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Research paper

Evolutionary model and risk analysis of ship collision accidents based on complex networks and DEMATEL

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ABSTRACT

To manage and control ship collision risk, this paper aims to develop a quantitative risk analysis approach based on complex networks and Decision-making Trial and Evaluation Laboratory (DEMATEL), to study the evolution of ship collision accidents. Firstly, through the search, selection and analysis of accident investigation reports of ship collisions in the world, 46 Risk Influential Factors (RIFs) were identified, and a network model for the evolution of ship collision was established. Secondly, a risk analysis of the evolution model for ship collision accidents was conducted by utilizing the topology characteristics of the complex network theory. Thirdly, a robustness analysis was used to identify 10 key RIFs involved in ship collisions from a global network perspective, and the grey relation analysis technique was employed to verify the key RIFs. Finally, the DEMATEL method was utilized to identify 11 key RIFs from a perspective of causality, and corresponding risk control measures were proposed to mitigate those key RIFs. The research results provide theoretical support for identifying the key RIFs and controlling the risk transmission of ship collision, and have practical significance for preventing the occurrence of ship collision accidents and ensuring the safe navigation of ships.

1. Introduction

Due to rapid economic and trade globalization, maritime transport has become the primary method for international freight transportation (Shu et al., 2023a; Wang et al., 2021). According to the 2019 data report by the United Nations Conference on Trade and Development, the total volume of global maritime trade in 2018 alone exceeded 11 billion tons (UNCTAD, 2019). Furthermore, it is anticipated that the global maritime trade growth rate will maintain at 3.4% from 2019 to 2024, highlighting the importance of waterborne transportation for the swift progress of the worldwide economy (Cao et al., 2023b). Nevertheless, the increased prosperity in maritime transportation has resulted in more incidents (Huang et al., 2023). According to the statistics, the count of marine accidents and fatalities in 2021 rose significantly as compared to that of 2020 (Wang et al., 2023b). Globally, the International Maritime Organization (IMO) statistics indicate an increase in deaths from 109 to 132 in 2021, which represents an increase of more than 20%. Additionally, the number of accidents is expected to increase from 244 to 280, representing nearly a 15% increase (UNCTAD, 2019). The frequency of marine accidents not only leads to significant loss of life and property, but also presents a grave danger to the marine ecology and environment because of the diverse range of accidents (Liu et al., 2023a). Ship collisions represent the leading component of marine accidents (Liu et al., 2023b). Between 1978 and 2008, collisions constituted 46.23% of all marine accidents worldwide (Marino et al., 2023). Reducing the risk of collisions in shipping is highly valuable and holds practical significance (Shu et al., 2023b).

Ship navigation is a complex and dynamic process, requiring

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collaboration between humans and machines (Animah and Shafiee, 2021). To fully understand the potential risks and hazards that accompany sea navigation, a meticulous examination of the factors influencing ship safety is necessary (Fang et al., 2024). These factors encompass human, vessel, and environmental elements. Precise analyses of these components can help develop targeted strategies for preventing and controlling marine accidents in an integrated manner (Callesen et al., 2021). Various safety issues that affect ship navigation can only be resolved effectively by adhering to strict standards (Valcalda et al., 2022).

Research into ship collision accidents has advanced the analysis of their Risk Influential Factors (RIFs) from the simple domino theory to complex linear models. However, most studies on cause and effect still rely on chain structures (Özaydın et al., 2022). In real life, very few accidents follow a completely chain structure, and the various factors that lead to an accident interaction and contribute to each other. Therefore, the network structure of the analysis model for the accident has a stronger adaptability. The complex network theory utilises a graph theory and other models to represent complex systems, providing new insights into analysing the internal connections and causal relationships between accident RIFs (Sui et al., 2022). Complex networks are useful quantitative tools for describing vast, complex systems, enabling the analysis of risks and investigation of evolutionary mechanisms (Zhang et al., 2023). Nowadays, there is extensive research in areas such as aerospace (Zheng and He, 2021), energy systems (Geng et al., 2021), and rail transport (Ilalokhoin et al., 2023) in terms of the use of complex networks to assess safety issues. However, there is no empirical research or reviews regarding the analysis of marine accidents, specifically collision accidents, requiring a new study to fill the gap.

The primary aim of this study is to utilize the complex network theory and the Decision-making Trial and Evaluation Laboratory (DEMATEL) technique to investigate the relationships between the RIFs of ship collisions, and use the Grey Relation Analysis (GRA) to verify the validity the proposed method. Through a combination of these approaches, the weaknesses of these approaches can be addressed, and it will be possible to propose customized measures to reduce the frequency of collision accidents at sea.

The study is organised into several sections. Section 2 provides an overview of different research methods related to ship collisions and complex network studies. In Section 3, the RIFs of ship collision accidents are described, and a complex network model of the ship collision RIFs is developed. In addition, the methods used to analyse the networks of ship collision RIFs are proposed in this section. Section 4 presents a detailed account of the establishment and analysis of the network model for ship collision RIFs. Section 5 gives a summary of the key findings.

2. Literature review

2.1. Research methods for ship collision accident analysis

Ship collision accidents pose a significant harm to the maritime industry, therefore, numerous researchers have undertaken extensive research on this type of marine accident. Diverse research methods have been employed, including but not limited to Bayesian networks (Cao et al., 2023b; Özaydın et al., 2022), Fault trees (Sarıalioğlu et al., 2020; Zhao et al., 2022), and the Analytic Hierarchy Process (AHP) (Wang et al., 2023b; Yildiz et al., 2022). Among them, Bayesian networks have the capacity to forecast and assess the trend of risk changes, and can attain a more precise judgement by consolidating information from the overall evaluation, previous information, and sample information (Cao et al., 2023b). Obeng et al. (2022) introduced an object-oriented Bayesian network model for appraising the likelihood of small fishing vessels capsizing, evaluating important RIFs, and identifying crucial measures to diminish risks. Cao et al. (2023b) employed a Bayesian network model to examine the links between the severity of marine accidents and the RIFs. The accident tree enabled the identification of diverse pathways to the final event and the quantification of event probability. Zhao et al. (2022) used fuzzy fault tree analysis and Bayesian networks to assess the probability of marine casualties. Ugurlu and Cicek (2022) used fault tree analysis to qualitatively and quantitatively analyse RIFs in ship collision accidents, providing the probability and importance of RIFs while defining the minimum segmentation set. The AHP deals with decision-making by treating objects as systems. It uses decomposition, comparative judgement and comprehensive thinking approaches (Shafiee and Animah, 2022). By combining qualitative and quantitative analysis, it is able to address many practical problems that cannot be solved by conventional optimization approaches. Hu and Park (2020) employed the AHP to identify a set of fundamental risk influential factors and vulnerabilities pertaining to ship collisions. They then introduced a novel algorithm for assessing risks associated with ship navigation. Sahin and Senol (2015) facilitated the evaluation process of maritime accidents by utilizing expert consultation and the fuzzy AHP. Chen et al. (2019) proposed a classification system through frequency estimation, causal analysis, etc., described and discussed representative methods, and emphasized the need for improvement of these methods in identifying collision candidates, which can help to develop better risk analysis models. Marino et al. (2023) presented recent advances in ship collision risk assessment, highlighting emerging technologies and revealing the diversity of approaches to analysing collision risk. To evaluate the relationship between maritime traffic flow complexity and the likelihood of collision accidents, a predictive analytics method is proposed to evaluate the complexity of maritime traffic flow from a microscopic perspective (Zhang et al., 2022).

While traditional risk assessment methods have led to advancements in accident analysis, they possess certain constraints in their applications (Zhang et al., 2021b). For example, if a Bayesian network model involves too many RIFs as its nodes, it will be cumbersome and challenging to configure the relevant conditional probabilities of the nodes with many parents. While the accident tree views accidents as a linear process, there is limited research on the analysis of the correlation between sub-RIFs and overlooking such correlation could easily result in an error-prone result. If there are numerous indicators in the AHP, the data statistics can be extensive, and the determination of weights can be difficult to obtain (Zhang et al., 2021a).

As aforementioned, ship collision accidents are characterized by complex, non-linear interactions among various RIFs, including human, ship, environmental, and management factors (Cao et al., 2023a). Such interactions make them typical examples of complex systems. The link between different factors within the system, especially the nature of human-machine integration, heightens the likelihood of collisions and their correlation, thereby increasing the complexity of constructing accident models.

2.2. Application of complex network models in accident analysis

Complex networks play a crucial role in the field of complexity science and can be employed to study any intricate system. They offer insight into the structure, topological features, and regulations governing the elements present in complex systems, thereby facilitating a deeper comprehension and appreciation of the internal structural dynamics of such systems.

Complex networks have introduced novel approaches to investigating intricate systems from innovative perspectives, such as those found in society, management, engineering, medicine and beyond (Wang et al., 2023a). This has facilitated the formation of an emerging discipline that intersects multiple fields and combines various methodologies. This theory has been developed based on graph theory research, with the capability to analyse the relationships between causal factors within complex systems and uncover the topological features of complex systems. Recently, this theory has been adopted in the analysis of risk issues in industries. The complex network model uncovers universal principles in intricate systems using network analysis techniques. Key analysis metrics comprise network density, average path length, node degree and degree distribution, and clustering coefficients. Complex networks are brief representations of intricate systems. They abstract constituent units of the system as nodes and the interrelationships between each unit as edges, studying network topology and dynamic behaviour. This approach has been extensively applied in researching transportation networks.

