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Research paper

# A novel integrated method for heterogeneity analysis of marine accidents involving different ship types

Wenjie Cao [a], Xinjian Wang [a,b,c,d,e,*], Jian Li [a,d], Zhiwei Zhang [a,b], Yuhao Cao [b], Yinwei Feng [a,b,**]

[a] Navigation College, Dalian Maritime University, Dalian, 116026, PR China
[b] Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, Liverpool, L3 3AF, UK
[c] Seafarers Research Institute, Dalian Maritime University, Dalian, 116026, PR China
[d] Key Laboratory of Navigation Safety Guarantee of Liaoning Province, Dalian, 116026, PR China
[e] Key Laboratory of International Shipping Development and Property Digitization of Hainan Free Trade Port, Hainan Vocational University of Science and Technology, Haikou, 570100, PR China

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ABSTRACT

Existing studies have noted differences in risk influential factors (RIFs) across various ship types but often fail to provide a detailed analysis and targeted countermeasures. This study proposes a novel marine accident analysis model that integrates the Complex Network (CN), the Weighted Influence Non-linear Gauge System (WINGS), and the Adversarial Interpretive Structure Model (AISM), to analyse the differences in RIFs for accidents involving different ship types. Firstly, based on 910 marine accident investigation reports covering four major ship types (bulk carriers, container ships, fishing vessels and oil tankers), a RIFs database is established, and the potential relationship between RIFs is mined by association rules. Secondly, Risk Interaction Networks (RINs) for each ship type are constructed, and their topological characteristics are analysed. Subsequently, a dynamic analysis model, named WINGS, is developed to analyse the causal relationship between RIFs from the perspective of dynamic information transmission. Finally, the AISM is established to determine the causal hierarchical relationships among these RIFs. The findings highlight significant differences in the critical RIFs of accidents across different ship types, illustrating the distinct risk profiles and necessitating tailored prevention strategies. This research advances multidimensional factor analysis from static to dynamic, facilitating the development of more tailored preventive measures. **The source code is publicly available at:** https://github.com/FengYinLeo/CWA-Model.

## 1. Introduction

Marine transport is the backbone of global trade and plays a crucial role in international trade and global economic development (Feng et al., 2024b; Wang et al., 2023b). However, with the booming global marine trade, the size of ships and the density of marine traffic are increasing, leading to a higher risk of marine accidents (Cao et al., 2023b). According to the Annual Overview of Maritime Casualties and Accidents, a total of 23,814 marine accidents involving injuries and fatalities are reported between 2014 and 2022 (European Maritime Safety Agency, 2023). Given that marine accidents often cause significant casualties, property losses, and environmental damage (Zhang et al., 2022a), the International Maritime Organization and other relevant authorities have implemented numerous measures to prevent such accidents (Wan et al., 2023). Nevertheless, it remains difficult to completely avoid marine accidents (Lee and Yu, 2023). Therefore, to reduce the occurrence of accidents and improve the safety of marine transportation, it is crucial to study the risk influential factors (RIFs) of marine accidents (Li and Yang, 2023).

Although numerous studies on marine accidents exist, many are limited to analysing specific ship types or specific types of accidents, and there is a lack of research comparing accidents involving various ship types. In fact, the specific causes of accidents differ among various ship types. For example, studies have shown that fishing vessels are more

* Corresponding author. Navigation College, Dalian Maritime University, Dalian, 116026, PR China.
** Corresponding author. Navigation College, Dalian Maritime University, Dalian, 116026, PR China.
*E-mail addresses:* X.Wang1@ljmu.ac.uk (X. Wang), fyinwleo@dlmu.edu.cn (Y. Feng).

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susceptible to accidents such as foundering and collisions due to bad weather and sea conditions (Özaydın et al., 2022; Rezaee et al., 2016). Improper loading and unloading of containers can easily lead to accidents such as loss of containers and over boarding of containers (Callesen et al., 2021). Bulk carriers and oil tankers are prone to serious fires and explosions due to improper cargo loading and unloading procedures (Chen et al., 2020). Therefore, it is necessary to compare and analyse the RIFs for marine accidents involving different ship types.

Previous studies have demonstrated that the RIFs contributing to marine accidents are characterized by uncertainty and complexity (Ma et al., 2022c). Quantitative investigations into RIFs are essential to furnish comprehensive and precise analyses across diverse accident scenarios involving various ship types. In comparison to traditional methodologies such as Fault Tree Analysis (FTA), Event Tree Analysis (ETA), and Bayesian Networks (BN), Complex Network (CN) theory, as a method for quantitative risk analysis, offers advantages in revealing the correlation between accident RIFs and identifying key RIFs (Feng et al., 2024c; Xin et al., 2024; Zhang et al., 2025). Moreover, CN can be easily and effectively integrated with other methods to analyse RIFs from multiple perspectives. While marine accidents result from a combination of various RIFs, the impact of an individual RIF on accidents cannot be overlooked. The Weighted Influence Non-linear Gauge System (WINGS) methodology, derived from the Decision-making Trial and Evaluation Laboratory (DEMATEL), can consider both of these key points simultaneously. WINGS not only visualizes the causality and intensity of impacts among RIFs but also reflects the impact intensity of an individual RIF (Wang et al., 2023c). However, WINGS may not efficiently obtain a hierarchical structure of causal relationships among RIFs in complex systems. The Adversarial Interpretive Structure Model (AISM) can construct a multilevel structure between RIFs, but it cannot simultaneously determine their impact on the system (Chen et al., 2023a). Therefore, this study proposes a comprehensive analytical model, called CN-WINGS-AISM (CWA) model. The aim is to identify the key RIFs contributing to accidents across various ship types and investigate the heterogeneity among the RIFs for accidents involving different ship types. This study addresses the gap of previous studies that have insufficient knowledge of the heterogeneous coupling relationship between accident RIFs. Moreover, this study provides valuable insights for maritime safety authorities in developing diverse programs to prevent various ship types of accidents.

The rest of the content in this study is organized as follows: Section 2 reviews relevant studies on risk analysis of marine accidents and their methodologies. Section 3 describes the data sources and the methodology used in this study. Section 4 analyses the results from different perspectives and provides discussion. Section 5 presents the practical implications of the research findings, offering targeted management recommendations for accidents involving different ship types. Section 6 summarizes the entire work and provides recommendations for future research.

## 2. Literature review

The rapid growth of marine transport in recent years has significantly increased the demand for scientific research on ensuring maritime safety (Chan et al., 2023; Jovanović et al., 2024; Wang et al., 2022). One of the key tasks for researchers to develop effective prevention strategies and thus reduce the probability of future accidents is to find the root causes of marine accidents (Sakar et al., 2021). To address this issue, many quantitative risk assessment (QRA) methods have been proposed and widely used in the field of marine accident analysis, including FTA, ETA, BN, CN, DEMATEL, and so on. Table 1 displays literatures that have applied these methods in recent years, along with descriptions of their advantages and disadvantages.

Analysis of the existed studies shows that FTA and BN are the more traditional approaches in the risk analysis of marine accidents. For example, Lutfi Tunçel et al. (2023) conducted a quantitative risk

**Table 1**
Various quantitative risk assessment methods in marine accident analysis.

| Research paper | Method | Strength | Weakness |
|---|---|---|---|
| Lutfi Tunçel et al. (2023) | Fuzzy-FTA, CS-I | Provided specific solutions to prevent potential fire and explosion (F&E) accidents on bulk carriers. | Unable to obtain sufficient fire and explosion (F&E) accident reports on such ship types. |
| Sakar et al. (2021) | FTA, BN | An assessment model combining FTA and BN was proposed to investigate the causes of grounding accidents, which was informative for studies related to dynamic risk assessment of grounding accidents. | Required adequate data to ensure model prediction accuracy. |
| Sokukcu and Sakar (2022) | FTA, BN | An assessment model combining FTA and BN was proposed to study the causes of ship to ship (STS) crashes and became a useful tool for risk analysis during STS manoeuvring. | Required expert involvement, otherwise affects modeling effectiveness. |
| Özaydın et al. (2022) | BN, ARM | Proposed a network structure that enables qualitative and quantitative analyses of occupational accidents on board fishing vessels. | Relying on expert opinion to build a network is subjective. |
| Ma et al. (2022c) | CN, ETA | A methodology was proposed that enables the quantification and modelling of the risk propagation process of ship grounding accidents. | Accident classification boundaries are influenced by factors other than criticality and sensitivity. |
| Lan et al. (2023) | CN, ARM | Proposed a model for targeted mitigation measures to prevent ship collision accidents. | Focus on ship collisions with limited accident data, which limits the generality of the results. |
| Soner (2021) | Fuzzy-DEMATEL | Provided a systematic and powerful analytical model for confined space accident analysis. | Reliance on expert judgements. |
| Ma et al. (2022a) | HFACS, DEMATEL, FCM | A novel hybrid approach that combined the strengths of HFACS, DEMATEL and FCM to provide a more detailed and objective assessment of the uncertainties and interacting human factors involved in marine accidents. | Easy to miss information; Inadequate transformation of the interaction matrix. |
| Ma et al. (2022b) | DEMATEL, ISM, Fuzzy-BN | Integrated the superiorities of DEMATEL, interpretive structure model (ISM) and Fuzzy-BN in dealing with risk factors with uncertain. | The influence of heterogeneous experts is not considered; Insufficient accident data. |
| Shi et al. (2024) | DEMATEL, CN | For the first time, a combination of CN and DEMATEL methods was advocated for the study of RIFs in ship collision accidents. | Accident reports are artificially extracted with a high degree of subjectivity. |

analysis of fire and explosion accidents on bulk carriers using Fuzzy-FTA and Cut Set Importance Measurement (CS-I). Sakar et al. (2021) and Sokukcu and Sakar (2022) investigated the primary causes of ship grounding and collision accidents, respectively, using the FTA-BN approach. Given the large number of RIFs in marine accidents, characterized by a high degree of complexity, traditional methods such as FTA and BN are prone to encountering state explosion problems (Shi et al., 2024). In recent years, CN has been widely utilized in the study of marine accidents (Shi et al., 2024). CN can effectively illustrate the intricate correlations between RIFs. For instance, Yan et al. (2023) investigated the link between RIFs leading to collisions between ships and wind turbines using systems theory and CN. Feng et al. (2024c) employed CN and Association Rule Mining (ARM) to construct a causality network for marine accidents, identifying key RIFs that influence the severity of marine accidents. Ma et al. (2022c) employed the ETA method to extract accident chains from accident reports, constructing CNs to identify key RIFs for ship grounding accidents.

Given that causality analyses are particularly important in accident studies, DEMATEL has been introduced to this field as a methodology capable of visually presenting the causal relationships between RIFs and the intensity of their effects (Demirci et al., 2023; Kuzu, 2021). For example, Shi et al. (2024) combined the approaches of CN and DEMATEL to elucidate the causal relationships among key RIFs in ship collision accidents. They also proposed strategic measures to reduce the risk of such accidents and prevent the evolution of associated risks. While accidents cannot be separated from the coupling between various RIFs, the impact of an individual RIF on accidents cannot be ignored in reality. However, DEMATEL overlooks the impact intensity of an individual RIF on accidents. Based on this, the WINGS method is proposed, which not only inherits all the advantages of DEMATEL but also reflects the impact intensity of an individual RIF (Wang et al., 2023c).

