicates that targeted control of critical RIFs is more effective in preventing the evolution of evacuation accidents. Deliberate attacks based on the total strength of nodes can collapse the network more quickly than those based on total degree, closeness centrality, and betweenness centrality. Furthermore, deliberate attacks targeting nodes based on total degree and betweenness centrality have nearly the same impact on network robustness, which also suggests that ranking nodes by their total strength better identifies the key nodes in the RIFs network for passenger ship evacuation accidents. During the deliberate attacks that focused on the total strength of nodes, the network's robustness was reduced by 80.8% with just 6 nodes attacked, bringing the network close to collapse. In contrast, random attacks at this point reduced the network's robustness by only 46.2%. Therefore, the total strength value of nodes is used as a key indicator for selecting critical RIFs to analyse risk control measures. Based on the above analysis, the top 5 nodes in terms of their total strength are S1 (The spread of hazards on board), P3 (Competitive behaviour), M2 (Poor assembly/evacuation decision), M3 (The captain's improper handling of the emergency), P4 (Panic/herd behaviour), which should be considered as key RIFs. Node A (Casualties and injuries to personnel) is excluded as it represents the outcome of an accident.

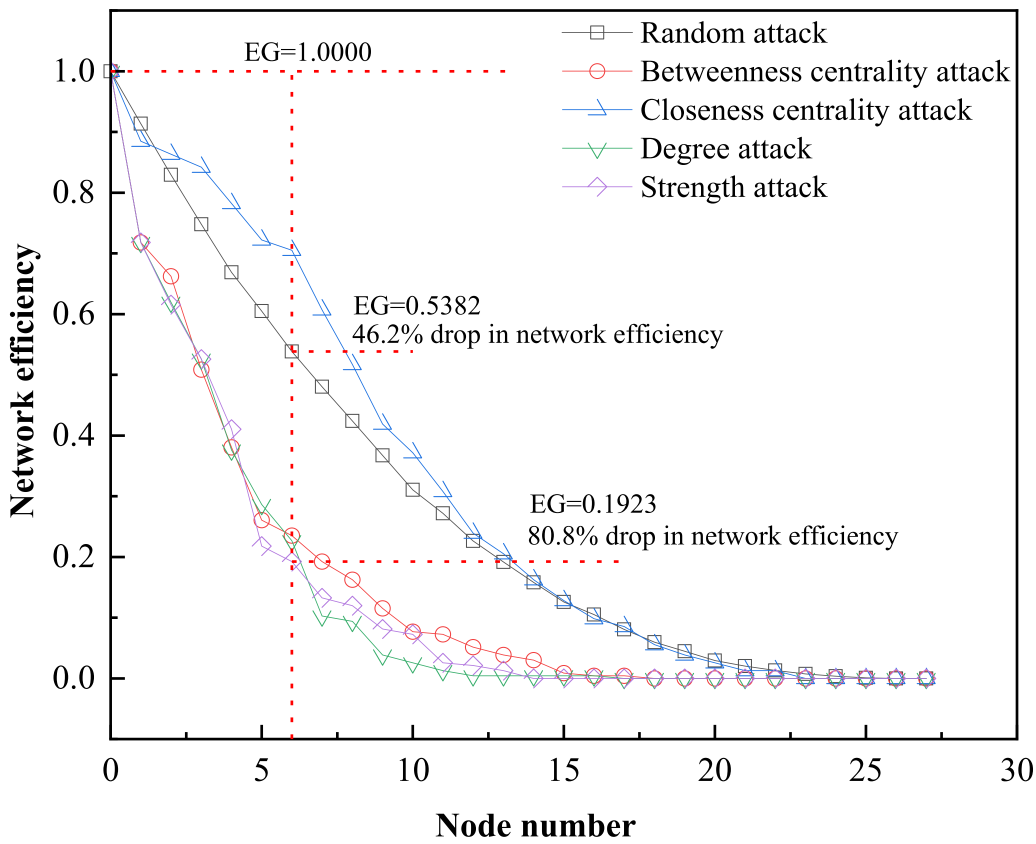


Fig. 6 The robustness analysis results of RIFs network.