Currently, complex networks are widely used in analysing traffic accidents (Liu et al., 2023a). Li et al. (2020) proposed a method for analysing key nodes and links based on the minimum connected dominating set in the field of aerospace. Their method employed an immune particle swarm optimization algorithm to find the minimum connected dominating set of the network, simultaneously processing key nodes and links in complex networks. In the realm of subway accidents, Li et al. (2017) developed a subway accident network model based on the complex network theory, which disclosed the structural attributes and principles of the subway operation network. Wang et al. (2020) constructed a national railway powerless topological network using railway stations as nodes and inter-city railway traffic services as edges. Then the new network was constructed by taking the inter-city train service as the edges, and the topological properties of the two networks and the differences between the important nodes and edges were analysed. Zhou et al. (2014) examined the topological traits and patterns of subway construction accident networks based on the complex network theory. Instead of analysing a single accident, they used the network theory to explore the complexity of the subway construction accident network (SCAN), and demonstrated that SCAN is resilience to random attacks. For rail transport, Cao et al. (2023b) created a Chinese high-speed rail topology network which consists of 499 nodes and 32,607 edges. They combined all stations within a city to form one node, and the network was built based on train frequency between cities. The topological properties of the network were analysed and revealed small-world and scale-free characteristics. Liu et al. (2019) enhanced and supplemented the established complex network theory by outlining network topology indicators that were merged with railway operation features, thus assisting railway operators in establishing more specific strategies and methods for preventing accidents. As an illustration, Zhou et al. (2015) applied an event-chain-based network technique to form a causal network of railway accidents, exemplified through UK railway data. Through an analysis of the network topology parameters, they identified the primary causal factors and event chains.

The aforementioned studies show that complex networks technique are effective in investigating the evolutionary features of accidents in complex systems. Although it can make analysis from the impact of RIFs on accident consequences, as well as the interactions between RIFs during the accident process, it can’t analyse the RIFs from a causal perspective. In recent years, the DEMATEL technique has attracted substantial attention for analysing the causality of intricate structural systems. Therefore, another method that can be analysed to show the causal relationship between RIFs, i.e., DEMATEL, is introduced. The DEMATEL method is suitable for scrutinizing the correlation between RIFs that influence accidents, particularly causal relationships. It requires less on data collection than common probabilistic methods, and the method uses the graph theory supplemented by matrix theory for analysis, which can complement the results obtained from the analysis of complex network methods. In addition, DEMATEL also provides the contextual relationship between the considered factors and is represented by matrices and graphs (Khatun et al., 2023). Mentes et al. (2014) combined GRA and the DEMATEL methods to prioritize the causes of ship failures. Mentes et al. (2015) further optimized the risk analysis method for cargo ship damage, based on Formal Safety Assessment (FSA), which combined fuzzy set theory (FST), Ordered Weighted Geometric Average operator (OWGA), and DEMATEL, and the most common causes of unintentional damages on cargo ships at coastal and open seas of Turkey were identified. Özdemir and Güneroglu (2015) proposed the use of DEMATEL and Analytical Network Process (ANP) methods for quantitative assessment of human error in offshore operations. Celik and Akyuz (2016) proposed an analytical method that combined the DEMATEL method with Interval type-2 fuzzy sets (IT2FSs) to analyse important accident causal factors and their effects based on causal diagrams.

Despite the fact that these two approaches are more attractive than the classical risk analysis approach and that each of them has been applied in the maritime domain, few studies used these two approaches in a complementary combination. This results in a new research question as to if the Complex Network and DEMATEL could be used in a synergised manner to generate new insights for better maritime risk control and accident prevention. Aiming to examine the cause-and-effect connection among RIFs thoroughly, this study conducts marine accident analysis by incorporating topology characteristics of complex network with a DEMATEL structural modelling method, to propose rational measures to mitigate accident risks and prevent further risk evolution.

2.3. New contributions

The successful implementation of complex network models in public transportation fields, including railways, aviation, and subways, indicates the method’s universality. To overcome the challenges of studying collisions using conventional approaches, this study for the first time, advocates the combined usage of complex network modelling and DEMATEL technique to investigate the RIFs of ship collisions.

1) The marine accident investigation reports of ship collisions between 2007 and 2022 were comprehensively searched, screened and analysed to extract the accident chain and RIFs. Then, a complex network of RIFs of ship collision accidents was developed, and the RIFs were identified as nodes and the relationship between RIFs was defined as edges between these nodes.
2) The established evolution network model for ship collision accident is analysed using the topology characteristics, the robustness analysis was used to identify key RIFs involved in ship collisions from a perspective of global network, and the grey relation analysis technique was employed to verify the key RIFs.
3) Furthermore, the DEMATEL method was utilized to identify the primary RIFs from a perspective of causality, and targeted strategies were proposed for preventing ship collision accidents, so as to reduce the likelihood of such accidents.

As maritime transport trade is rapidly developing, conducting an RIF analysis of ship collision accidents based on complex networks and DEMATEL holds significant research importance.

3. Materials and methods

In order to comprehensively and scientifically analyse the risk evolution in the process of ship collision, this study proposes a risk analysis model that contains two stages, as shown in Fig. 1. The first stage is the identification part of ship collision RIFs. Based on collected ship collision accident investigation reports, the causal chains of ship collision accidents are extracted and a risk indicator hierarchy system is developed. The second stage is the risk analysis part. Firstly, the risk evolution network model of ship collision RIFs is established based on the complex network theory. Then, the topological characteristics of complex networks are descripted, robustness analysis is used to find key RIFs from a perspective of global network, and GRA is utilized to verify the effective of above analysis result. Finally, the DEMATEL method is applied to identify final key RIFs from a perspective of causality, and the risk control measures are proposed to mitigate those key RIFs.

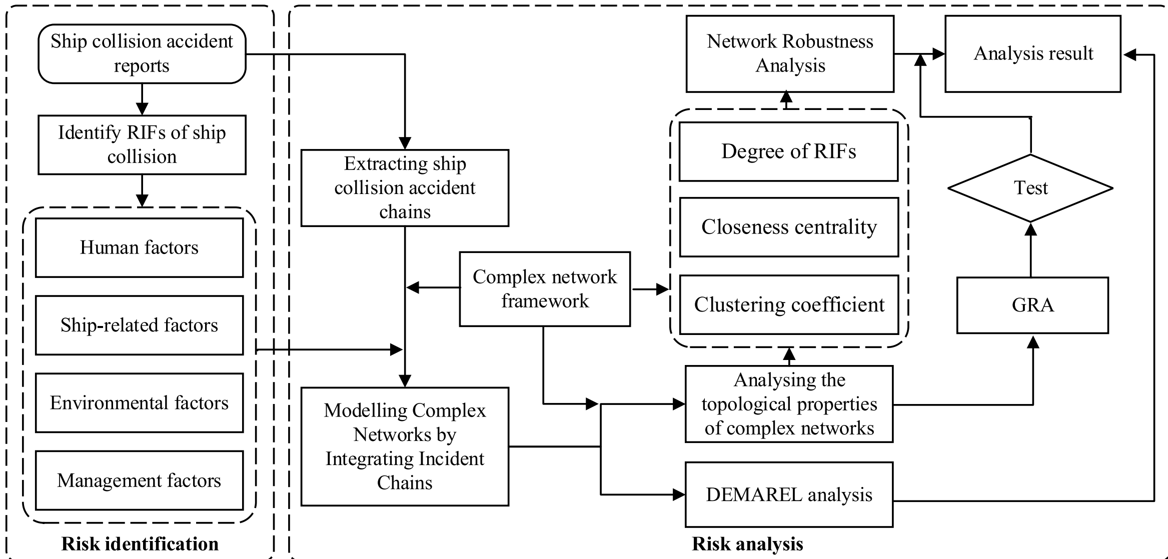

Fig. 1. The methodological framework of this study.

3.1. Risk influential factors of ship collision accidents

Accidents are often caused by unsafe acts, unsafe conditions and a lack of management, involving RIFs from complex human, ship-related, environmental and management perspectives. These RIFs interact to impact the process of safe navigation of ships.

3.1.1. Human factors

Human factors are the main contributing factor in marine casualties. The operation of ships involves many crew members, from the captain through the first mate to ordinary sailors. If their actions are not standardized and correct, it can directly result in marine accidents. Investigations into accidents at sea have found that around 80% of the marine accident are related to human error (Aydin, 2023). Previous accident analysis has shown that human factors are the most significant and challenging ones to control in the RIFs of collision accidents (Liu et al., 2023b).

The majority of human factors are operational errors caused by human error, which is influenced by the technical level and competence of crew members, professional ethics and literacy, physical and mental health and psychological quality (Xia et al., 2023).

3.1.2. Ship-related factors

Two key indicators for evaluating a ship's ability to navigate safely are its manoeuvrability and seaworthiness. Ship manoeuvrability varies with ship types, and is crucial for collision avoidance operations such as ship turning performance, acceleration and deceleration performance, starting and braking performance. Ensuring the manoeuvrability of ships allows the crew to handle successfully and avoid hazards at a safe distance. The seaworthiness status of a ship mainly covers ship hull performance, cargo type, and equipment performance. It is essential to conduct a stringent check of the above aspects before sailing. In order to guarantee a secure navigation, it is essential for navigational officers to utilize modern technology such as navigation aids, positioning equipment, and communication device. This is especially important when facing sudden challenges, such as engine failure and narrow water areas. By comprehensively understanding the ship's real-time navigation status, navigational officers can expertly handle the ship and avoid dangerous accidents such as collisions. Therefore, it is crucial to monitor the ship's status.