Furthermore, considering the limitation of WINGS in directly and efficiently capturing the causal hierarchy among RIFs in accidents, it is necessary to integrated it with complementary methods. As a method that effectively constructs a directed graph or network structure of hierarchical relationships between a set of elements, ISM has unique advantages in analysing the causes of accidents and understanding RIFs (Wu et al., 2023). Therefore, ISM is often used to construct multi-level asymptotic hierarchies among constituents in complex systems (Wu et al., 2023). In addition, researchers often enhance the generalizability of ISM by combining it with other methods. For example, Ma et al. (2022b) proposed a new method integrating the advantages of DEMATEL, ISM, and fuzzy Bayesian network (FBN). This approach explored the causal relationships among the main RIFs leading to accidents involving maritime transport of hazardous materials and performed a detailed quantitative assessment. The new method was superior in dealing with uncertain RIFs. However, traditional ISM follows a single extraction rule, resulting in a less reliable hierarchy. As an enhanced ISM method, AISM incorporates the idea of game rivalry and can reflect the hierarchical structure of RIFs more comprehensively (Li et al., 2024). Xing et al. (2023b) integrated the methods of AISM and DEMATEL to conduct a comprehensive analysis of the key RIFs that contribute to fire accidents and developed preventive measures for these RIFs.

These studies described above have made a significant contribution to the field of marine accidents; however, there are still some gaps that warrant further exploration. Firstly, current research primarily concentrates on marine accidents involving specific ship types, such as container ships or oil tankers, while investigations into the RIFs of accidents across various ship types are relatively scarce. Secondly, although a few studies have delved into accidents involving different ship types, they generally overlook the collective impacts of various RIFs on marine accidents and lack comprehensive insights into accident RIFs. Finally, prior studies have paid limited attention to the heterogeneous coupling relationships between different levels of RIFs and have not provided a comprehensive and specific understanding of the transmissibility of RIFs in marine accidents. The literature review shows that by combining CN, WINGS, and AISM, it is possible not only to identify key RIFs and their impact levels in marine accidents, but also to establish the adversarial hierarchical topology of key RIFs and efficiently perform heterogeneity analysis of marine accidents across different ship types. To address the gaps of previous research, this study makes the following contributions:

(1) A CWA model is proposed, facilitating the establishment of risk interaction networks (RINs) for accidents involving different ship types. The key RIFs in accidents across various ship types are explored via an in-depth analysis of the topological characteristics of RINs.
(2) Utilizing the CWA model, this study analyses the causal relationships between the RIFs of marine accidents for each ship type from the perspective of dynamic information transfer, thereby revealing the impacts of different RIFs on marine accidents.
(3) The RIFs of accidents across four ship types are hierarchically classified, and their causal relationships are further explored. By analysing the heterogeneous coupling relationships between these hierarchies, the countermeasures for accidents across four ship types are proposed.

## 3. Materials and methodology

### 3.1. Data source and pre-processing

In this study, marine accident investigation reports spanning 2000–2019 from the databases of seven global maritime agencies were collected—such as the China Maritime Safety Administration (China MSA), Federal Bureau of Maritime Casualty Investigation (BSU), National Transportation Safety Board (NTSB), Japan Transportation Safety Board (JTSB), Australian Transport Safety Board (ATSB), Canadian Transportation Safety Board (TSB), and the Marine Accident Investigation Branch (MAIB).

An analysis of the investigation reports from the aforementioned databases revealed that different countries uploaded accident records with varying levels of detail, and some of the data contained inaccuracies and/or were incomplete. Therefore, accident reports with incomplete data need to be excluded to ensure the authenticity and integrity of the dataset. For example, some accident reports do not list the environmental conditions that contributed to the accident, and these should be excluded according to the aforementioned principles. Details of the screening process for these marine accident investigation reports can be found in previous related studies (Cao et al., 2023a; Feng et al., 2024a, 2024c; Wang et al., 2021).

The data pre-processing is divided into four stages. First, after filtering and removing duplicate accident reports, 1294 accident reports were obtained. Second, as shown in Fig. 1, bulk carriers, container ships, fishing vessels, and oil tankers are the most frequent ship types involved in marine accidents. Therefore, this study focuses on analysing the heterogeneity of marine accident RIFs for these four ship types. Further screening of the accident investigation data for these vessels yielded 910 marine accident reports. Finally, based on relevant studies (Cao et al., 2023a; Fan et al., 2020; Wang et al., 2021), this study constructed a first-level RIFs indicator system encompassing human factors, ship factors, environment factors, management factors and accident information, along with 36 second-level RIFs from the perspective of system safety engineering. The distribution of the accident RIFs is shown in Fig. 2. The categories, serial numbers, and descriptions of the RIFs are detailed in Table A1 of Appendix A.

### 3.2. Association Rule Mining (ARM)

ARM is a straightforward and practical data mining technique that identifies frequent item sets among uncertainties and generates strong

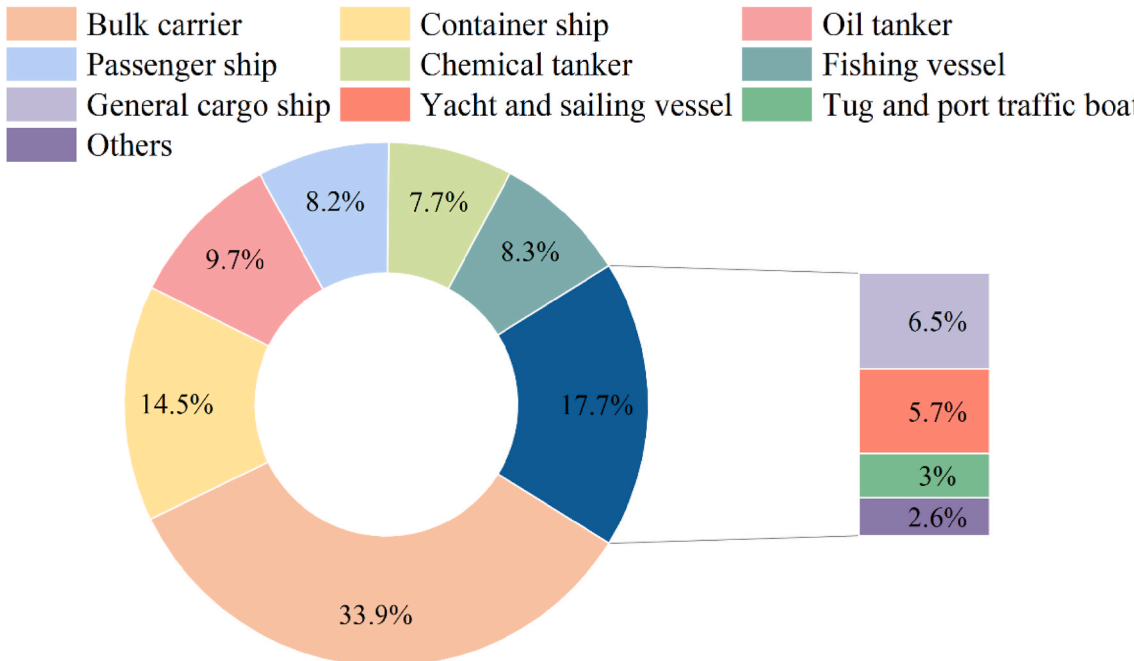


**Fig. 1.** Distribution of the number of marine accidents by ship types.

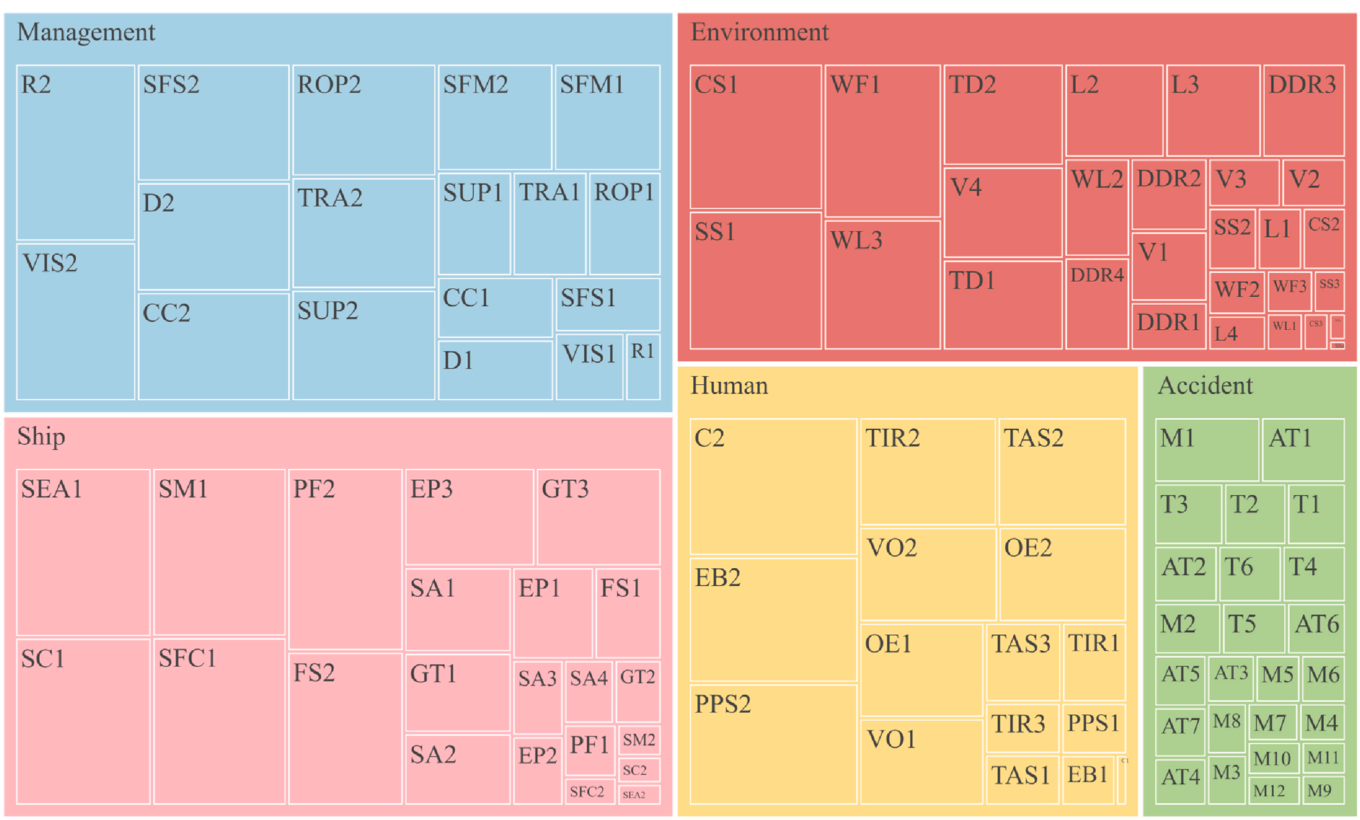


**Fig. 2.** Tree diagram of all RIFs.

association rules from large datasets (Aljehani and Alotaibi, 2024), it prioritizes identifying patterns within data over confirming hypotheses and remain unaffected by missing data. Therefore, in this study, association rules are mined for the marine accident data of the four ship types: bulk carriers, container ships, fishing vessels, and oil tankers. ARM furnishes a critical database for subsequent CN analysis, thereby enhancing this study's understanding of the relationships among accident RIFs. The calculation formula of ARM is shown in Equations (1)–(3).

$$Support(E) = \frac{L_E}{L} \tag{1}$$

$$Confidence(E \Rightarrow F) = \frac{Support(EF)}{Support(F)} \tag{2}$$

$$Lift(E \Rightarrow F) = \frac{Confience(E \Rightarrow F)}{Support(F)} \tag{3}$$

where $Support(E)$ indicates the degree of support for itemset $E$; $L_E$ indicates the number of occurrences of itemset $E$ in the data; $L$ indicates the number of all the data; $Confidence(E \Rightarrow F)$ indicates the confidence from itemset $E$ to itemset $F$; and $Lift(E \Rightarrow F)$ indicates the lift from itemset $E$ to itemset $F$.