4.2 The analysis results of DEMATEL

In this study, Eqs. (4) to (10) are used to calculate the influence degree, influenced degree, centrality degree, and cause degree of each node in the RIFs network, the calculation results of those indexes are shown in Table 3.

Table 3 The results of influence degree, influenced degree, central degree and reason degree.

RIFs	r_i	c_j	FI	EI
M1	0.673	0.683	1.356	-0.010
M2	0.923	1.065	1.988	-0.143
M3	0.787	0.940	1.727	-0.152
M4	0.680	0.081	0.761	0.598
C1	0.523	0.063	0.586	0.461
C2	0.610	0.000	0.610	0.610
C3	0.529	0.200	0.730	0.329
C4	0.339	0.065	0.404	0.274
C5	0.618	0.094	0.712	0.523
P1	0.053	0.031	0.084	0.022
P2	0.344	0.826	1.170	-0.483
P3	0.703	1.628	2.331	-0.925
P4	0.463	1.024	1.487	-0.561
P5	0.146	0.158	0.305	-0.012
S1	1.715	1.608	3.323	0.107
S2	0.190	0.000	0.190	0.190
S3	0.624	0.513	1.138	0.111
S4	0.777	0.190	0.968	0.587
E1	1.206	0.000	1.206	1.206
E2	0.140	0.000	0.140	0.140
E3	0.042	0.000	0.042	0.042
O1	0.031	0.000	0.031	0.031
O2	0.295	0.000	0.295	0.295
O3	0.575	0.000	0.575	0.575
O4	0.094	0.000	0.094	0.094
O5	0.031	0.000	0.031	0.031
A	0.000	3.943	3.943	-3.943

As shown in Table 3, the RIF with the highest influence degree is S1 (The spread of hazards on board), followed by E1 (Rough sea state) and M2 (Poor assembly/evacuation decision), etc. The most influenced RIF is A (Casualties and injuries to personnel), followed by P3 (Competitive behaviour) and S1 (The spread of hazards on board), and so on. Among them, RIFs S1 (The spread of hazards on board) and M2 (Poor assembly/evacuation decision) not only have a higher degree of influence but are also more significantly influenced by other factors. This indicates that they not only receive information from a larger number of factors but also transmit information to a wider range of factors. During the emergency evacuation process, special attention should be given to these two factors to safeguard the lives of personnel.