3.1.3. Environmental factors

The navigational conditions of a ship are heavily influenced by the external environment. Multiple elements such as wind force, wind direction, wind speed and other marine meteorological factors can notably impact a vessel's navigation. These factors lead to the ship swaying under the influence of wind and waves when navigating in rough weather, resulting in decreased navigation stability. Additionally, they make it challenging for the operator to identify targets accurately. The inability to make reasonable navigational decisions increases the likelihood of ship collisions. Hydrological factors, including current direction, tidal height, wave height and tidal current, pose recurrent problems for ships at sea. Particularly in shallow water regions, variations in tidal range frequently cause complications. Navigating through high waves results in a challenging task for controlling the ship's speed and course, increasing the probability of operating errors and collisions. In addition to the two aforementioned dynamic environmental factors, the geographical and navigational environmental factors within a navigation area also significantly affect ships. Geographical environmental factors comprise vital information, such as shallow water, restricted waters, shoals and reefs in proximity to the route. Many waterways permit only one vessel to traverse at a time, and the water depth and margin of safe water depth can influence navigational speed, steering efficiency, and other ship indicators. The navigational environment of ships comprises pilot facilities, navigational aids, obstacle distribution, and traffic flow characteristics. It exerts a profound impact on ship safety, particularly during entry and exit port areas. Any equipment failure in any of these areas can cause ship collision accidents to occur.

3.1.4. Management factors

Management factors typically include pertinent regulations established by shipping companies, maritime administrations and other institutions, as well as taking into consideration aspects such as manning, crew training and labour relations. Following the implementation of the International Safety Management (ISM) code, the majority of international vessels have been able to effectively implement a safety management system in compliance with the regulations' mandates. Ship equipment has been enhanced, and there has been significant improvement in communication between ships and shipping companies. However, variations exist among different shipping companies, and discrepancies in the execution of the ISM code result in a range of issues. The safety management system could lack sufficient operability and its objectives and requirements are often too general, making implementation difficult to achieve when applied to practical scenarios. Furthermore, crew members and company personnel could have not undergone in-depth training in all necessary aspects of the safety management system documents, ultimately resulting in ineffective execution. Additionally, a company's training plan could be incomprehensive enough to address the issue at hand. The safety management system implementation requires a reasonable and effective supervision and restraint mechanism to ensure the system's continuity and self-improvement. It is hence crucial to examine management factors in detail.

3.1.5. Accident report analysis

Based on the official websites of the IMO and national maritime authorities, including the United States, Australia, the United Kingdom, Japan, China, Norway, Poland, Germany, Canada and Malta, 300 ship collision accident reports between 2007 and 2022 were collected. Through the integrity analysis of reports, 207 accident reports were kept after the screening process, as shown in Fig. 2. RIFs were then extracted from these 207 accident reports. During the extraction process, it was found that there were a large number of repetitive or similar descriptions of these RIFs, due to differences in the investigation agencies. Therefore, those similar RIFs were categorized and merged. With reference to existing literatures (Cao et al., 2023a; Wang et al., 2021, 2023c), RIFs were categorized into four groups: human factors, ship-related factors, environmental factors, and management factors. To ensure the rigor of these RIFs, five experts were invited to evaluate the verified these RIFs, and the names of some RIFs were modified. The basic information of these experts is shown in Table 1. Then through analysis of marine accident investigation reports and expert judgment, Table 2 is obtained by refinement.

3.2. Complex network analysis

3.2.1. Overview of complex networks

In essence, a complex network denotes a highly intricate arrangement of nodes alongside corresponding relationships between them. The components comprising complex networks are often simple, yet the interaction mechanisms between these components exhibit extreme complexity (Wang et al., 2023a). These networks demonstrate complexity primarily through five overarching features, including node diversity, edge diversity, the large scale of the network, the complex structure and the dynamic complexity of the network (Deng et al., 2023).

Complex networks can describe the frameworks of numerous open complex systems, ranging from technology to biology to society, and are valuable instruments for analysing their topological structures.

3.2.2. Analysis of network topology characteristics

The parameters employed to examine the topological properties of intricate networks usually comprise degree (degree of node linked with others), degree centrality, node betweenness, and proximity centrality

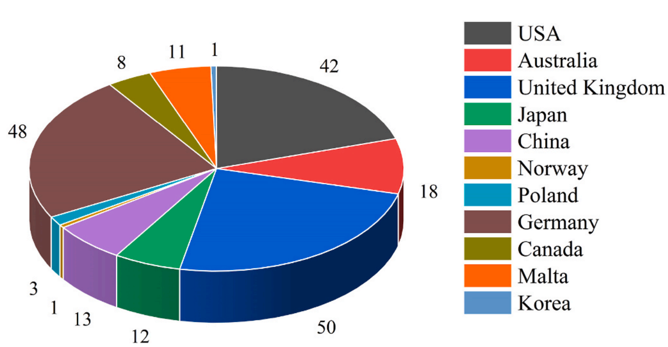

Fig. 2. Sources of ship collision reports.

Table 1
The background information of the employed experts.

Expert No.	Age (year)	Time at sea (year)	Job Title	Field and Experience
Expert A	46	10	Officer of the Maritime Administration	Engaged in maritime supervision for 15 years
Expert B	39	5	Associate professor, second officer	Engaged in research related to marine accident analysis for 10 years
Expert C	36	3	Associate professor, third officer	Engaged in research related to ship safety for 8 years
Expert D	64	8	Chief officer and professor	Engaged in research related to maritime safety for 35 years
Expert E	48	16	Captain and associate professor	Engaged in theory and practice related to marine navigation for 21 years

(Wang et al., 2023a).

(1)Degree of nodes

In complex network theory, the node degree is defined as the number of other RIFs connected to the RIF. Degree centrality determines the significance of a node (RIF) according to its degree, whereby a greater degree value correlates with increased importance. In this study, it can be used to describe the number of the links between a target RIF and the other RIFs. Equation (1) (Zhou et al., 2015) demonstrates this relationship:

$$k_i = \sum_{j=1, j \neq i}^{n} a_{ij} \tag{1}$$

where k_i is the degree of the i^{th} RIF, and n is the total number of RIFs. If there is a relationship between RIFs i and j, a_{ij} is 1, otherwise it is 0.

The degree of a RIF is the aggregate of the number of RIFs and the number of subsequent factors.

The influence of a RIF within a network can be measured by its degree, with higher degree RIF being more important. Degree centrality not only indicates the correlation between RIFs, but also varies depending on network size. In other words, the maximum possible degree increases as the network becomes larger.

(2) Minimal path system

The term "path" in a complex network typically denotes a sequence of nodes, where each adjacent pair of nodes in the sequence is connected by an edge. The length of a path is determined by counting the number of edges in the node sequence. In this study, the minimal path linking two RIFs is the path with the fewest number of variables connecting those RIFs. Its length is determined by counting the edges in the minimal path. The aim of creating a complex network in this study is to acquire the fastest and shortest path leading to an accident, followed by setting up a preventive mechanism along this route to minimize the chance of risks.

Usually, the minimal path length between RIFs v_i and v_j is denoted as $d(v_i, v_j)$, and d_{ij} is the distance between RIFs.

By calculating the minimal path between RIFs in the complex network model, the network diameter and the average path length of the complex network can be obtained. The calculation process is shown as Equation (2) (Deng et al., 2023):

Table 2
The RIFs of ship collision accidents.

Node category	Node code	Node description	Node category	Node code	Node description
Human factors	**H1**	Lookout negligence	Ship-related factors	**S25**	Difficult to detect by electronic devices
	H2	Lack use of good seamanship		**S26**	Poor ship structural design
	H3	Improperly and ineffective avoidance		**S27**	Improper equipment description
	H4	Poor communication		**S28**	Uncontrolled ship drift
	H5	Insufficient cooperation	Environmental factors	**E29**	Poor visibility
	H6	Decision error		**E30**	Density traffic
	H7	Insufficient skill level and inexperience		**E31**	Effect of tide
	H8	Improper ship handling		**E32**	Hydrodynamic effect
	V9	Violation of rules		**E33**	High backlight intensity
	H10	Improper duty arrangements		**E34**	Complex navigation environment
	H11	Improper use of radar		**E35**	Bad weather
	H12	Unused safe speed		**E36**	Noise and vibration
	H13	Improper signal display	Management factors	**M37**	Incomplete rules
	H14	Improper shore-based command		**M38**	Lack of supervision
	H15	Poor physical condition		**M39**	Incomplete risk assessment
	H16	Improper equipment layout		**M40**	Lack of safety education
	H17	Inattention		**M41**	Insufficient manning
	H18	Improper route design		**M42**	Lack of skill training
	H19	Absence without leave		**M43**	Incompetence of crew
	H20	Insufficient language ability		**M44**	Unseaworthiness
	H21	Improper information processing		**M45**	Chart defect
	H22	Alcoholism or drug dependency		**M46**	Insufficient shore-based support
Ship-related factors	**S23**	Equipment failure	Accident result	**A47**	Collision
	S24	Improper equipment maintenance			

$$L_{RIF} = \frac{1}{n(n-1)} \sum_{i \neq j \subseteq G} d_{ij} \tag{2}$$

where, n is the total number of RIFs in the network, and the distance between RIFs v_i and v_j is d_{ij}. The average path length of a complex network is relatively small (Lee and Yu, 2023). Through the computation of the average path length in a complex network model, it can be concluded that the network exhibits the small-world characteristics and the structural properties of the complex network.