To enhance the analysis of marine accident data across various ship types, the Apriori algorithm, a classical ARM algorithm (Liu et al., 2024) is utilized to identify frequent itemsets and uncover valuable

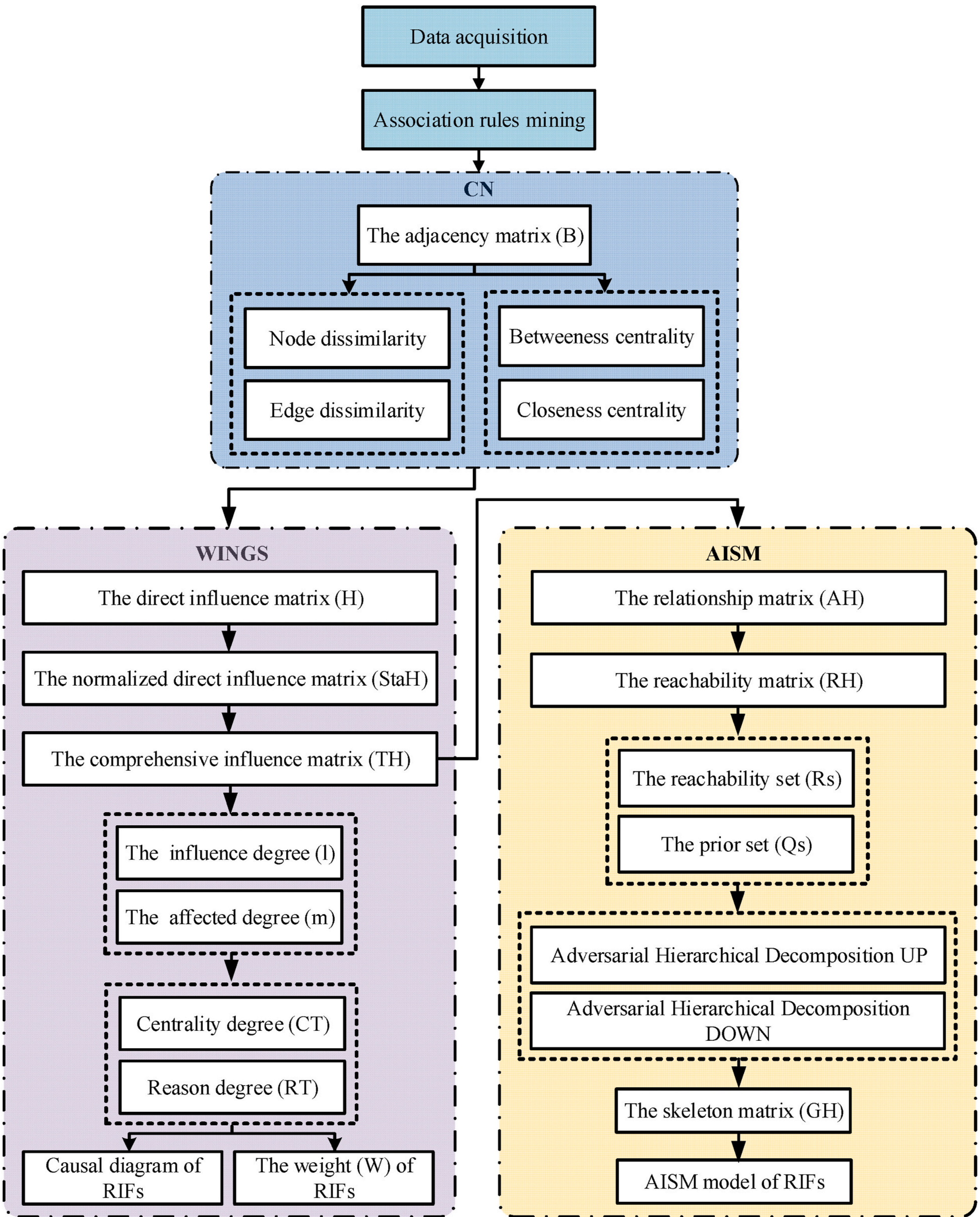


**Fig. 3.** The flowchart of CWA modelling procedure.

associations or relationships within large databases (Feng et al., 2024c). The core idea involves incrementally increasing the size of itemsets to identify frequent ones and subsequently generating association rules from these frequent itemsets.

### 3.3. CWA model

This study integrates the CN theory, the WINGS system, and the AISM model to propose a comprehensive analytical model, named CWA, for marine accident analysis. Fig. 3 illustrates the framework of the CWA model. First, based on CN theory, RINs of RIFs for marine accidents involving different ship types are constructed, and topological analyses of these RINs are performed. Second, the centrality, causality, and weight of the RIFs are calculated and analysed using WINGS. Finally, AISM is applied to identify the internal connections of the RIFs and establish the logical hierarchical relationships between RIFs.

#### 3.3.1. Complex Network (CN)

CN represents complex systems as networks where elements are nodes and relationships are edges (Shi et al., 2024). It has been widely used to assess the safety and reliability of safety systems, such as risk coupling related to human, ships, management, and the environment (Feng et al., 2023; Shi et al., 2024). Therefore, this study proposes using CN to provide insights into the RIFs of marine accidents and establish links between them.

(1) The construction of RINs

RINs are built from association rules to explore RIFs couplings in marine accidents (Feng et al., 2024c). Let the interaction network of RIFs for marine accidents involving different ship types be denoted as $RIN = (A, DiF)$. Let $A = \{x_1, x_2, \dots, x_n\}$ denote the set of nodes and $DiF = \{dif_1, dif_2, \dots, dif_n\}$ denote the set of edges of the network. Then, the mathematical expression of the RIN can be described as the adjacency matrix $B$. The formulas are shown in Equations (4)–(6).

$$B = \begin{array}{c} \\ x_1 \\ x_2 \\ \vdots \\ x_n \end{array} \begin{array}{c} \begin{array}{cccc} x_1 & x_2 & \cdots & x_n \end{array} \\ \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1n} \\ b_{21} & b_{22} & \cdots & b_{2n} \\ \vdots & \vdots & & \vdots \\ b_{n1} & b_{n2} & \cdots & b_{nn} \end{bmatrix} \end{array} \tag{4}$$

$$b_{ij} = Confidence(x_i \Rightarrow x_j) f_{ij} \tag{5}$$

$$f_{ij} = \begin{cases} 1, \textit{when the i event triggers the j event} \\ 0, \textit{else} \end{cases} \tag{6}$$

where $n$ is the total number of nodes in the network; $b_{ij}$ represents the connection from node $x_i$ to node $x_j$; $Confidence(x_i \Rightarrow x_j)$ indicates the weight of the edge from node $x_i$ to node $x_j$ in the network; and $f_{ij}$ signifies whether node $x_i$ to node $x_j$ is connected, assigning a value of 1 if connected and 0 if not.

(2) The topological features of RINs

Topological features are metrics that characterize the connections and relationships between nodes or elements in a network structure. Key features include:

1) Node dissimilarity

Node dissimilarity, denoted as $Nd$, is a measure used to quantify the degree of difference between nodes in two networks. It reveals the similarities and differences between different network structures by comparing the degree distribution of nodes, the sets of neighbours, feature vectors, and the structural similarity between two networks (Feng et al., 2021). Consider two networks, denoted as networks $Web_1$ and $Web_2$, with node degrees of $d_{1i}$ and $d_{2i}$, respectively. The comparison of node dissimilarity can be expressed using the standard deviation of node degree, as shown in Equation (7).

$$Nd = \sqrt{\frac{1}{N_1}\sum_{i=1}^{N_1}(d_{1i} - \overline{d}_1)^2} - \sqrt{\frac{1}{N_2}\sum_{i=1}^{N_2}(d_{2i} - \overline{d}_2)^2} \tag{7}$$

where $N_1$ and $N_2$ are the number of nodes in networks $Web_1$ and $Web_2$, respectively. $\overline{d}1$ and $\overline{d}2$ are their average node degrees, respectively.

2) Edge dissimilarity

Edge dissimilarity, denoted as $Ed$, measures the extent to which edges (connections) differ between two networks. The presence of dissimilarity between the edges of two networks may indicate significant differences in the distribution of connection weights (Feng et al., 2021). Suppose the edge weights of the two networks are $w_{1i}$ and $w_{2i}$, respectively. The calculation formula is shown in Equation (8).

$$Ed = \sqrt{\frac{1}{M_1}\sum_{i=1}^{M_1}(w_{1i} - \overline{w}_1)^2} - \sqrt{\frac{1}{M_2}\sum_{i=1}^{M_2}(w_{2i} - \overline{w}_2)^2} \tag{8}$$

where $M_1$ and $M_2$ are the number of edges in networks $Web_1$ and $Web_2$, respectively. $\overline{w}_1$ and $\overline{w}2$ are their average edge weights, respectively.

3) Betweenness centrality coefficient

The betweenness centrality coefficient represents the number of shortest paths passing through nodes in a network (Feng et al., 2017; Shi et al., 2024). The betweenness centrality coefficient reflects the pivotability and transmissibility of the node. The calculation formulas are shown in Equations (9) and (10).

$$C_v = \sum_{\substack{\forall i,j \in A \\ i \neq v \neq j}} \left( \frac{\beta_{ij}(v)}{\beta_{ij}} \right) \tag{9}$$

$$CG_v = \frac{C_v}{(p-1)(p-2)} \tag{10}$$

where $\beta_{ij}(v)$ denotes the number of shortest paths from node $x_i$ to node $x_j$ passing through node $x_v$; $C_v$ denotes the betweenness of node $x_v$; $p$ denotes the number of nodes in the network; and $CG_v$ denotes the betweenness centrality coefficient of node $x_v$.

4) Closeness centrality coefficient

The closeness centrality coefficient measures the average distance of a node to all other nodes in the network. If a node has a shorter average distance to other nodes, it has a higher closeness centrality coefficient (Wang et al., 2023a). The closeness centrality coefficient is used to identify nodes with high accessibility in the network, which may be more likely to disseminate information or influence other nodes. The formula is shown in Equation (11).

$$GG_i = \frac{p-1}{\sum_{j=1, j\neq i}^{p} k_{ij}} \tag{11}$$

where $GG_i$ denotes the proximity centre factor of node $x_i$ and $k_{ij}$ denotes the shortest path length from node $x_i$ to $x_j$.