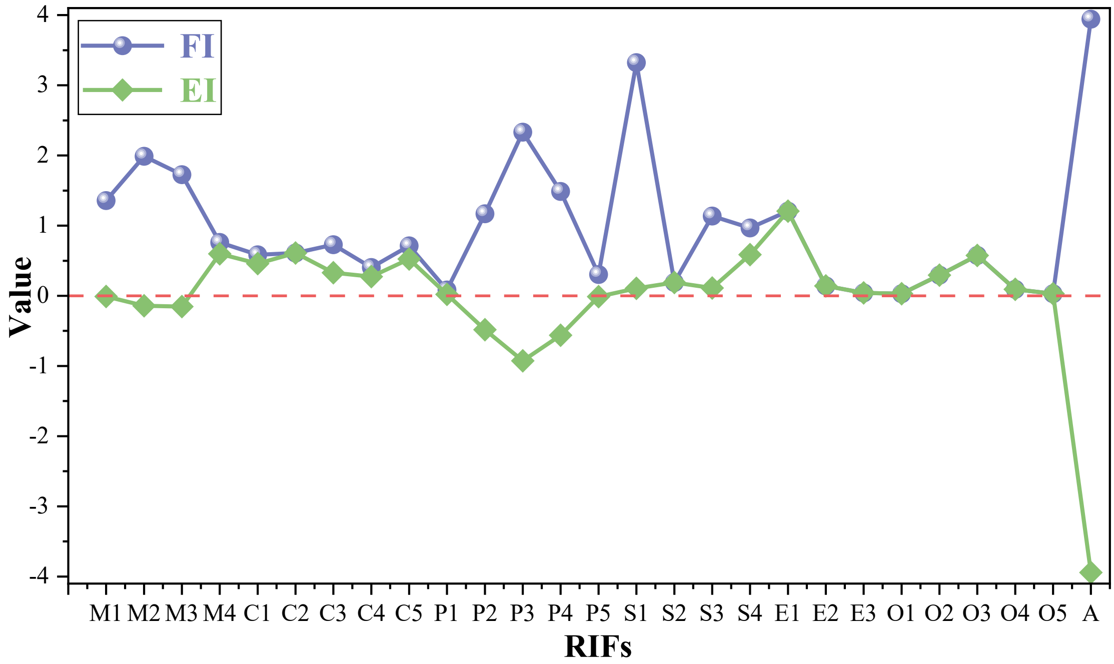


Fig. 7 The centrality and cause degree values of RIFs.

For the analysis of centrality degree and cause degree, a causality diagram is constructed by plotting cause degree and centrality degree of each RIF on a two-dimensional coordinate system, as shown in Fig. 7. In Fig. 7, RIFs located above the X-axis indicate a direct influence on the occurrence of evacuation accidents, while those below the X-axis represent outcome factors influenced by causal factors, indirectly affecting evacuation accidents. The higher the centrality degree, the more critical the RIFs. Consequently, it's evident that the RIF with the highest centrality degree is A (Casualties and injuries to personnel), followed by S1 (The spread of hazards on board), and P3 (Competitive behaviour), etc. These factors are direct triggers of accidents, and by effectively controlling them, the development of an accident can be halted, thereby preventing its occurrence. Notably, RIF A is the final outcome of an accident, making it crucial to focus on other significant RIFs. According to DEMATL theory, RIFs are classified into cause and outcome factors. RIFs with a cause degree greater than 0 are categorized as cause factors, while those with a cause degree less than 0 are considered outcome factors. During the risk evolution process, the higher the cause degree, the more factors it influences, making the accident more challenging to control. The RIF with the greatest degree of cause is E1 (Rough sea state), followed by C2 (Inadequate safety awareness of crew) and M4 (Inadequate safety awareness of captain), and so on. These factors are primarily indirect contributors to accidents, which they don't directly cause accidents but increase the likelihood of evacuation incidents. By managing these factors, the risk of loss of life can be minimized.

In this study, when considering the ranking of influence and influenced degrees, it is decided to prioritize the ranking of centrality and cause degrees of each RIF, using the influence and influenced degrees as secondary criteria. The selection criteria include being in the top 5 of either centrality or cause degrees or in the top 5 of influence or influenced degrees (Xing *et al.*, 2023). As a result, S1 (The spread of hazards on board), M2 (Poor assembly/evacuation decision), M3 (The captain's improper handling of the emergency), P3 (Competitive behaviour), P4 (Panic/herd behaviour), and E1 (Rough sea state) are identified as the key RIFs that should be controlled during evacuation to prevent casualties.

4.3 The analysis results of ISM

In the overall influence matrix, the sum of the mean value and standard deviation of all factors is 0.07. Therefore, unimportant causal relationships between factors in the integrated influence matrix are excluded by using a threshold of λ=0.07. Next, the overall influence matrix Q is obtained using Eq. (11), and then Eq. (12) is applied to derive the reachability matrix. Using the reachability matrix, Eq. (13) is employed to construct the reachable set, prior set, and their intersection. The elements of the set are then hierarchically divided, and the ISM model is created, as shown in Fig. 8. This model demonstrates that the impact of the passenger ship evacuation accident is divided into nine layers. At the L1 layer, only RIF A is affected by other RIFs, making RIF A the final outcome of the accident. To better understand the relationship between these RIFs, this study begins its analysis from the L2 layer.