(3) Closeness centrality

The average distance between network nodes and other nodes can be represented by the closeness centrality of complex network nodes. A correlation between RIFs can be determined by calculating the closeness centrality of nodes, which leads to the determination of RIFs importance. The centrality value of a node is indicative of its importance, with higher values implying greater importance. Equation (3) provides this value (Sui et al., 2022).

$$B_{RIF_i} = \frac{n-1}{\sum_{j=1}^{n} d_{ij}} \tag{3}$$

By assessing the closeness centrality of RIFs, it becomes feasible to establish how to decrease the likelihood of risk happening via chain breaking.

(4) Clustering coefficient

In complex network model, the clustering coefficient of each RIF is a fraction. The numerator is the number of true connected edges between the RIFs that are associated with the RIF, and the denominator is the ratio of the maximum number of potential connected edges between the RIF and its neighbouring RIFs. The network's clustering coefficient is the average clustering coefficient of all RIFs in the network. The clustering coefficient of nodes can be calculated using Equation (4) (Deng et al., 2023).

$$F_{RIF_i} = \frac{2L_i}{k_i(k_i-1)} \tag{4}$$

where F_{RIF_i} is the clustering coefficient of RIF i, L_i is the actual number of edges between neighbouring nodes of RIF_i.

The clustering coefficient of a complex network is indicative of the amalgamation of various nodes within the network. When RIFs have explicit clustering properties, the average path length of complex networks is shorter and the clustering coefficient is larger.

3.3. Network robustness analysis

The connectivity of a network's nodes may suffer failures, but the network's robustness reflects its capacity to maintain such connectivity. Any local network failures can significantly impact the overall network structure and functioning. It is crucial to disrupt the structure of the network model of risk evolution of ship collision and lower the network connectivity to impede the evolution of risk, ultimately thwarting any potential accidents. To fast and effectively prevent the progression of RIFs, a thorough analysis of network robustness is completed on significant network nodes using prior identification.

From the perspective of the nature of the sources of network damage, research on network vulnerability can be divided into two types: deliberate attacks and random accidents. Deliberate attacks often target important nodes, while random accidents are random and irregular. Network vulnerability leads to a reduction in the overall functionality of the system during disasters, so removing nodes to reduce the robustness of the network is also one of the means to prevent collision accidents from occurring.

Network efficiency, often regarded as the mean path length of a network, is a common metric used to evaluate network robustness. In this study, the reciprocal of the minimal path length d_{ij} between nodes is used to calculate network efficiency. If the distance between two nodes is infinite, the reciprocal distance is 0. The resulting average path length is always finite. After an attack, for the convenience of calculation, the efficiency $1/d_{ij}$ between two nodes in the network with no links is set to 0. Equation (5) (Deng et al., 2023) demonstrates the process by which network efficiency can be derived.

$$E = \frac{1}{n(n-1)} \sum_{i \neq j \subseteq G} \frac{1}{d_{ij}} \tag{5}$$

3.4. Grey relation analysis

Assessing node importance through a single indicator is one-sided in practice (Wang et al., 2023a). Comprehensive consideration of multiple factors is necessary for risk analysis. Different parameters from various dimensions should be used to statistically analyse the impact of nodes on the network. The comprehensive effects of multiple factors, including human factors, ship-related factors, environmental factors and management factors, determine maritime casualties. The factors are interdependent and exert varying degrees of impact on accidents. Due to the incomplete comprehension of the collision process and the complex nature of accidents, it is impossible to fully establish the internal linkages between the RIFs. Consequently, the GRA method provides a useful approach for investigating the relationship between marine casualties and their underlying RIFs (van Diessen et al., 2022).

The ship system is regarded as a grey system during the maneuvering process, and the correlations between the different RIFs can be identified by analysing the similarities and differences in their changing trends. A higher correlation is observed if the changing trends are similar, and vice versa (van Diessen et al., 2022). The core of GRA is the calculation of the degree of correlation: the reference sequence $X_0{}' = (x_0(1)', x_0(2)', \ldots, x_0(N)')$ is selected, and other factors are recorded as comparison sequences as $X_i{}' = (x_i(1)', x_i(2)', \ldots, x_i(N)')$, and $n+1$ data sequences form a matrix, as shown in Equation (6):

$$(X_0{}', X_1{}', \ldots, X_n{}') = \begin{bmatrix} x_0(1)' & x_1(1)' \cdots x_n(1)' \\ x_0(2)' & x_1(2)' \cdots x_n(2)' \\ \vdots & \vdots \quad \ddots \quad \vdots \\ x_0(N)' & x_1(N)' \cdots x_n(N)' \end{bmatrix}_{N\times(n+1)} \tag{6}$$

where, N is the length of the variable sequence.

In order to unify the dimensionality of the numerical values in the sequence and to avoid variables with small orders of magnitude that cannot have sufficient influence on the analysis results, the multi-attribute data sequence matrix $(X_0{}', X_1{}', \ldots, X_n{}')$ is dimensionless according to the Equation (7):

$$x_i(k) = \frac{x_i(k)'}{\frac{1}{N}\sum_{k=1}^{N} x_i(k)'} (i = 0, 1, \ldots, n; k = 1, 2, \ldots, N) \tag{7}$$

The final dimensionless matrix is obtained as shown in Equation (8):

$$(X_0, X_1, \ldots, X_n) = \begin{bmatrix} x_0(1) & x_1(1) \cdots x_n(1) \\ x_0(2) & x_1(2) \cdots x_n(2) \\ \vdots & \vdots \quad \ddots \quad \vdots \\ x_0(N) & x_1(N) \cdots x_n(N) \end{bmatrix}_{N\times(n+1)} \tag{8}$$

Record the correlation coefficient between X_0 and X_i as Equation (9):

$$\xi_{0i}(k) = \frac{\min\limits_{1\le i\le n}\min\limits_{1\le j\le N}|x_0(j) - x_i(j)| + \rho\cdot\max\limits_{1\le i\le n}\max\limits_{1\le j\le N}|x_0(j) - x_i(j)|}{|x_0(k) - x_i(k)| + \rho\cdot\max\limits_{1\le i\le n}\max\limits_{1\le j\le N}|x_0(j) - x_i(j)|} \tag{9}$$

where, ρ is the resolution coefficient used to control the discrimination of the correlation coefficient $\xi_{0i}(k)$, which is taken as a value in (0, 1). Since the smaller ρ, the greater the discrimination between the correlation coefficients, the values are usually taken between 0.1 and 0.5 based on actual situations.

The correlation coefficient $\xi_{0i}(k)$ is a positive number less than 1 and reflects the degree of correlation between sequence X_0 and X_i at the kth value. The degree of correlation ζ_{0i} between the reference sequence X_0 and the comparison sequence X_i is comprehensively reflected by N correlation coefficients, as shown in Equation (10):

$$\zeta_{0i} = \frac{1}{N}\sum_{k=1}^{N} \xi_{0i}(k) \tag{10}$$

GRA can be used to establish the correlation between various RIFs and collision accidents, making it possible to determine the cause of accidents more accurately. However, this high accuracy is achieved based on a large amount of accident data. Therefore, in this study, GRA is used as a validation method to test the identified significant RIFs.

3.5. DEMATEL analysis

The DEMATEL technique is a structured analytical approach employing graph theory and matrix tools for problem analysis. In complex network models, an influence matrix can be created by DEMATEL, founded on the logical interrelationships of each node; determining the degree of influence of each node on other nodes, and obtaining the degree of cause and centrality of each node, in turn, establishing the position of the RIFs connected to each node within the system (Animah and Shafiee, 2021). The matrix representation of complex network models can be considered as the impact matrix of DEMATEL, as demonstrated in Equation (11) (Zheng et al., 2022).

$$A = \begin{array}{c} \\ v_1 \\ v_2 \\ \vdots \\ v_i \\ \vdots \\ v_n \end{array} \begin{array}{c} \begin{array}{ccccccc} v_1 & v_2 & \cdots & v_j & \cdots & v_n \end{array} \\ \begin{bmatrix} 0 & e_{12} & \cdots & e_{1j} & \cdots & e_{1n} \\ e_{21} & 0 & \cdots & e_{2j} & \cdots & e_{2n} \\ \vdots & \vdots & \ddots & \vdots & \cdots & \vdots \\ e_{i1} & e_{i2} & \cdots & e_{ij} & \cdots & e_{in} \\ \vdots & \vdots & \cdots & \vdots & \ddots & \vdots \\ e_{n1} & e_{n2} & \cdots & e_{nj} & \cdots & e_{nn} \end{bmatrix} \end{array} \tag{11}$$

where, the value of e_{ij} is 0 or 1 ($i = 1, 2\cdots n$, $j = 1, 2\cdots n$). If $e_{ij} = w_{ij}$, it indicates that two nodes are connected, and the weights between the nodes is w_{ij}. While $e_{ij} = 0$, the two nodes are not connected.