#### 3.3.2. WINGS

WINGS can be used to assess interrelationships between system components by evaluating the strengths and influences of factors

(Olorvida et al., 2023). The aim of this study is to analyse the characteristics of RIFs in marine accidents involving different ship types and the causal relationships between them, to reveal the intertwined relationships between RIFs in complex systems. In this study, the WINGS model is used and constructed using data-driven CN data. The advantages of this approach are manifold. On the one hand, compared to the traditional WINGS method, the data-driven WINGS model reduces the subjectivity associated with expert scoring, enhancing the objectivity and credibility of the analysis. On the other hand, the WINGS model addresses the challenges of CN in analysing non-linear correlations and influences between RIFs, thereby more accurately revealing the interactions between RIFs in complex systems. The methodology follows these steps:

Step 1: Add the impact intensity of the RIFs to the diagonal of the RIN matrix to obtain the direct influence matrix $H$ of the marine accident, as shown in Equations (12) and (13).

$$H = (h_{ij})_{n\times n} \tag{12}$$

$$h_{ij} = \begin{cases} \frac{L_E}{L}, i = j \\ b_{ij}, i \neq j \end{cases} \tag{13}$$

where $L_E$ indicates the number of occurrences of itemset $E$ in the data, $L$ indicates the number of all data, and $b_{ij}$ indicates the intensity of the influence of node $x_i$ on node $x_j$.

Step 2: Normalize the direct influence matrix to obtain the normalized direct influence matrix $StaH$, as calculated in Equations (14) and (15).

$$Nopa = \frac{1}{\left(\max\,(c_1, c_2, \cdots, c_n)^2 + \max\,(g_1, g_2, \cdots, g_n)^2\right)^{1/2}} \tag{14}$$

$$StaH = Nopa \times H \tag{15}$$

where $Nopa$ is the normalisation parameter; $c_n$ denotes the sum of row $n$ of the direct influence matrix; and $g_n$ denotes the sum of column $n$ of the direct influence matrix.

Step 3: Utilize the theory of transmissibility of impacts to generate a comprehensive influence matrix $TH$, calculated as shown in Equation (16).

$$TH = \sum_{k=1}^{\infty} StaH^k = StaH \cdot (Eh - StaH)^{-1} = (t_{EF})_{e\times e} \tag{16}$$

where $\cdot$ represents the inner product of the matrix; $Eh$ represents the unit matrix; and $t_{EF}$ represents the comprehensive influence of factor $E$ on factor $F$ in the comprehensive influence matrix.

Step 4: Calculate the influencing degree, influenced degree, centrality degree, and reason degree of RIFs, along with the weights of each RIF, using the comprehensive influence matrix, as depicted in Equations (17)–(21).

$$l_E = \sum_F t_{EF} \tag{17}$$

$$m_E = \sum_E t_{FE} \tag{18}$$

$$CT_E = l_E + m_E \tag{19}$$

$$RT_E = l_E - m_E \tag{20}$$

$$W_E = \frac{\left(CT_E{}^2 + RT_E{}^2\right)^{1/2}}{\sum_E \left(CT_E{}^2 + RT_E{}^2\right)^{1/2}} \tag{21}$$

where $l_E$ is the influencing degree of factor $E$, $m_E$ is the influenced degree of factor $E$, $CT_E$ is the centrality degree of factor $E$, $RT_E$ is the reason degree of factor $E$, and $W_E$ is the weight of factor $E$.

#### 3.3.3. AISM

ISM methods are widely utilized for analysing the components of complex systems and their interdependencies (Chen et al., 2023b; Xing et al., 2023a). The fundamental principle is to break down the constituent elements of a complex system into several sub-elements and then derive a hierarchical diagram guided by the outcomes of a series of topological operations. In contrast, AISM integrates Generative Adversarial Networks (GANs) into ISM, creating adversarial hierarchical topologies and reflecting factor hierarchies more comprehensively (Chen et al., 2023a). Compared to the single extraction rule of traditional ISM, AISM can comprehensively reflect the hierarchical structure of factors. This study integrates the centrality degree and reason degree of RIFs using the WINGS method to conduct an in-depth analysis of RIFs interrelationships. However, the mechanism of interaction between the RIFs remains unclear. Therefore, this study has constructed an adversarial hierarchy topology using the AISM method, which intuitively illustrates the progressive causality and action pathways among RIFs of marine accidents. AISM can be divided into the following steps:

Step 1: Utilize the intercept threshold to eliminate less influential relationships in $TH$, thereby creating the relationship matrix $AH$. $AH$ represents the strong interaction relationship between the factors, with calculation formulas provided in Equations (22)–(26).

$$z_t = \frac{\sum_E (l_E + m_E)}{x^2} \tag{22}$$

$$\sigma_t = \left(\frac{\sum_E \sum_F (t_{EF} - z_t)^2}{x^2}\right)^{1/2} \tag{23}$$

$$la = z_t + \sigma_t \tag{24}$$

$$AH = (ah_{EF})_{x\times x} \tag{25}$$

$$ah_{EF} = \begin{cases} 1, if\ t_{EF} > la \\ 0, else \end{cases} \tag{26}$$

where $z_t$ represents the average degree of influence between factors; $\sigma_t$ represents the overall standard deviation of the degree of influence between factors; and $la$ represents the intercept threshold.

Step 2: Solve the reachability matrix using Boolean operation rules. The formulas are provided in Equations (27) and (28).

$$B_1 = AH + Eh, B_2 = B_1 \odot B_1, B_3 = B_2 \odot B_1, \cdots, B_n = B_{n-1} \odot B_1 \tag{27}$$

$$RH = (n_{EF})_{x\times x} = B_n = B_{n-1} \neq B_{n-2} \tag{28}$$

where $RH$ is the reachability matrix; $B_n$ is the transition matrix in Boolean operations.

Step 3: Construct UP-type and DOWN-type hierarchies in a cause-and-effect oriented manner using the reachability set, the prior set, and the intersection of the reachability set and the prior set. The formulas are provided in Equations (29)–(31).

$$Rs(x_E) = \{x_F | n_{EF} = 1\} \tag{29}$$

$$Qs(x_F) = \{x_E | n_{FE} = 1\} \tag{30}$$

$$Ts(Ha_E) = RS(Ha_E) \cap QS(Ha_E) \tag{31}$$

where $Rs(x_E)$ denotes the reachability set arrival of $x_E$; $Qs(x_E)$ denotes the prior set departure of $x_E$; and $Ts(x_E)$ denotes the intersection of the reachability set and the prior set of $x_E$.

For UP-type hierarchies, when $Rs(x_E) = Ts(x_E)$, extract the factors in $Rs(x_E)$ and place them at the top, then remove all elements in the reachability set that intersect with $Ts(x_E)$ to form a new reachability set and intersection. For DOWN-type hierarchies, when $Qs(x_F) = Ts(x_F)$, extract the factors in $Qs(x_F)$ and place them at the bottom, then remove all elements in the prior set that intersect with $Ts(x_E)$ to form a new prior set and intersection. Iterate until all factors are removed.

Step 4: First, solve the strong connectivity components of the reachability matrix using Tarjan's algorithm (Pearce, 2016). Then, construct the reduced-point matrix based on these strong connectivity components (an example of reduced-point matrix construction is shown in Fig. 4). Finally, derive the skeleton matrix using the shrinkage equation. The formulas are provided in Equations (32) and (33).

$$RH \xrightarrow{Tarjan} RH' \tag{32}$$

$$GH = RH' - (RH' - Eh) \odot (RH' - Eh) - Eh \tag{33}$$

Step 5: Construct UP-type and DOWN-type topologies based on the skeleton matrix $GH$ and the respective UP-type and DOWN-type hierarchies.

## 4. Results and discussion

### 4.1. The construction of RINs

To explore the potential connections between the RIFs, this study employs ARM to mine the interrelationships between RIFs. After several experiments, this study determines the minimum support threshold and the minimum confidence threshold to be 0.3 and 0.5, respectively. The association rules are then mined using the Apriori algorithm on the accident data across four ship types. A total of 2557 association rules are generated. Among them, 644 association rules are mined for bulk carriers, 550 for container ships, 792 for fishing vessels, and 571 for oil tankers.

Based on the mined association rules, this study constructs RINs for each of the four ship types, consisting of nodes and directed edges, using Equations (4)–(6). Fig. 5 shows the RIN for bulk carriers, while the RINs for other ship types are detailed in Figure B1 of Appendix B. Among them, the RIN of bulk carriers consists of 44 nodes and 644 directed edges, the RIN of container ships consists of 44 nodes and 550 directed edges, the RIN of fishing vessels consists of 41 nodes and 792 directed edges, and the RIN of oil tankers consists of 42 nodes and 571 directed edges.

To assess the effectiveness of the CWA model, this study compares it with the traditional BN model. BN model has become a crucial method in marine accident research due to its effectiveness in addressing complex probabilistic relationships (Cao et al., 2023a; Fan et al., 2020; Xia et al., 2023). To highlight the advantages of the proposed model, a detailed comparative analysis was conducted. The analysis evaluates both models using the same dataset and performance metrics, focusing specifically on mutual information as a key measure for assessing dependencies between variables and the information shared by RIFs. The detailed description of the analysis process and results can be found in Appendix C.

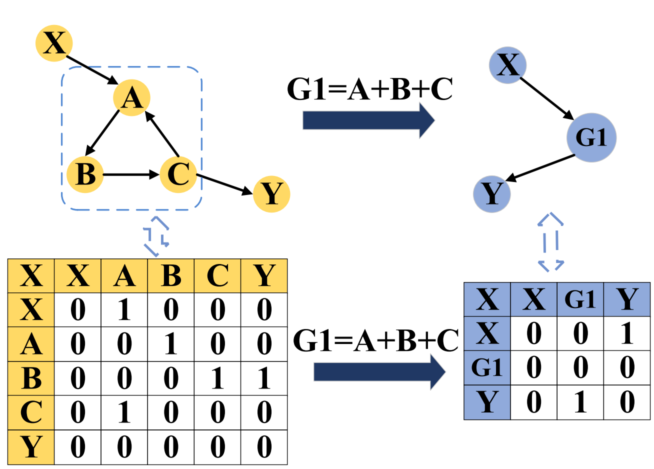


**Fig. 4.** Constructing the shrinking nodes matrix.

### 4.2. The characteristics indicator analysis of RINs

#### 4.2.1. Node dissimilarity and edge dissimilarity

Fig. 6 displays the node and edge dissimilarities between the RINs of different ship types. Fig. 6 indicates that node and edge dissimilarities are the largest between the RINs of fishing vessels and oil tankers, suggesting significant variability in the RIN structure of these two ship types. This is reflected to some extent in the significant differences in the RIFs of marine accidents between these two ship types. This discrepancy may arise from the substantial differences in ship size, route selection, and crew skill between fishing vessels and oil tankers (Tian et al., 2024; Ung, 2019). Fig. 6(a) shows that the nodal dissimilarity between the RINs of bulk carriers and container ships is minimal, indicating a similarity in their RIN structures. This similarity suggests that some RIFs are common to marine accidents involving both bulk carriers and container ships. This phenomenon may be attributed to both ship types being cargo ships with similar safety management strategies (Zhang et al., 2022b). Fig. 6(b) reveals that the edge dissimilarity between the RINs of bulk carriers and oil tankers is minimal, indicating a high similarity in how their edges are connected. This similarity suggests that, despite differences in the composition of nodes in the RINs for bulk carriers and oil tankers, the correlations between their accident RIFs may be relatively similar. Based on this finding, this study can further explore the possible reasons for this similarity. For example, despite differences in cargo types and ship operations, the technical characteristics of their ship structures and navigational operations may be similar (Campanile et al., 2018). Additionally, they may use similar types of engines and navigational equipment. Thus, although the composition of nodes in the RINs differs somewhat, the way the edges are connected is very similar. Studying these differences will help maritime authorities better understand the characteristics and risks of different ship types, enabling them to formulate targeted safety management measures to reduce the likelihood of accidents and enhance overall maritime safety.