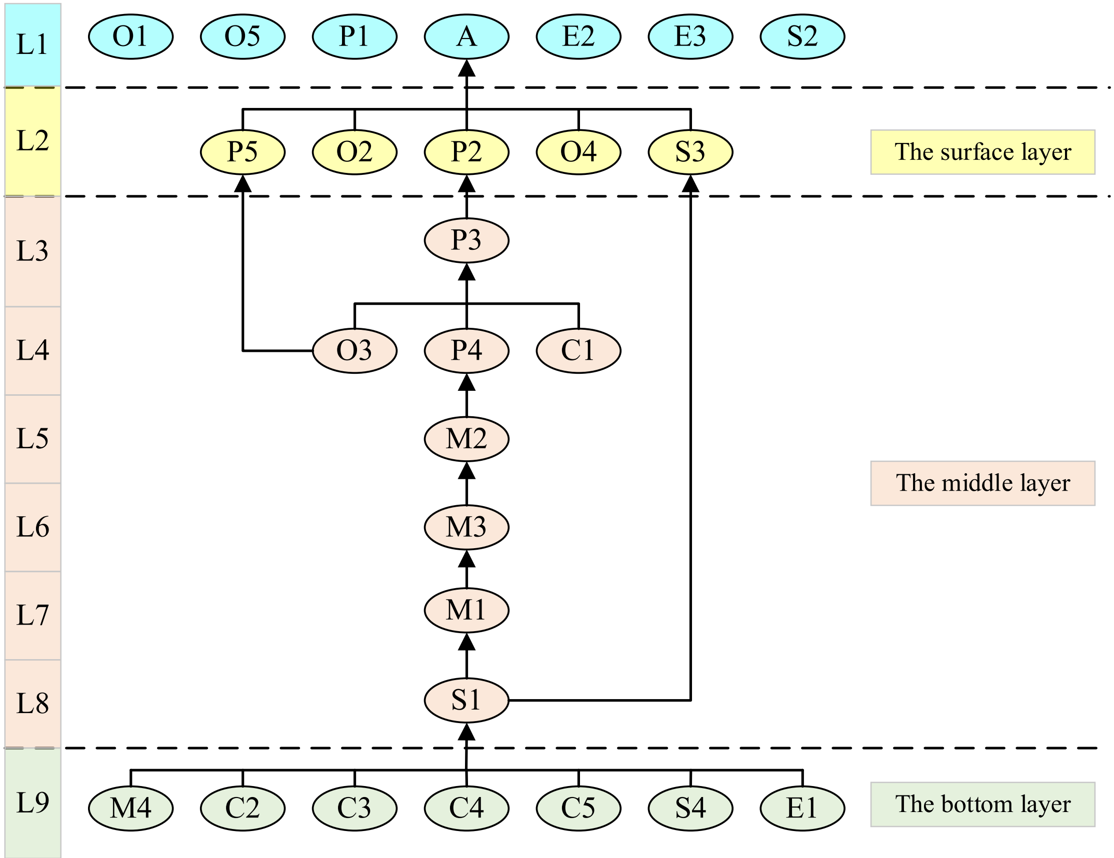


Fig. 8 The ISM model of influencing factors.

The L2 layer is summarised as surface factors, the L3 to L8 layers as middle factors, and the L9 layer as bottom factors. In the passenger ship evacuation accidents, the RIFs of surface factors have the most direct influence on casualties and are influenced by other RIFs. RIFs at this layer include P5, P2, O2, O4, and S3, indicating that passenger behaviour, management factors, and ship factors directly affect casualty events in an accident. Therefore, countermeasures can be implemented to safeguard lives by addressing these RIFs. The middle factors act as intermediaries, influenced by underlying factors, while also affecting the surface factors. RIFs at this layer include the captain's behaviour (M1, M2, M3), crew behaviour (C1), passenger behaviour (P3, P4), ship factors (S1) and management factors (O3). These middle factors are indirect, involving complex components across five dimensions. For example, in layer L4, factors in three different dimensions, C1, O3 and P4, can all transmit information to P3 to further influence surface factors. It shows that the intermediate factor conduction path is complex and difficult to control. The bottom layer factors represent the basic factors in the RIFs of passenger ship evacuation accidents, which lead to the occurrence of casualties by influencing all middle and surface factors. RIFs at this layer include crew behaviour (C2, C3, C4, C5), captain's behaviour (M4), ship factors (S4) and environmental factors (E1). These factors are the initial triggers for accidents. As illustrated in Fig. 8, once these factors are present, they can trigger risky situations on the passenger ship, initiating a chain of events that may eventually lead to casualties. Additionally, they exert long-term influence on the upper layers of the system and must be considered critical factors.