Normalize the influence matrix, then calculate the normative impact matrix to obtain the comprehensive influence matrix T, as shown in Equation (12) and Equation (13) (Zheng et al., 2022):

$$A_N = A \times \lambda \tag{12}$$

$$T = A_N \cdot (I - A_N)^{-1} = (t_{ij})_{n\times n} \tag{13}$$

where λ is the normalized parameter, I is the identity matrix, and t_{ij} represents the overall impact of the i^{th} row node on the j^{th} column node in the overall influence matrix.

Apply the comprehensive impact matrix to calculate different indicators of the DEMATEL methodology, such as the Impact Degree value (D), the Affected Degree value (E), the Centrality Degree value (DE), and the Cause Degree value (ED). Equations (14)–(17) (Zheng et al., 2022) present the respective calculation process.

$$D_i = \sum_{j=1}^{n} t_{ij} \tag{14}$$

$$E_i = \sum_{j=1}^{n} t_{ji} \tag{15}$$

$$DE_i = D_i + E_i \tag{16}$$

$$ED_i = D_i - E_i \tag{17}$$

4. Results and discussion

4.1. The establishment of accident RIFs network

A causal chain of ship collision accident, highlighting the accident occurrence process, is established for each report based on the RIFs and the resulting ship collision events. Based on the causal chains of marine accidents, the relationship matrix of nodes is established. If there is an arrow pointing from a column node to a row node in the causal chain, then the matrix element corresponding to that column node and row node is 1. If that arrow appears twice during the merging of the causal chain, then the matrix element is 2, and so on. If no arrow exists between the two nodes, the matrix element is 0. Based on the node relationship matrix, a complex network diagram is drawn to obtain the RIFs network model of ship collision accidents. The process is shown in Fig. 3.

The ship collisions are rarely isolated incidents. An evolutionary structural model has been established based on the logical relationship and order of occurrence of indicators to illustrate the complex network of RIFs that contribute to these accidents. The accident chain combination process as shown in Fig. 3 is applied to 207 accident reports, then all the accident chains are aggregated and combined into an accident network, and the node impact matrix of the accident network is obtained. The accident impact matrix is imported into Python, and the network algorithm and drawing function of Python are used to visualize the matrix to obtain Fig. 4.

Fig. 4 shows the RIFs and their evolutionary relationships in the collision accident network which consists of nodes and connecting edges. These nodes and edges create risk transmission chains associated with various indicators. Since the accident network model of RIFs is formed by combining a large number of accident causal chains, many similarly accident occur multiple times during the combination process. The number of occurrences of link edges between RIFs is assigned as weights to the matrix elements of the accident impact matrix during the combination of accident causal chains. The weights are calculated as shown in Fig. 3. This accident impact matrix is used as an impact matrix in the DEMATEL analysis to calculate the causality between RIFs. It is important to note that each RIF in the graph can act as a risk transfer indicator that may result in accidents.

The network for assessing collision risk in ships has revealed the multiple factors impacting unsafe human behaviour that can ultimately result in a collision accident. The RIFs are multifaceted, for instance, H11 (Improper use of radar), may be impacted by H7 (Insufficient skill level and inexperience), H15 (Poor physical condition), H17 (Inattention), H21 (Improper information processing), S24 (Improper equipment maintenance), and E30 (Density traffic). Each RIF can impact various unsafe behaviours, such as lack of supervision, which can lead to ineffective avoidance, negligence, unused safe speed, and absence without leave. Additionally, a single type of human error occurs in every collision accident, while the factors that trigger multiple types of human error are diverse. Therefore, implementing chain-breaking control measures can attain the aim of preventing or slowing down ship collision accidents by intercepting RIFs which may trigger several human errors concurrently and by obstructing their evolutionary pathway.

4.2. Results analysis based on topology characteristics

According to Fig. 5, the majority of accident RIFs exhibit low degree values, with 10 RIFs displaying high degree values (*i.e.*, over 22 value). These RIFs are identified as H1 (Lookout negligence), H2 (Lack use of good seamanship), H3 (Improperly and ineffective avoidance), H4 (Poor communication), H6 (Decision error), H7 (Insufficient skill level and inexperience), H8 (Improper ship handling), H11 (Improper use of radar), H17 (Inattention), and E30 (Density traffic). A high degree value signifies that these RIFs can be easily impacted by other RIFs and serve as the central nodes of complex network models - also referred to as hub nodes - that are essential hubs in the risk transmission chain. The mean degree value of the complex network model for ship collisions is 16, with merely 17 nodes surpassing the average value. The degree of most nodes is small, while the degree of a few nodes is large. Therefore, this model adheres to the scale-free property. This also shows that the established accident network is a complex network, which can be analysed with the relevant characteristics of complex networks theory.

Lower degree nodes have limited connections in complex network models, resulting in a relatively minor influence on accident networks. The probability of those accident RIFs directly leading to accidents is low. These findings imply that improving the prevention and control of higher degree nodes is an effective strategy for reducing accident occurrence.

The clustering coefficient is also a significant indicator in the evaluation of complex network models. Fig. 6 displays the clustering coefficients for each node. The network model's clustering coefficients range from 0.3 to 1.0, with more than 50% of the nodes having coefficients larger than 0.6. The calculated average data clustering coefficient of the network is 0.67, which indicates that each node in the network is closely connected with other nodes in the network. If the efficiency of the interaction between RIFs is higher, the accident develops more rapidly, and the prevention is more difficult, which conforms to the characteristics of complex network community structure. Upon assessing the importance and risk evolution of nodes, it is apparent that the shortest path for each node is relatively short and the discrepancy is insignificant. The model's network diameter is 1.64, indicating that a RIF can cause a collision with a maximum of two evolutionary steps. The small average diameter and high clustering coefficient of the model aligns with small world characteristics. Thus, the ship collision risk evolution model suggests that generated RIFs easily transfer risk to other RIFs, which rapidly lead to final accident ship collisions.

To examine the variations in the significance of diverse contributing factors which lead to accidents, this study conducts an analysis of the nodes' degrees and their respective shares of contribution in the direct cause of accidents. The probability of each node being the cause of the accident is also significantly different, as illustrated in Fig. 7. Various RIFs contribute to collisions at sea, including H1 (Lookout negligence), H2 (Lack use of good seamanship), H3 (Improperly and ineffective avoidance), H4 (Poor communication), H6 (Decision error), H7 (Insufficient skill level and inexperience), H8 (Improper ship handling), and H9 (Violation of rules). It is evident that in most cases, human factors directly lead to collisions. Environmental and managerial factors contribute to the occurrence of high accident rates at specific locations,

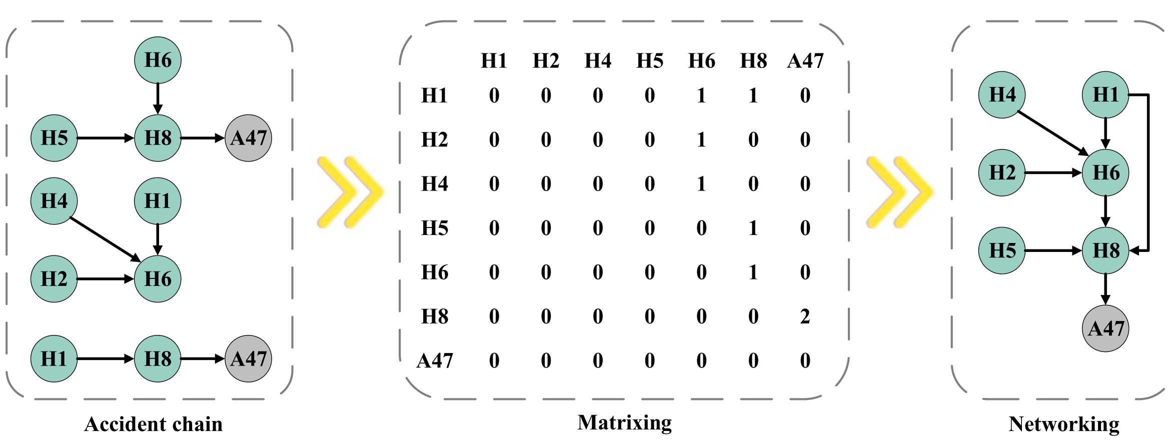

Fig. 3. The fusion process of accident chain.