#### 4.2.2. Nodal betweenness centrality coefficient and closeness centrality coefficient

Both the betweenness centrality coefficient and closeness centrality coefficient can reflect the pivotal role of nodes in complex systems for information transfer to some extent (Wang et al., 2023a). Therefore, they are analysed together. Fig. 7 shows the distribution of betweenness centrality coefficient and closeness centrality coefficient for the RINs of the four ship types. In the RIN of bulk carriers, SFM1 (Inadequate company safety management) exhibits the highest betweenness centrality coefficient. For container ships, WL3 (Fairway width/ship length $\geq$2) has the highest betweenness centrality coefficient. Among the RIN of fishing vessels, WF1 (Wind force is 0–5) possesses the highest betweenness centrality coefficient. Similarly, in the RIN of oil tankers,

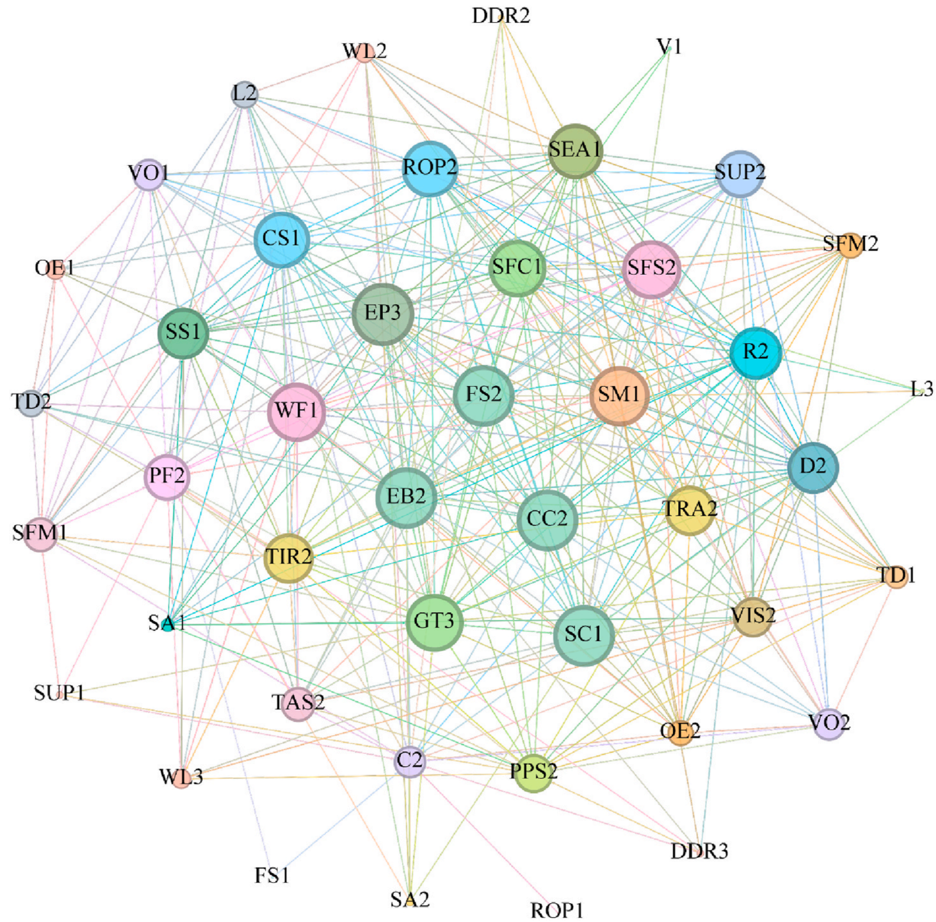


**Fig. 5.** RIN of accident RIFs involving bulk carriers (Created using Gephi).

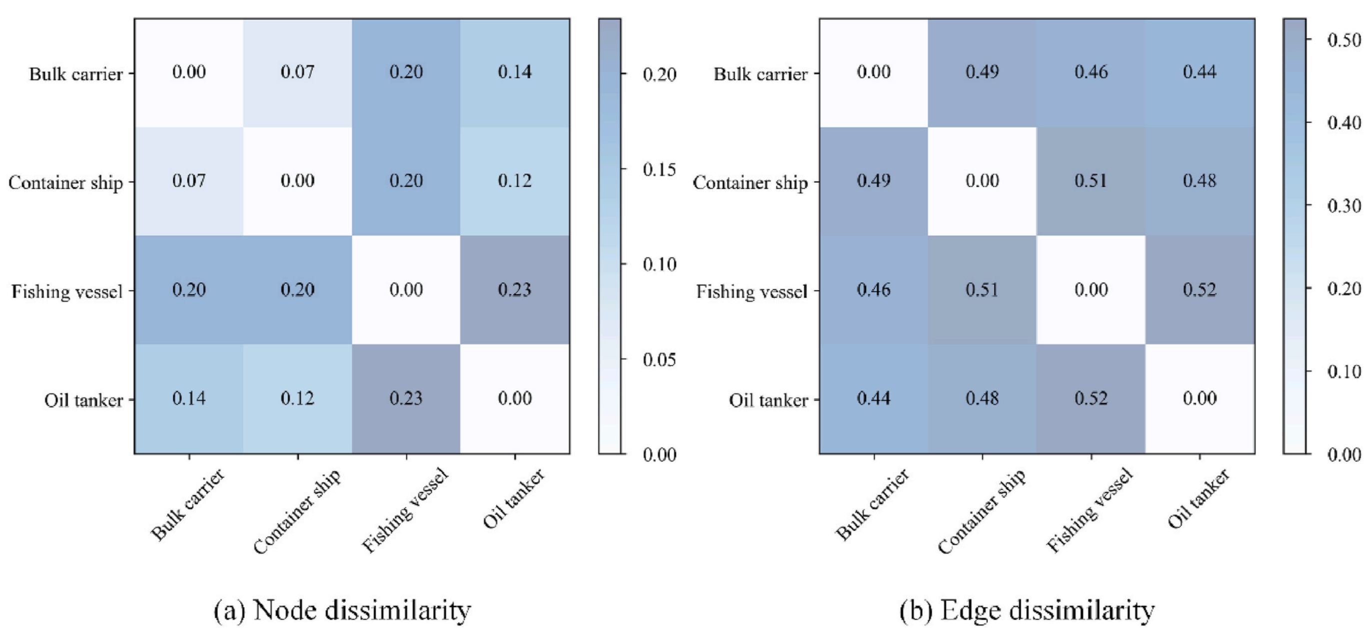


**Fig. 6.** The dissimilarity result of RINs (Created using Python).

SEA1 (Seaworthiness) features the highest betweenness centrality coefficient. A larger betweenness centrality coefficient of the RIFs indicates a more significant pivotal role in connecting different nodes in the RIN.

In the RIN of fishing vessels, the RIFs with large closeness centrality coefficient are PF2 (PSC/FSC inspection assured), VIS2 (No administrative violations in supervision), CC2 (Good company safety culture), SUP2 (Adequate administrative supervision), and EB2 (Good

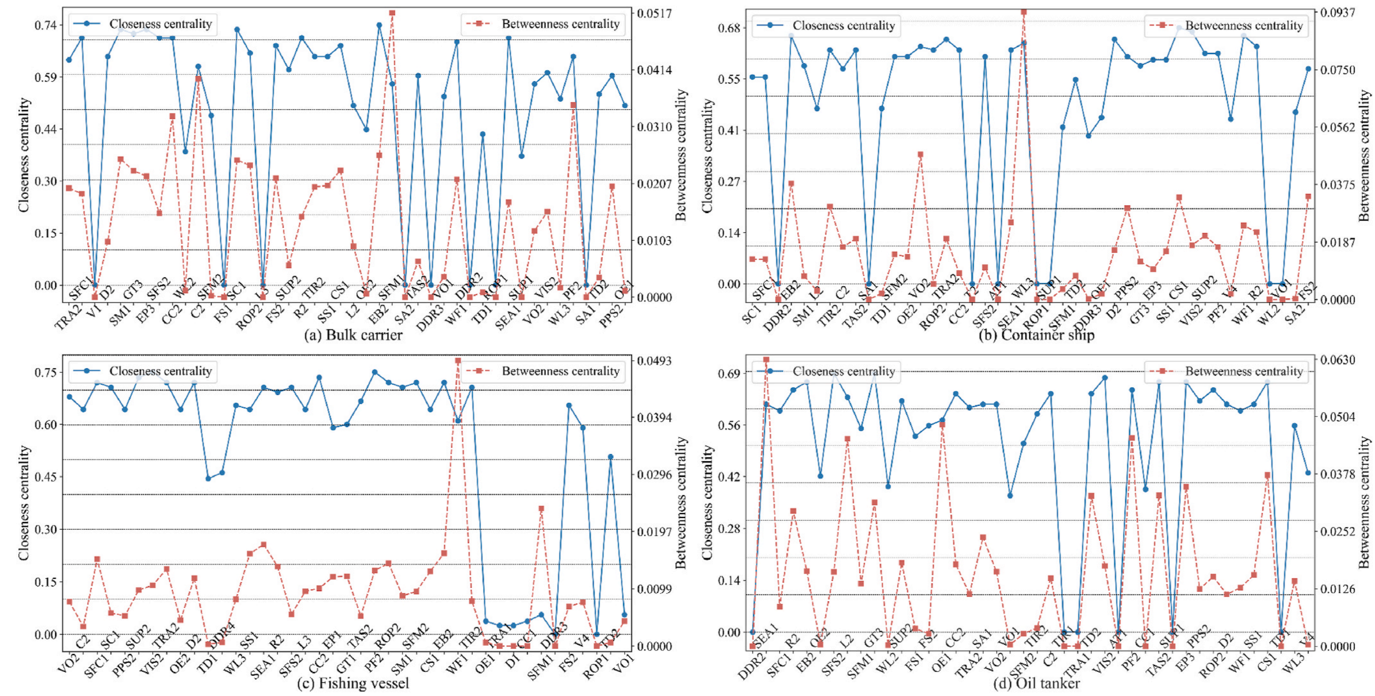


**Fig. 7.** Distribution of nodal betweenness centrality coefficient and closeness centrality coefficients.

educational background of the crew). Table 2 shows the RIFs with larger closeness centrality coefficient in the RINs of other ship types.

These RIFs are centrally located within the RIN, with short distances to other RIFs, allowing for rapid propagation. For example, in the RIN of fishing vessels, the closeness centrality coefficient of EB2 (Good educational background of the crew) is larger, categorizing it as a human factor. In an emergency, crew members with poor educational backgrounds may struggle to communicate effectively with foreign crew members, reducing inter-team collaboration efficiency and potentially leading to marine accidents. Numerous studies have shown that 89 to 95 percent of marine accidents are related to human factors (Guan et al., 2023), underscoring the importance of human factors in RINs.

A comprehensive analysis of the nodal betweenness centrality coefficient and closeness centrality coefficient of the RINs for bulk carriers, container ships, fishing vessels, and oil tankers reveals significant differences in their RIN structures and key nodes. In the RIN of bulk carriers, the company's safety management level holds a key position, and inadequate safety management may lead to frequent accidents. In the RIN of container ships, the ratio of channel width to ship length is the key node, directly affecting navigation safety. In the RIN of fishing vessels, wind magnitude is an important node in the propagation of accident RIFs, significantly impacting the evolution of fishing vessel accidents. In the RIN of oil tankers, the seaworthiness of ships is underscored as a pivotal RIF, significantly impacting both maneuvering and safety aspects.