4.4 Discussion and implications

Improving the efficiency of passenger ship evacuation and reducing the number of casualties has always been a central task for IMO and national maritime administrations. Achieving this goal, requires a comprehensive understanding of passenger evacuation accident, including the progression from the initial hazard through risk evolution to the completion of the rescue. The evolution process, in particular, involves the assembly, abandonment, and search and rescue stages. There are two main strategies to control risk evolution in the RIFs network of passenger ship evacuation accidents. The first strategy is to eliminate the conditions that trigger bottom layer through preventive measures. The second strategy is to intervene the key nodes within the middle layer of the network or to reduce the risk status of these nodes to block the risk propagation, thereby preventing risk evolution.

According to the analysis results, human factors, ship factors and environmental factors are the main RIFs during the emergency evacuation from passenger ships. After filtering and merging similar RIFs, 12 key RIFs are identified. They are M2 (Poor assembly/evacuation decision), M3 (The captain's improper handling of the emergency), M4 (Inadequate safety awareness of captain), C2 (Inadequate safety awareness of crew), C3 (Improper emergency response to accident), C4 (Improper binding/fastening of cargo), and C5 (Ship manipulation), P3 (Competitive behaviour), P4 (Panic/herd behaviour), S1 (The spread of hazards on board), S4 (Power/manoeuvring equipment failure), and E1 (Rough sea state). Based on these key RIFs, this study proposes targeted countermeasures from the perspectives of controlling key RIFs at the bottom layer, and blocking key RIFs at the middle layer. The specific countermeasures are shown in Table 4.

Table 4 The proposed risk prevention and countermeasures.

Methods	RIFs	Prevention and countermeasures
Risk source control	M4 Inadequate safety awareness of captain	Strengthening safety education and training, conducting regular safety awareness assessments and tests; regularly enhancing safety awareness through accident case studies.
	C2 Inadequate safety awareness of crew	Increase the frequency of safety training, strengthen the construction of a safety culture, and carry out training based on accident case to raise individual safety awareness; implement a strict assessment

		system.
	C3 Improper emergency response to accident	Organise regular emergency drills to assess the crew's ability to handle emergencies; improve the emergency response process to ensure that all crew members are familiar with it and are able to carry it out proficiently.
	C4 Improper binding/fastening of cargo	Develop and strictly enforce standards for cargo lashing/tie-downs and conduct regular inspections; train crew members in proper cargo lashing/tie-downs and ensure that all crew members are able to perform them correctly.
	C5 Ship manipulation error	Regular operational skills tests are conducted for crew members, and those who do not pass the tests are provided with operational skills training to improve their ability to operate the vessels.
	S4 Power/manoeuvring equipment failure	Establish a sound system of equipment maintenance and inspection to ensure the proper functioning of power and manoeuvring equipment; formulate emergency plans and conduct relevant drills to deal with equipment failure situations.
	E1 Rough sea state	Through the meteorological forecasting system to obtain timely information on sea conditions and rationally adjust routes; training crews in operating skills under adverse sea conditions to enhance coping ability.
Interruption of risk evolution process	M2 Poor assembly/evacuation decision	Develop detailed muster and evacuation plans that are regularly updated and rehearsed; use evacuation simulation software for decision support training.
	M3 The captain's improper handling of the emergency	Improve emergency management training for captains, conduct regular simulation drills and related management courses; establish detailed emergency plans and review them regularly.
	P3 Competitive behaviour	Implement group evacuation strategies to minimise cross-flow and congestion, based on the design of the ship and the distribution of passengers; and strengthen the leadership and co-ordination skills of crew members during emergencies to ensure that they are able to effectively direct and manage the evacuation process.
	P4 Panic/herd behaviour	Formulate detailed evacuation plans and conduct regular drills to familiarise passengers with the evacuation procedures; step up publicity and education to enhance passengers' self-rescue capabilities and reduce panic and herd behaviour.
	S1 The spread of hazards on board	Regularly conduct internal risk assessments and hidden danger inspections of ships; strengthen internal management to ensure the normal operation of ship equipment and systems.