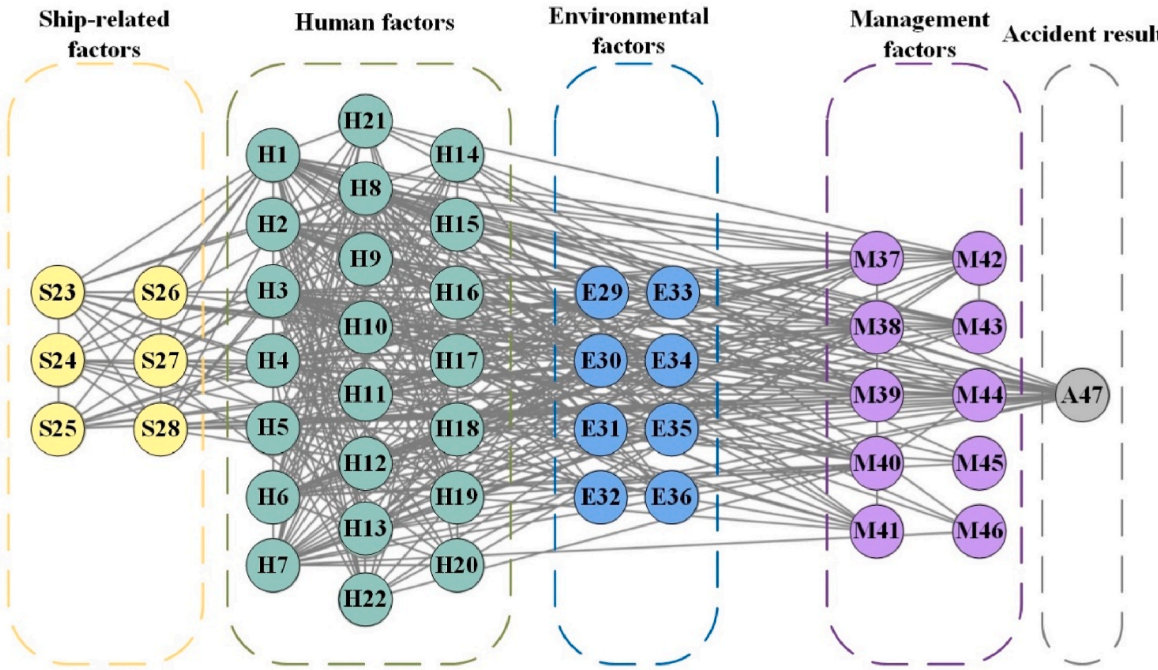

Fig. 4. The complex network model for the evolution of ship collision RIFs.

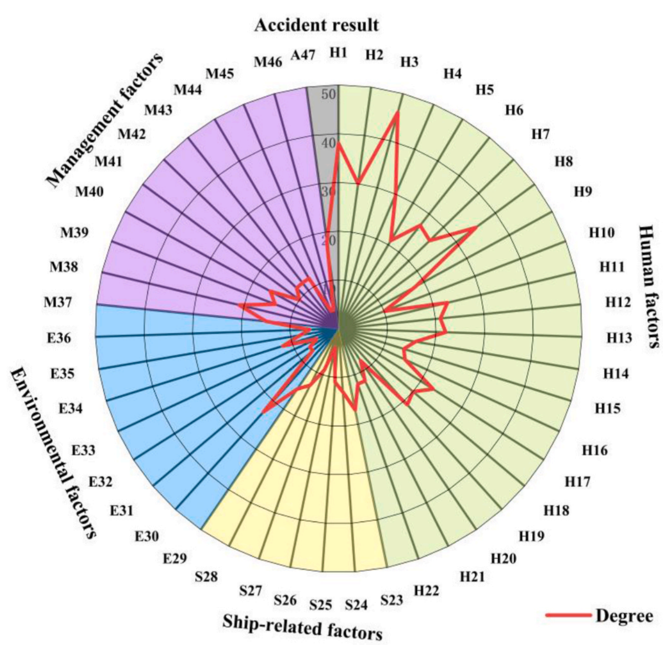

Fig. 5. The degree of RIFs.

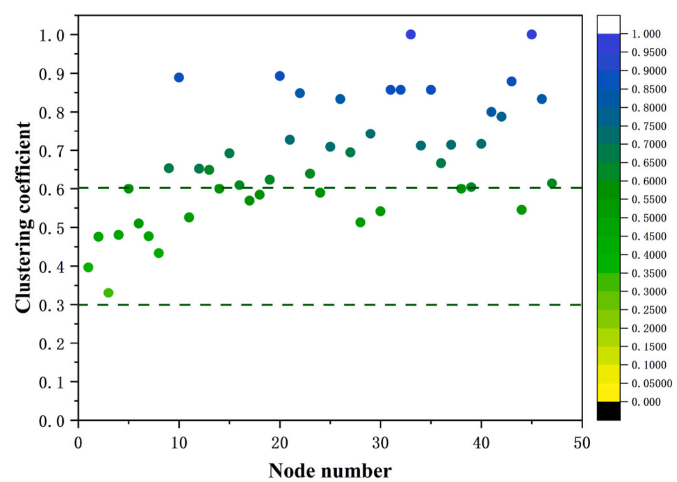

Fig. 6. The clustering coefficient of RIFs.

indicating that indirect factors (*i.e.,* H7, M37, M38, M39, M40 and M42) significantly affect the development of accident risk.

Fig. 8 displays the closeness centrality of the nodes. Upon analysis of the graph, it is evident that nodes with a high centrality include: H1 (Lookout negligence), H2 (Lack use of good seamanship), H3 (Improperly and ineffective avoidance), H4 (Poor communication), H6 (Decision error), H7 (Insufficient skill level and inexperience), H8 (Improper ship handling), H11 (Improper use of radar), H17 (Inattention), and E30 (Traffic density). This suggests that these nodes are in close proximity to other nodes, with a very short shortest distance, situated at the centre of the network, and capable of rapidly influencing other nodes.

4.3. *Results analysis based on robustness analysis*

After analysing complex network models, estimating crucial barriers along the risk evolution pathway can facilitate the formulation of risk control strategies. Fig. 9 illustrates changes in network efficiency of complex network models during various mode attacks. Notably, random attacks produce a relatively gradual reduction in network efficiency compared to deliberate attacks. After attacking 10 nodes, the efficiency of the targeted network model was less than 0.4, while the efficiency of the random attack disrupted network model was around 0.63. Once about thirty nodes are attacked, the complex network model, which relied on accident rate, closeness centrality, and degree, collapsed almost entirely.

The rate of decline in network efficiency can be concluded as follows. In deliberate attacks, the key nodes in the network are attacked first, which can isolate more nodes in the network. This can cause the network to crash, thereby preventing the network from evolving to node A47 (Collision). For example, when attacking node H1 (Lookout negligence)

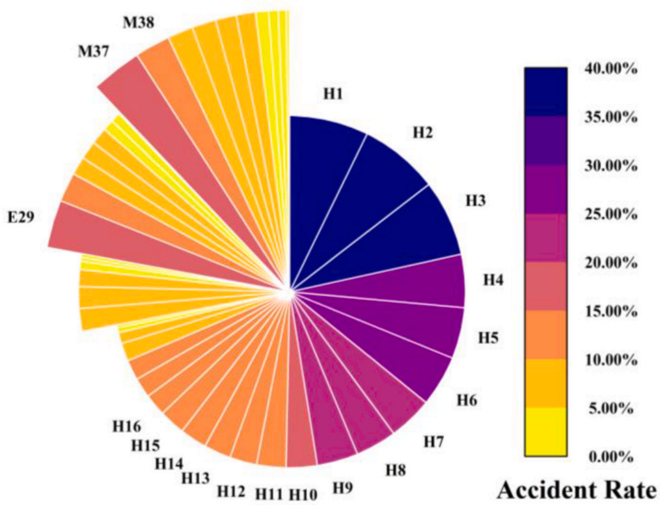

Fig. 7. The RIFs' accident rate.

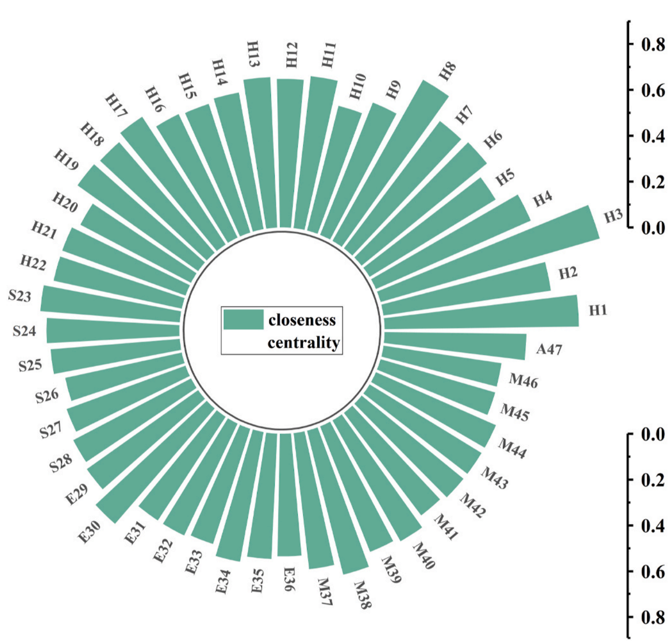

Fig. 8. The closeness centrality of RIFs.

in the network, 45 accident chains in the complex network model can be disabled and the 79 accidents recorded in the accident report can be prevented from occurring. When nodes are attacked randomly, the probability of attacking key nodes is small. Only when more nodes are attacked at the same time, the network structure will change greatly, which is difficult to prevent the risk evolution of the network.

According to Fig. 9, deliberate attacks predicated on node degree, proximity centrality, and accident incidence rate instigate a more rapid decrease in network efficiency in complex network models. Based on the aforementioned parameters, the 10 key RIFs are H1 (Lookout negligence), H2 (Lack use of good seamanship), H3 (Improperly and ineffective avoidance), H4 (Poor communication), H5 (Insufficient cooperation), H6 (Decision error), H7 (Insufficient skill level and inexperience), H8 (Improper ship handling), H11 (Improper use of radar), E30 (Density traffic).