**Table 2**
The RIFs with large closeness centrality coefficient.

| Ship types | RIFs |
|---|---|
| Bulk carriers | EB2 (Good educational background of the crew), SM1 (Adequate manning of ships), EP3 (Engine power ≥3000 KW), SC1 (Complete and valid ship certificates) and GT3 (Gross tonnage ≥3000t) |
| Container ships | CS1 (Current speed <2 kn), VIS2 (No administrative violations in supervision), EB2 (Good educational background of the crew), WF1 (Wind force 0–5) and TRA2 (Adequate company training) |
| Oil tankers | GT3 (Gross tonnage ≥3000t), SFS2 (No defects in the company's safety management system), VIS2 (No administrative violations in supervision), CS1 (Current speed <2 kn) and EP3 (Engine power ≥3000 KW) |

### 4.3. The causality analysis of RIFs

This section analyses the causal relationships between the RIFs using centrality degree, reason degree, and weight. Firstly, the RIN matrix is transformed into the direct influence matrix $H$ using Equation (12). Secondly, the direct influence matrix $H$ is normalized using Equations (14) and (15) to obtain the normalized direct influence matrix $staH$. Then, the comprehensive influence matrix $TH$ is derived from Equation (16). Finally, the causal distribution and weight distribution of each RIF are plotted using the centrality degree values, reason degree values, and weight values.

Centrality degree ($CT$) is an indicator that assesses the importance and influence of each RIF in marine accidents. The reason degree ($RT$) distinguishes whether the RIFs act as initiators or recipients of influence. The weight ($W$) combines the attributes of centrality degree and reason degree and minimizes the impact of positive and negative values in causality, thereby more accurately reflecting the combined importance of each RIF. Through an in-depth analysis of centrality degree, reason degree, and weight, this study comprehensively analyses the mechanisms of marine accidents and the interrelationships between RIFs, providing an important insight for developing effective prevention strategies. Fig. 8 illustrates the causal distribution of the RIFs for the marine accidents across four ship types, while Fig. 9 displays the distribution of the weight of these RIFs.

As depicted in Fig. 8, the most prominent RIFs influencing marine accidents involving container ships are CS1 (Current speed $<$ 2kn), VIS2 (No administrative violations in supervision), EB2 (Good educational background of the crew), WF1 (Wind force 0–5), and R2 (Adequate regulations for the administration). The centrality values of these RIFs are 0.0783, 0.0780, 0.0767, 0.0717, and 0.0703, respectively. Table 3 shows the RIFs for other ship types with larger values for the centrality degree.

When $RT > 0$, it indicates that this RIF is a causal factor affecting other RIFs. A larger value of $RT$ suggests that this RIF is more likely to influence other RIFs within complex systems. When $RT < 0$, it indicates that the RIF is an outcome factor susceptible to the influence of other

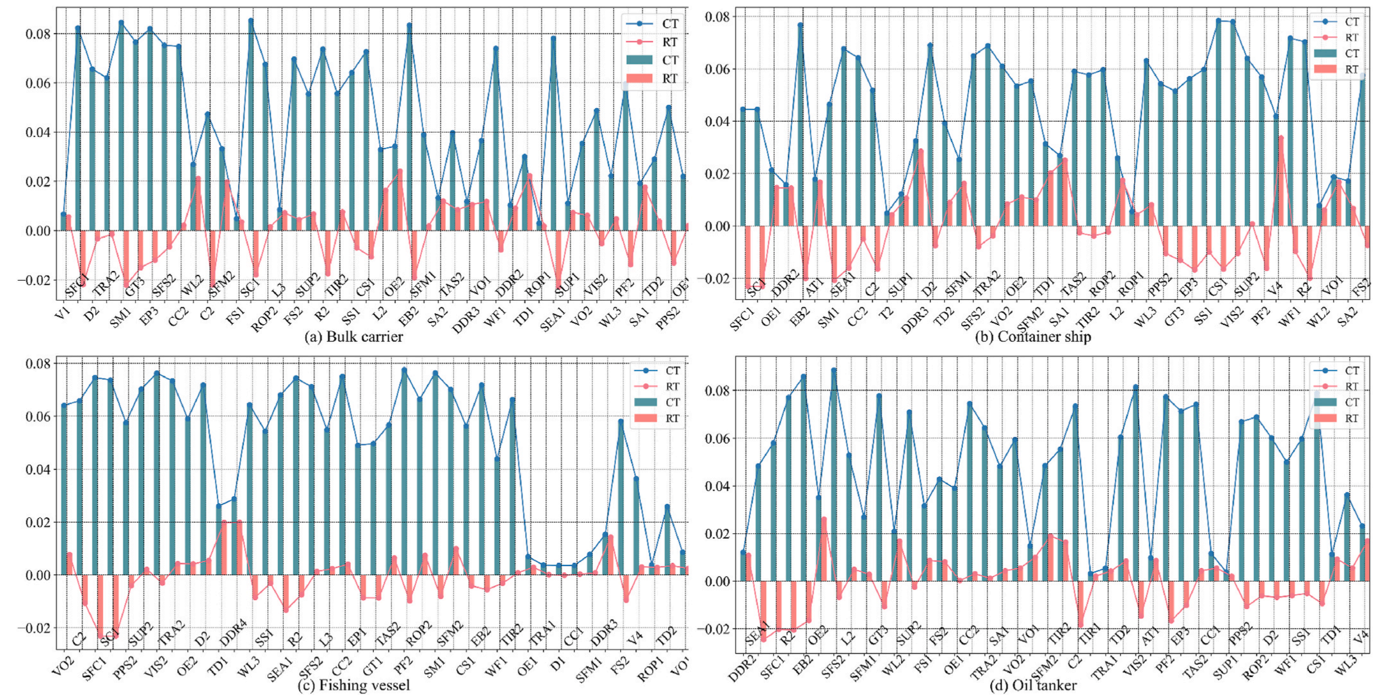


**Fig. 8.** Causal distribution of RIFs.

RIFs. The smaller the value of *RT*, the more susceptible the RIF is to the influence of other RIFs within a complex system. For oil tanker accidents, the three most prominent RIFs among the causal factors are OE2 (No operational error for the crew), SFM2 (Adequate company safety management), and V4 (Visibility good and very good - Vis ≥5 nm). The three most prominent RIFs among the outcome factors of oil tanker marine accidents are SEA1 (Seaworthiness), R2 (Adequate regulations for the administration), and SFC1 (Seafarers' certificates complete and valid). Table 4 shows the RIFs of other ship types with larger values for the reason degree.

Therefore, when considered together, causal factors with large centrality degree values are key RIFs and primary drivers of accidents. Taking oil tanker accidents as an example, the most significant RIFs include CC2 (Good company safety culture), TAS2 (5 ≤ The crew's time at sea <10 years), TRA2 (Adequate company training), and TD2 (High traffic density). These RIFs play a crucial role in the accident chain and can serve as initial triggers before an accident occurs. Different RIFs function in various ways and can have adverse effects throughout the voyage. For example, company management factors, represented by CC2 (Good company safety culture) and TRA2 (Adequate company training), pose significant risks in ship operations and can hinder emergency responses, thus contributing to accidents. Enhanced management and preventive measures for these RIFs are crucial to minimizing the risk of accidents and ensuring safety at sea. Simultaneously, outcome factors with large centrality degree values play a crucial role in the transmission of risk within the system. For fishing vessel accidents, key RIFs include PF2 (PSC/FSC inspection assured), SM1 (Adequate manning of ships), VIS2 (No administrative violations in supervision), SFC1 (Seafarers' certificates complete and valid), R2 (Adequate regulations for the administration), and SC1 (Complete and valid ship certificates). These RIFs are significantly influenced by other RIFs. However, due to their high centrality degree values, any alteration in them could profoundly impact the evolution of marine accidents. Therefore, special attention needs to be paid to these RIFs (e.g., safety management systems and the educational background of the crew) to mitigate their negative impacts and prevent them from exacerbating marine accidents further. In order to mitigate the risk of accidents and ensure maritime safety, it is imperative to verify the stability and compliance of these critical RIFs through appropriate measures.

Examined from a causal perspective, this study offers insights into the dynamic transfer of information among RIFs. By analysing the impact of each RIF on others, the causality among key RIFs during an accident can be revealed. Such analyses help to understand the dynamic mechanisms of accident occurrence, as well as the interactions and impacts among different RIFs within the accident. Using the example of an oil tanker accident, it can be observed that SFS2 (No defects in the company's safety management system) is one of the most influential RIFs. In a causality analysis, this study can further explore the impact of this RIF on other RIFs. For example, an effective company safety management system promotes regular inspection and maintenance of the ship's equipment, thereby reducing the risk of accidents. Conversely, deficiencies in the management system may lead to the crew disregarding safety regulations, thereby increasing the likelihood of accidents. Additionally, another significant RIF is EB2 (Good educational background of the crew). The impact of the crew's educational background on accident occurrence can be examined through causality analyses. A solid educational background equips crew members with the capability to respond effectively to emergencies, consequently reducing the occurrence of accidents. Conversely, crew members with lower levels of education may struggle to respond appropriately to emergencies, thereby heightening the risk of accidents. Analysing the causal relationships between these RIFs can enhance the understanding of the dynamics of the accident process. Specifically, deficiencies in management systems can result in incomplete enforcement of safety regulations, subsequently influencing crew behaviour and response capabilities, ultimately heightening the risk of accidents. Analysing this dynamic information transfer helps to unveil the root causes of accidents and serves as a crucial reference for developing effective prevention strategies.

By integrating centrality degree, reason degree, and weight to analyse accidents involving four ship types, this study can identify both similarities and differences among them regarding key RIFs. While human factors, such as the educational background of the crew, may share commonalities across ship types, distinct differences in specific RIFs of accidents are evident among them. Bulk carrier accidents are notably influenced by RIFs such as the ship's main engine power and navigational density, whereas marine accidents of container ship tend to