This study utilizes the CN, DEMATEL and ISM models to explore the identification and management of key RIFs during emergency evacuations of passenger ships. It also proposes strategies that emphasize source control and interventions at key nodes. This study not only offers theoretical support for enhancing evacuation efficiency and reducing casualties but also highlights significant practical implications in the following areas:

(1) Passenger safety: The research results directly contribute to optimizing the evacuation procedures and emergency management measures for passenger ships, ensuring that passengers can evacuate in a more orderly and efficient manner during emergencies. By identifying and controlling key RIFs, the negative impact of panic and improper behaviour on evacuation efficiency can be minimized, significantly enhancing passenger safety.

(2) Passenger shipping industry: This study provides scientific evidence for passenger shipping companies to optimize ship operations, and management. By introducing more accurate risk assessment and management strategies, passenger shipping companies can reduce accident risks, enhance operational safety, lower insurance costs and operational risks, and increase market competitiveness. Moreover, the improved safety guarantees help build passenger trust and satisfaction, promoting the sustainable development of the passenger shipping industry.

(3) Maritime authorities: This study provides the International Maritime Organization and national maritime authorities with scientific risk control strategies and analysis models. Based on this model and strategies, maritime authorities can accurately identify and analyse key RIFs in the evacuation process, effectively eliminate the conditions that trigger risks, and implement interventions at critical points. Additionally, the authorities can more effectively develop and enforce evacuation safety standards and emergency plans, strengthening ship safety supervision and accident prevention to achieve the core goal of reducing casualties.

(4) Other stakeholders: Stakeholders such as port management agencies, and crew training institutions will also benefit significantly from the risk analysis models and control strategies proposed by this study. Port management agencies can enhance their emergency handling capabilities by optimizing port facilities and evacuation routes. Crew training institutions can leverage this study's results to refine training content and methods, strengthening crew emergency response capabilities and safety awareness, ultimately improving overall maritime safety.

5. Conclusions

This study employs a method combining CN with DEMATEL and ISM to analyse the RIFs in evacuation accidents of passenger ships. This study comprehensively considers RIFs related to human, ship, environment, and management factors in assembly, ship abandonment, search and rescue aspects, identifying the critical RIFs. These RIFs integrate results from multiple analytical methods, providing comprehensive theoretical support for ensuring safe evacuation and formulating multi-attribute decision-making plan to prevent casualties during the evacuation process.

Although this study provides valuable insights into the analysis of passenger ship evacuation accidents, it has several limitations that should be addressed in future work. Firstly, the construction of the accident chain relies on manual analysis of accident investigation reports, which can introduce subjectivity into the results. Secondly, the data used in the study primarily focus on major casualty accidents involving large passenger ships worldwide, resulting in a limited sample size. Finally, the model developed in this study requires further validation through additional accident investigation reports. Therefore, future research should aim to use more scientific methods to analyse accident reports, reduce human subjectivity, expand data sources to include a broader range of passenger ship accidents, improve the study's comprehensiveness, validate the model with additional samples, and enhance the accuracy of the results.

Data Availability Statement

All data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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