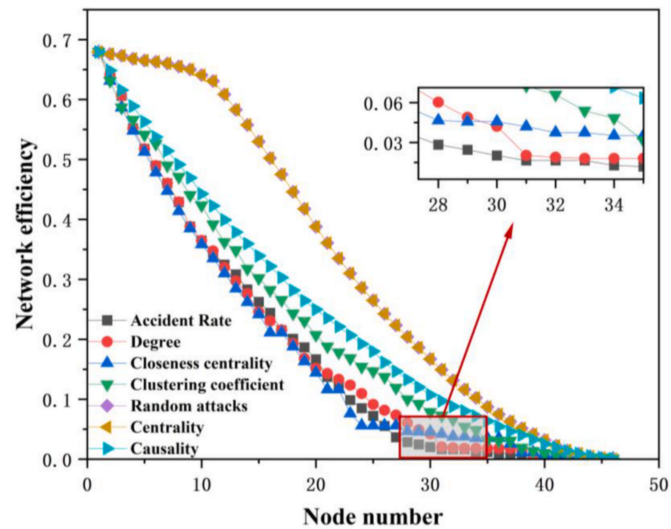

Fig. 9. The results of network robustness analysis.

4.4. Results analysis based on GRA

In order to verify the relevance and importance of the selected indicators, the parameter of GRA is used to evaluate the selected indicators again. The importance of the 10 key RIFs in the progression and advancement of ship collision catastrophes can be determined, so as to propose safety measures for prevention and control throughout the operation.

As can be seen in Fig. 10, the importance ranking of RIFs is basically consistent with the importance ranking obtained from the analysis in the complex network method. It can be seen that the key RIFs identified by complex network method are reliable and they are the key RIFs in the evolution of ship collision risk.

Although the GRA method can more accurately analyse RIFs with strong correlation, its analysis of accident risk evolution is more one-sided. Moreover, the GRA method requires a large amount of data for comparative analysis, and fail to distinguish RIFs with lower correlation. Therefore, this study adopts the method of robustness analysis as the main method to analyse the established network of ship collision RIFs. Then, the GRA method is used to verify the effectiveness of robustness analysis by analysing the RIFs with strong correlation, which is more

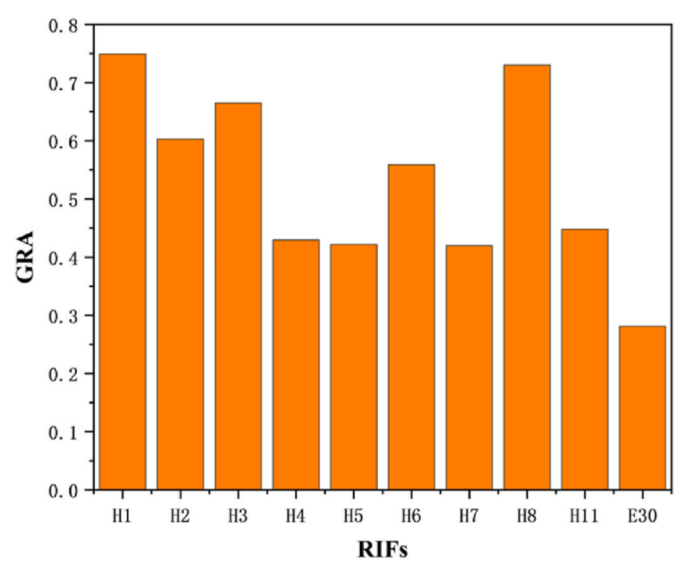

Fig. 10. The node importance results of complex network.

advantageous in improving the comprehensiveness of the accident results.

4.5. Results analysis based on DEMATEL

Using the complex network model for ship collision RIFs, the DEMATEL technique calculates the centrality and causal degree of each node in the network. The higher the centrality, the more influential the factors are in the system. Factor attributes are classified based on causality. If a value is larger than 0, this indicates that the factor is a causal one and is more likely to impact other factors. If a value less than 0, this means that the factor is more susceptible to other factors. The calculated centrality and degree of causality are shown in Fig. 11.

Based on the results obtained from the DEMATEL analysis, RIFs are categorized into five categories based on their ability to influence as shown in Table 3 (Khatun et al., 2023).

RIFs with medium influence and higher impacts on complex networks are selected by Centrality Degree. Namely H1 (Lookout negligence), H2 (Lack use of good seamanship), H3 (Improperly and ineffective avoidance), H4 (Poor communication), H5 (Insufficient cooperation), H6 (Decision error), H7 (Insufficient skill level and experience), H8 (Improper ship handling), and H12 (Unused safe speed), H13 (Improper signal display), H17 (Inattention), H19 (Absence without leave) and M38 (Lack of supervision). These factors mainly contribute to accidents directly, so controlling them can regulate the progression of accidents and avert their occurrence.

According to the theory of DEMATEL, RIFs for accidents can be divided into two categories based on their Cause Degree value. Factors with a Cause Degree larger than 0 are considered as causal factors, whereas factors with a Cause Degree less than 0 are outcome factors. During the risk evolution process, Cause Degree with a higher value can influence more RIFs, leading to an increased range of accident effects and making accident prevention more challenging. There are six RIFs that have a Cause Degree value larger than medium influence, H7 (Insufficient skill level and inexperience), M37 (Incomplete rules), M38 (Lack of supervision), M39 (Incomplete risk assessment), M40 (Lack of safety education), and M42 (Lack of skill training). These factors mainly serve as indirect factors of accidents, meaning their presence does not cause accidents, but increases the likelihood of accidents occurring. By

Table 3
The DEMATEL-influence rate description.

Definition	Centrality Degree	Cause Degree
No influence	(0,10)	|0,5|
Low influence	(10,20)	|5,10|
Medium influence	(20,30)	|10,15|
High influence	(30,40)	|15,20|
Very High influence	(40,50)	|20,35|

controlling these factors, the likelihood of accidents can be decreased, hence reducing the risk of accidents. There are five RIFs with a Cause Degree value lower than medium influence, namely H1 (Lookout negligence), H3 (Improperly and ineffective avoidance), H6 (Decision error), H8 (Improper ship handling), and H12 (Unused safe speed). These RIFs exhibit a high degree of instability as outcome factors and are susceptible to changes in state caused by other RIFs. It is evident from the accident report that outcome factors tend to be the direct RIFs of accidents. By controlling these RIFs, it is possible to prevent accidents from escalating into their final outcomes, much in the same way that the control of high-risk factors can achieve (Cui et al., 2023).

The 11 key RIFs obtained by using the DEMATEL analysis method are based on the two parameters of cause degree and centrality, which are not comprehensive enough for the analysis of RIFs. By comparison, it is found that the RIFs obtained from the analysis of the complex network method only partially overlapped with the RIFs obtained from the DEMATEL analysis. Therefore, based on the results obtained from the comprehensive analysis of the robustness analysis method, supplemented by the results of the multi-perspective analysis of the DEMATEL method, 17 RIFs are finally obtained after merging duplicate RIFs as the key RIFs to control the risk of ship collision. The synergistic analysis of the two methods makes the final RIFs more comprehensively describing the risk of ship collision accidents.

4.6. Discussion and implications

Human factors are the primary cause of ship collisions. The shipping system is inseparable from the role of human beings. Common factors contributing to collisions include H1 (Lookout negligence), H2 (Lack use of good seamanship), H3 (Improperly and ineffective avoidance), H4

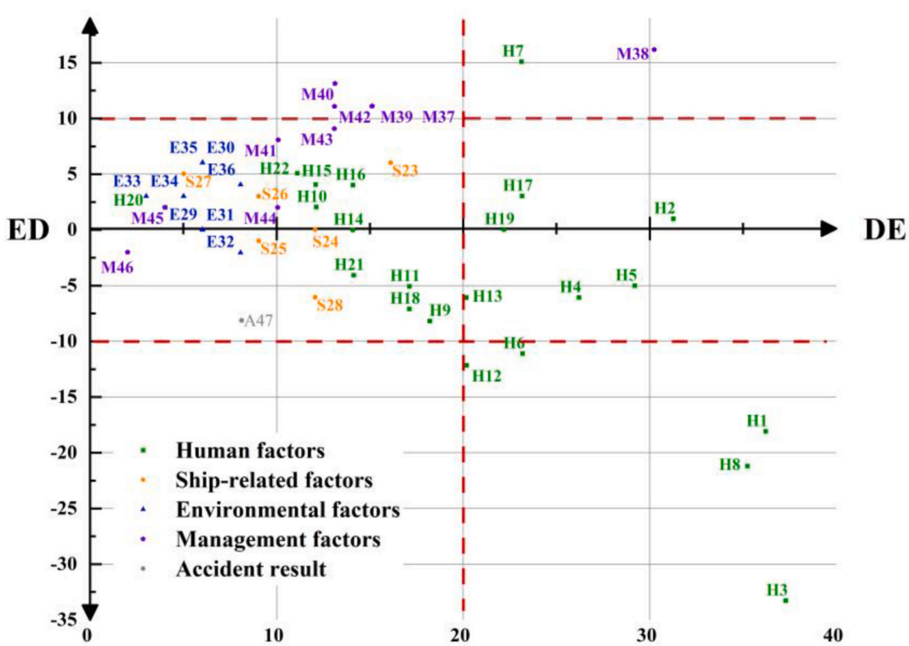

Fig. 11. The centrality degree and cause degree of RIFs.