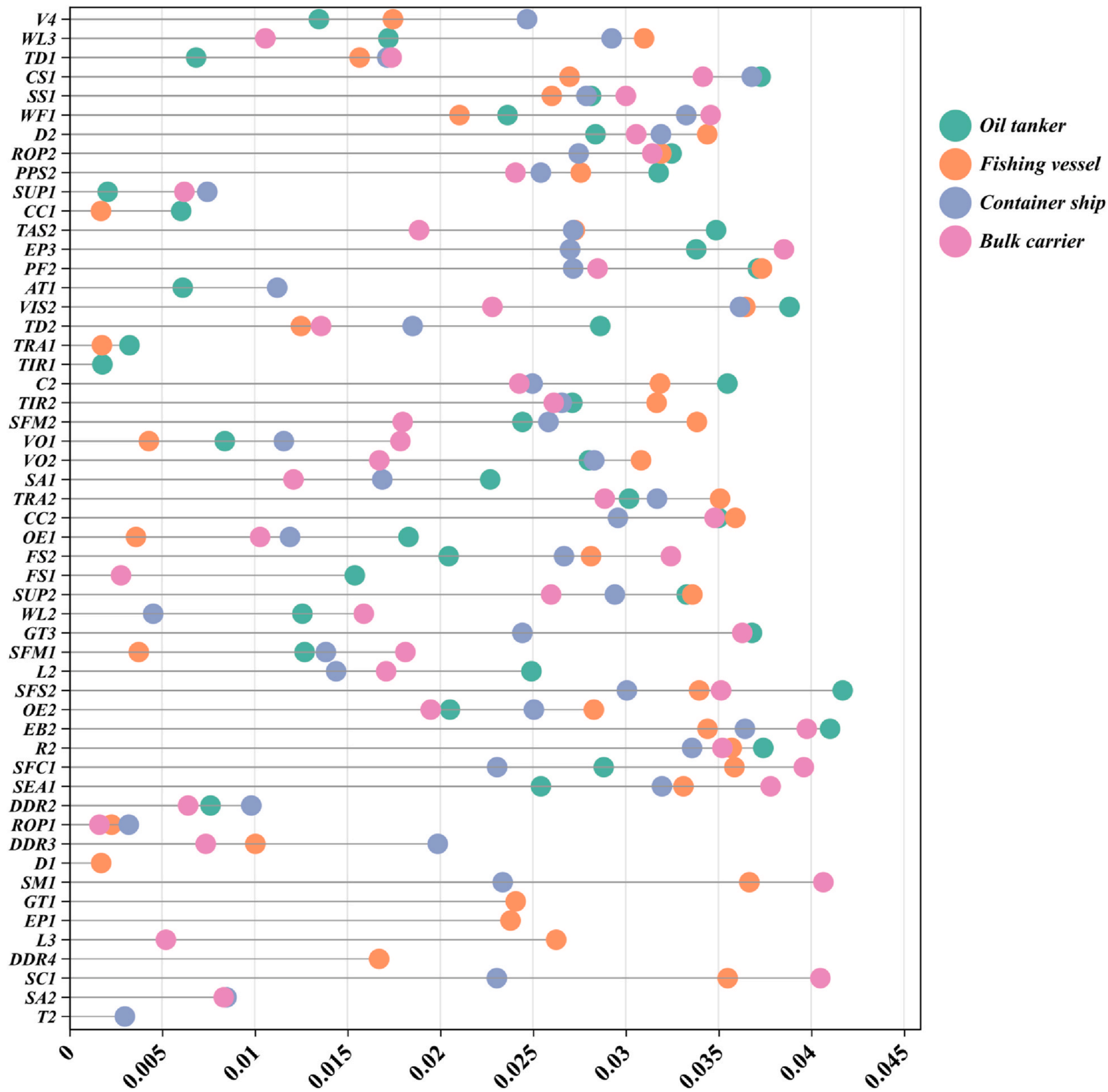


**Fig. 9.** The weight distribution of RIFs.

**Table 3**
The RIFs with large centrality degree values.

| Ship types | RIFs |
|---|---|
| Bulk carriers | SC1 (Complete and valid ship certificates), SM1 (Adequate manning of ships), EB2 (Good educational background of the crew), SFC1 (Seafarers' certificates complete and valid) and EP3 (Engine power ≥3000 KW) |
| Fishing vessels | PF2 (PSC/FSC inspection assured), SM1 (Adequate manning of ships), VIS2 (No administrative violations in supervision), CC2 (Good company safety culture) and SFC1 (Seafarers' certificates complete and valid) |
| Oil tankers | SFS2 (No defects in the company's safety management system), EB2 (Good educational background of the crew), VIS2 (No administrative violations in supervision), CS1 (Current speed <2 kn) and GT3 (Gross tonnage ≥3000t) |

**Table 4**
The RIFs with large reason degree values.

| Ship types | Causal factors | Outcome factors |
|---|---|---|
| Bulk carriers | OE2 (No operational error for the crew), TD1 (Low traffic density) and WL2 (1≤ Fairway width/ship length <2) | C2 (No communication problems for the crew), SM1 (Adequate manning of ships) and SEA1 (Seaworthiness) |
| Container ships | V4 (Visibility good and very good - Vis ≥5 nm), DDR3 (1.5 ≤ Depth-draft ratio <3) and SA1 (The ship age is 0–10 years) | SM1 (Adequate manning of ships), SC1 (Complete and valid ship certificates) and SFC1 (Seafarers' certificates complete and valid) |
| Fishing vessels | DDR4 (Depth-draft ratio ≥3), TD1 (Low traffic density) and DDR3 (1.5 ≤ Depth-draft ratio <3) | SEA1 (Seaworthiness), C2 (No communication problems for the crew) and SC1 (Complete and valid ship certificates) |

be affected by factors like current speed and the company's safety management system. Moreover, in the context of fishing vessel accidents, the maritime authority's management factors play a pivotal role in prevention at sea, while oil tanker accidents are more prone to be influenced by the management factors of the shipping company. Hence, conducting an in-depth and comprehensive analysis of the centrality degree, reason degree, and weight of RIFs in various ship types of accidents can facilitate a comprehensive understanding of their characteristics. This analysis can also provide a scientific basis and guidance for shipping safety management.

### 4.4. The hierarchical structure analysis of RIFs

This section analyses the coupling relationships between the RIFs by examining the hierarchical topology diagram. Firstly, this study employs an intercept threshold to eliminate less influential relationships in the comprehensive influence matrix *TH*, thereby establishing the relationship matrix *AH*. Secondly, Boolean operations are conducted using Equations (27) and (28) to derive the reachability matrix *RH*. Subsequently, the skeleton matrix *GH* is derived from the reachability matrix *RH* by reducing the points and edges of the matrix. Building upon this, the hierarchical structure of RIFs is elucidated using UP-type and DOWN-type extraction methods. Finally, a further hierarchical division of the set elements is conducted to illustrate the topology of the hierarchical structure. Among them, the UP/DOWN-type confrontation hierarchy topology of bulk carriers is illustrated in Fig. 10. The confrontation hierarchy topology for other ship types is provided in

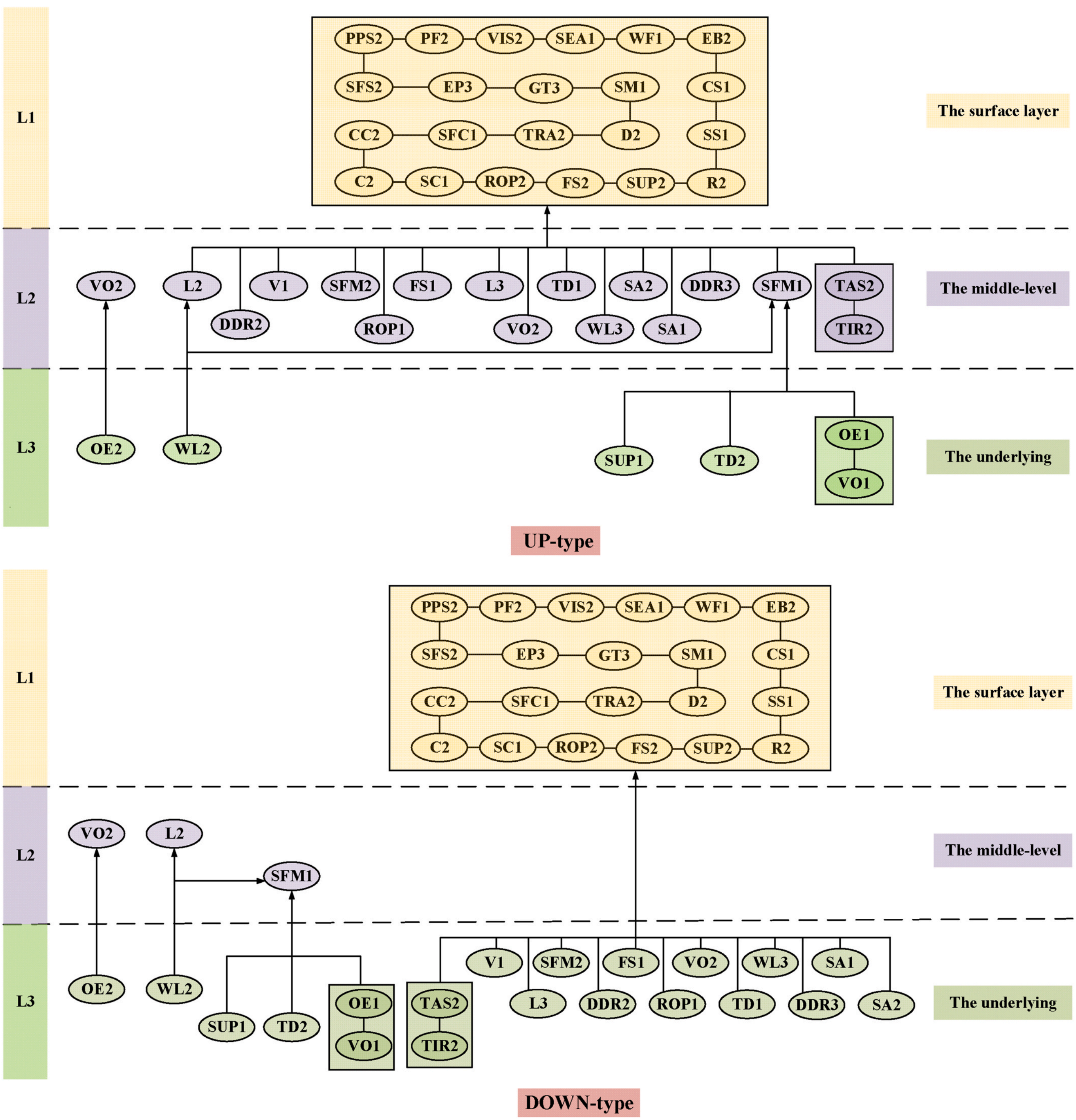


**Fig. 10.** Topological hierarchical structural model diagram for bulk carriers.

Figure D1 of Appendix D.

The UP-type confrontation hierarchy topology diagram divides the hierarchy based on result orientation, while the DOWN-type confrontation hierarchy topology diagram divides the hierarchy based on cause orientation. The reachability relationships between the RIFs for marine accidents are depicted by directed line segments. The rectangular box plots in Fig. 10 depict the formation of loops, signifying that the RIFs within the box plots are interconnected in a mutually reachability relationship, thus forming a strongly connected component. Simultaneously, the positioning of RIFs in the lower tier indicates a deeper rootedness, while those in the upper tier suggest a more direct influence. As shown in Fig. 10 and Figure D1 of Appendix D, the RIFs for marine accidents involving bulk carriers, fishing vessels, and oil tankers are divided into three levels: direct influencing factors (D-RIFs), indirect influencing factors (I-RIFs), and underlying influencing factors (U-RIFs). The RIFs for marine accidents involving container ships are divided into two levels: direct influencing factors (D-RIFs) and underlying influencing factors (U-RIFs).

(1) Loop analysis

Cyclic loops, also known as strongly connected components, are identified and merged using the Tarjan algorithm (Eisner, 2023). In this study, several strongly connected components are identified. Taking the adversarial hierarchical topology feature diagram of bulk carriers as an example, as shown in Fig. 10, the components PPS2/PF2/VIS2/SEA1/WF1/EB2/CS1/SS1/R2/SUP2/FS2/ROP2/SC1/C2/CC2/SFC1/TRA2/D2/SM1/GT3/EP3/SFS2, TAS2/TIR2, and OE1/VO1 form strongly connected components, each of which is analysed as a single node. Strongly connected components signify strong interaction dependencies among the RIFs they encompass. For instance, given that both OE1 and VO1 are human factors influencing the incidence of marine accidents, a failure in either OE1 or VO1 would signify the influence of human factors on marine accidents. Likewise, an issue with either TAS2 or TIR2 could suggest that the ship is not seaworthy. Hence, it is crucial to closely monitor these cyclically linked strongly connected components. A failure in any single RIF within these components may activate multiple RIFs simultaneously, potentially exacerbating the severity of the accident.