(Poor communication), H5 (Insufficient cooperation), H6 (Decision error), H7 (Insufficient skill level and inexperience), H8 (Improper ship handling), H11 (Improper use of radar), all of which are underlying RIFs of collisions. In addition, ship-related factors, such as S24 (Improper equipment maintenance), and management factors, such as M37 (Incomplete rules), may contribute to human factors. Additionally, environmental factors like E30 (Density traffic) can limit human perception and judgement, leading to incorrect decision-making or ship maneuvering behaviours. Thus, human factors not only directly result in accidents but also interact with other factors to jointly cause ship collisions.

In summary, the effective prevention of ship collision accidents involves isolating identified key nodes in the RIFs network and severing links between them and other nodes (Deng et al., 2023). For different RIFs, distinct risk prevention and control measures should be undertaken. Risk prevention and control measures primarily focus on two principles: "prevention" and "control". "Prevention" entails actions aimed at diminishing the probability of accidents during the regular operation of ships by evading the activation of hazards. "Control" refers to actions aimed at halting a hazard from evolving into an accident, following its activation. Fig. 12 illustrates the process of risk mitigation.

Based on the analysis results of robustness analysis and DEMATEL, 17 RIFs were selected as key and primary nodes for "prevention" and "control" after merging the similar items, they are, H1 (Lookout negligence), H2 (Lack use of good seamanship), H3 (Improperly and ineffective avoidance), H4 (Poor communication), H5 (Insufficient cooperation), H6 (Decision error), H7 (Insufficient skill level and inexperience), H8 (Improper ship handling), H12 (Unused safe speed), H13 (Improper signal display), H17 (Inattention), H19 (Absence without leave), M37 (Incomplete rules), M38 (Lack of supervision), M39 (Incomplete risk assessment), M40 (Lack of safety education) and M42 (Lack of skill training). Based on the above RIFs, targeted risk prevention and control measures are proposed in terms of controlling the sources of risk and interrupting the evolution of risk after discussion with the officer of the China Maritime Safety Administration. The RIFs are categorized into two parts, macro and micro, due to the difference between measures that can be done by shipboard personnel only and those that require a larger number of personnel. As shown in Table 4.

5. Conclusion

This study analysed 207 national and international ship collision reports, extracting and identifying RIFs and their accident chains, and summarizing a total of 46 RIFs. Of these, the highest 10 RIFs responsible for accidents are all related to human factors. The accident reports reveal that crew members' insufficient knowledge and experience,

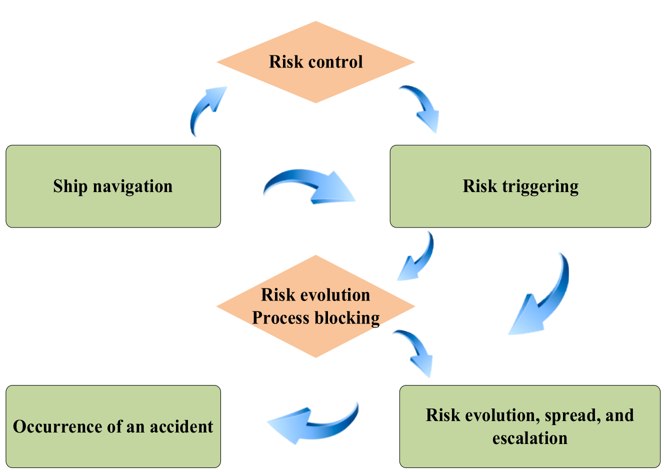

Fig. 12. The risk evolution and blocking of ship collision accidents.

Table 4
The risk prevention and control measures of ship collision.

Methods	Level	RIFs	Prevention and control measures
Hazard source control	Macro	Incomplete rules	Disorderly navigation and poor fairway conditions can increase the risk of collision. The maritime authorities should improve the conditions for channel positioning, aids to navigation and monitoring of the navigation order in accident prone waters.
		Insufficient skill level and Inexperienced	Carry out regular skills testing and training for crew members, provide skills improvement training for those who fail, and provide emergency and hazard response training for all crew members to improve their emergency management skills.
		Lack of skill training	Regularly organize skills training for crew members, learn how to use general marine equipment and ensure that crew members have sufficient ability to respond to emergency situations.
		Lack of supervision	Strengthen the construction of safety culture, enhance personal safety awareness, promote mutual supervision among crew members in addition to supervision by the master and the company, and create an atmosphere of safety work.
		Incomplete risk assessment	It is recommended that the master and pilot carry out regular risk assessments in order to control the occurrence of relevant RIFs during the ship's voyage and to take preventive measures.
		Lack of safety education	Regular safety briefings are held each year, and safety training is incorporated into the crew skills training process, with safety measures included in the scope of assessment to raise crew safety awareness.
	Micro	Lookout negligence	Put up warning signs in accident prone areas; train crew members before sailing to understand high-risk areas on the route and increase vigilance; increase crew rest time to prevent observation lapses due to fatigue.
		Unused safe speed	There is no fixed value for safe sailing speed and it should be flexible to the environment and the situation encountered. Adverse weather and high speed navigation in complex water areas should be avoided. In addition to collision avoidance, loss of control due to excessive deceleration should be avoided.

(continued on next page)

Table 4 (*continued*)

Methods	Level	RIFs	Prevention and control measures
		Improper signal display	Train crew members to issue sound signals in a timely manner based on weather and channel characteristics, and set up easily identifiable signal lights.
		Inattention	Attention should be paid to duty arrangements to ensure that crew members are not unable to maintain concentration due to fatigue or prolonged duty boredom.
		Absence without leave	Strengthen safety training for crew members and ensure that other crew members assist in the performance of their duties when they leave their positions for special reasons.
Interruption of risk evolution process	Macro	Poor communication	When using VHF to communicate with other vessels, a cautious attitude should be adopted to avoid mistakes such as mishearing, forgetting, and inconsistent words and actions during the call; communicate promptly when discovering other vessels, rather than using VHF communication to command them after taking evasive action; VHF may not be smooth within visible distance of the vessel, and other methods should be used to communicate in a timely manner.
		Lack use of good seamanship	In addition to assessing the traffic situation on the water surface in a timely manner, potential trends should also be anticipated. If the situation is complex and decisions cannot be made in a timely manner, timely assistance should be sought from the master or other experienced crew members.
		Improperly and effective avoidance	When taking evasive action, quick decisions should be made and quick action should be taken, rather than trying to reach a consensus with all personnel; appropriate rudder angles should be applied as early as possible to avoid a situation where the ship does not turn sufficiently and gets into an emergency situation; in the event of poor communication, it is necessary to avoid a collision as soon as possible, in accordance with the International Maritime Collision Avoidance Rules.
	Micro	Insufficient cooperation	In case of communication barriers between crew members, they should follow the captain's command uniformly and inform each other of the captain's decision to ensure that all crew members understand the captain's intention.
		Decision error	The master and pilot should study the ship and route information in advance, fully understand the sailing characteristics of the ship and the environmental characteristics of each water area on the route, and avoid making decisions based on a lack of understanding.
		Improper ship handling	Choose a captain and pilot with experience of sailing to ensure that they do not make incorrect manoeuvres due to a lack of understanding of the vessel.

improper ship operation, regulation violation, and inappropriate duty arrangements are related to 39.5%, 39.5%, 38%, 26.5%, 25.5%, 25.5%, 22%, 20.5%, 20.5% and 15.5% of the accidents. Furthermore, interactions between human error and other factors are responsible for most accidents.

After creating a comprehensive ship collision network evolution model with 47 nodes and 390 edges, robustness analysis method is firstly employed to identify 10 key RIFs from a global network perspective, and the GRA is used to verify the identified key RIFs. Then, the DEMATEL method is used to identify 11 key RIFs from perspective of causality. Finally, 17 RIFs are gained by merging duplicate RIFs. The 17 RIFs combined the results from both a global perspective and a causal association perspective, making the findings more comprehensive. In general, this study provides ample insights for managers to detect and manage ship collisions in waterways. By identifying significant RIFs that influence these collisions, it suggests measures to control the evolution network of such accidents.

Although this study is valuable for the accident studies for ship collisions, some limitations exist and need to be concerned in the future research. On the one hand, there is a strong subjectivity as the accident chain in this study is artificially extracted based on accident investigation reports. On the other hand, the accident reports used in this paper originate from all over the world, the region where the accidents occurred is wide, the results obtained from the analysis are more generalizable, the measures proposed based on them are less targeted and need to be further discussed and adjusted in practice. In the future research, it can be considered to extract accident chain by navigational data such as AIS data, and then build a complex network model. This can give more objective results, and may be a direction of subsequent research.

CRediT authorship contribution statement

Jiahui Shi: Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Zhengjiang Liu:** Validation, Supervision, Funding acquisition, Conceptualization. **Yinwei Feng:** Writing – original draft, Visualization, Methodology. **Xinjian Wang:** Writing – review & editing, Writing – original draft, Funding acquisition, Formal analysis, Conceptualization. **Haowen Zhu:** Validation, Data curation. **Zaili Yang:** Writing – review & editing, Methodology, Funding acquisition, Formal analysis. **Jin Wang:** Writing – review & editing, Visualization, Validation. **Huanxin Wang:** Formal analysis, Funding acquisition, Writing – review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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