(2) Analysis of isolated factors

From Figure D1(b) of Appendix D, it can be observed that D1/TRA1 forms an isolated strongly connected component within the RIN of fishing vessel. The D1/TRA1 component is not connected by directional lines to other RIFs, indicating that it neither influences nor is influenced by other RIFs. This implies that D1/TRA1 can directly impact the occurrence of marine accidents without needing to interact with other RIFs. This is because D1 (Inadequate company training) and TRA1 (Off-schedule company drill) cannot be addressed by altering RIFs such as environmental and human factors, they are primarily associated with the training strategy of company management and the scheduling of drill programs. Monitoring this isolated strongly connected component throughout the voyage is not feasible. Therefore, constant vigilance should be maintained on such isolated RIFs even before the ship sets sail, so as to mitigate the risks they pose during the sea voyage.

(3) Analysis of surface layer factors, middle-level factors and underlying factors

Table D1 of Appendix D presents the results of adversarial hierarchy analysis for the accidents involving four ship types. D-RIFs, as the resultant layer factors, occupy the highest level of the system and do not emit directed line segments, and they are solely influenced by other RIFs. These RIFs are the most direct factors affecting marine accidents. The effects of other factors in the system are transferred to the D-RIFs, which in turn directly lead to the occurrence of marine accidents, demonstrating the strong outcome property of the D-RIFs. I-RIFs, also known as transition layer factors, are influenced by U-RIFs and can subsequently transmit their effects to D-RIFs. They are both affected by U-RIFs and have an impact on D-RIFs, playing a pivotal role in carrying on and coordinating the linkage. They need to be taken into account when formulating prevention programs for marine accidents. U-RIFs have a strong causal influence on other RIFs, emitting only directed line segments in the topological diagram. These RIFs can directly or indirectly affect other RIFs in the system, playing a dominant role in the occurrence of marine accidents and should be focused on.

To conduct a comprehensive analysis of D-RIFs, I-RIFs, and U-RIFs, a complete topology diagram of the hierarchy is selected as an example for this study. As depicted in Figure D1(b) of Appendix D, a complete system exists in the DOWN-type adversarial hierarchy topology diagram of fishing vessels, namely, L3 → L2 → L1. The L3 layer includes RIFs such as CC1, DDR4, TD1, TAS2, ROP2, DDR3, V4, ROP1, TD2, OE1, D1, TAR1, and others. The L2 layer comprises RIFs such as SFM1, L3, VO1, and others. The L1 layer consists of FS2, TIR2, WF1, EB2, CS1, SFM2, SM1, R2, TRA2, VO2, C2, SFC1, SC1, PPS2, SUP2, VIS2, SEA1, SS1, WL3, D2, OE2, SFS2, CC2, EP1, GT1, PF2, and other RIFs. Complex interactions exist between the RIFs of L1, L2, and L3. Analysis of the RIFs at Layer L3 reveals that most of them pertain to the safety management factors of the company. The RIFs at Layer L3 are the core factors affecting marine accidents. This indicates that the safety management factors of the company underlie accidents at sea on fishing vessels, aligning with the conclusions of sections 4.2 and 4.3, thereby further confirming the consistency between these analyses. Layer L2 encompasses human, environmental, management, and other aspects of RIFs, indicating the diversity of I-RIFs. Therefore, effectively preventing and controlling these multifaceted I-RIFs will be a highly complex undertaking. These I-RIFs do not act directly but serve as intermediaries in the information transfer process. Thus, by effectively managing this layer, the information transfer channel from U-RIFs to D-RIFs can be blocked. In the L3 layer, the RIFs form a large strongly connected component, creating loops. D-RIFs directly contribute to maritime accidents. Using WL3 (Fairway width/ship length $\geq$2) as an example within this strongly connected component, controls to WL3, such as changes in the ratio of fairway width to ship length, may elevate the risk of capsizing, grounding, or mechanical damage to the vessel. Addressing D-RIFs can swiftly and effectively reduce the likelihood of accidents or alleviate their severity.

Through an in-depth analysis of the topology of the confrontation hierarchy of the accidents involving four ship types, this study reveals a common feature among them: human and management factors play significant roles in the occurrence of marine accidents across all four ship types. However, to comprehensively understand the nature of these accidents, further exploration of the complex inter-coupling of RIFs in the risk transfer phase is necessary. In the maritime field, human factors encompass various elements, including but not limited to, educational background, the physical and mental health of the crew. These factors frequently contribute to accidents and can worsen their consequences. For instance, when the crew is in poor physical or mental condition, it can lead to errors in ship maneuvering, potentially resulting in collisions or grounding events. At the management level, RIFs involve both maritime authorities and shipping companies, encompassing factors related to regulations, rectification of issues, and crew training, among others. Therefore, in preventing marine accidents, maritime authorities and shipping companies must ensure that crew training meets standard requirements and establish regular exercise programs. This practice will enhance the emergency response capabilities of crew members and strengthen the level of ship safety management, effectively reducing the risk of accidents. However, it is also important to recognize the variability that may exist between different ship types when confronted with maritime safety challenges. For marine accidents involving bulk carriers and fishing vessels, the influence of the ship's own attribute factors, such as ship age, main engine power, and ship tonnage, may be more pronounced. To mitigate the impact of these RIFs, attention should be directed towards ensuring the compliance of the ship's structure and loading conditions to maintain stability and safety in various conditions. Conversely, container ships and tankers face greater challenges due to environmental factors, such as adverse weather and channel congestion. Therefore, special consideration should be given to the impact of environmental factors when devising safety measures for these vessels. This may involve aspects such as meticulous voyage planning and the development of strategies to cope with extreme weather conditions.

In summary, targeted measures must be implemented for different ship types to focus on and manage the factors involved, aiming to minimize the risk of marine accidents. This necessitates active involvement from both ship operators and regulatory agencies, as well as interdisciplinary cooperation and an integrated management approach, all working together to ensure the safe and sustainable development of marine transport.

## 5. Implications

Based on the results and discussion presented in Section 4, the CWA model proposed in this study enables a thorough understanding and analysis of the interactions among RIFs for marine accidents of various ship types. Significant differences exist in the key RIFs associated with marine accidents across various ship types, highlighting the necessity for targeted management and prevention strategies. The following management recommendations are provided for marine accidents of different ship types, using the four primary ship types analysed in this study as examples:

(1) For bulk carriers, key RIFs include the company's safety management level, main engine power, and navigational density. To enhance the safety of bulk carriers, it is recommended to strengthen the company's safety management system, conduct regular safety inspections and drills, and improve the crew's safety awareness and operational skills. Additionally, the configuration of the main engine power should be optimized to ensure the reliable operation of equipment. Special management measures should be implemented in areas with high navigational density to mitigate the risk of accidents caused by equipment failure or congested traffic.

(2) For container ships, key RIFs include the channel width-to-length ratio, current speed, and the company's safety management system. It is recommended to optimize channel design and ship operational strategies for container ships to achieve a reasonable channel width-to-length ratio and reduce the risk of accidents. Additionally, the impact of current speed on navigation should be monitored and managed, and the effectiveness of the company's safety management system should be improved to enhance navigation safety and mitigate accidents caused by environmental factors.

(3) For fishing vessels, key RIFs include the crew's educational background, wind force, and regulatory management factors. To enhance the safety of fishing vessels, it is recommended to improve the education and training quality of crew members, particularly their emergency response capabilities. Additionally, regulatory authorities should strengthen their management and supervision to ensure compliance with safety standards, thereby reducing accidents caused by human factors and inadequate surveillance.

(4) For oil tankers, key RIFs emphasize the ship's seaworthiness and the management practices of the shipping company. To ensure the safety of oil tankers under various sailing conditions, it is recommended to prioritize the management of the vessel's seaworthiness. Additionally, enhancing the safety management standards of shipping companies, implementing stringent operation and maintenance procedures, and minimizing human errors will further improve the safety of oil tankers.

Overall, while the RIFs for marine accidents vary among different ship types, they all highlight the critical role of human and management factors. Ship operators, shipping companies and maritime authorities should focus on the following key areas: improving the education and professional skills of crew members, particularly their emergency response abilities; conducting regular safety training and drills to enhance crew members' emergency response capabilities; strengthening the management of shipping companies and establishing stringent operation and maintenance procedures to ensure the safety under various navigational conditions; utilizing advanced technological solutions to optimize ship design and operations, thereby reducing accidents related to equipment failures; and developing effective response strategies to address environmental challenges faced by different ship types. Specifically, for container ships and oil tankers, special attention should be given to voyage planning and safety measures, especially during adverse weather conditions and channel congestion.

In summary, critical RIFs for marine accidents vary in characteristics and complexities across different ship types and necessitate targeted management measures. Addressing these factors requires not only the active participation of ship operators and maritime authorities but also an advanced technical surveillance approach to achieve safe and sustainable marine transport. By thoroughly understanding and managing the key RIFs for various ship types, the risk of marine accidents can be effectively reduced, thereby promoting the long-term development of the maritime industry.

## 6. Conclusions

This study proposes an innovative analytical model known as CWA, a comprehensive method comprising CN, WINGS, and AISM. Through the application of this model, this study successfully analyses the differences in RIFs among marine accidents involving various ship types. The research results demonstrate notable disparities in the primary RIFs influencing marine accidents across various ship types. It offers new perspectives and methods for marine safety management.

This study innovatively provides valuable insights for the development of heterogeneous programs aimed at preventing accidents of different ship types. However, this study has some limitations, firstly, the database of this study only covers marine accident data from 2000 to 2019. Collecting marine accident data from additional years in future studies is necessary to conduct more scientifically robust analyses. Secondly, the RIFs database used in this study was manually extracted after screening marine accident investigation reports. Future studies should include sensitivity analyses to evaluate the impact of different data extraction methods on the results. Finally, the ARM technique employed in this study could not demonstrate the causality between RIFs. Future studies could explore more advanced causal data mining algorithms to uncover the causal relationships between RIFs.

## Data availability

Data will be made available on request. The source code is publicly available at: https://github.com/FengYinLeo/CWA-Model.

## CRediT authorship contribution statement

**Wenjie Cao:** Writing – original draft, Visualization, Methodology. **Xinjian Wang:** Supervision, Funding acquisition, Formal analysis, Conceptualization, Methodology, Writing – original draft. **Jian Li:** Visualization, Validation, Investigation. **Zhiwei Zhang:** Writing – review & editing, Visualization, Validation, Investigation. **Yuhao Cao:** Validation, Visualization, Writing – review & editing. **Yinwei Feng:** Writing – review & editing, Validation, Methodology.

## 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.

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## Appendix A. The RIFs database description of the marine accidents

**Table A1**
Marine accidents RIFs database.

| Level I | Level II | Variables | Value/definition | Corresponding values |
|---|---|---|---|---|
| Accident | Accident type | AT | collision, stranding/grounding, fire/explosion, contact, capsize/foundering, hull/machinery damage, other | 1,2,3,4,5,6,7 |
| | Month | M | January, February, March, April, May, June, July, August, September, October, November, December | 1,2,3,4,5,6,7,8,9,10,11,12 |
| | Time | T | 0000-0400, 0400–0800, 0800–1200, 1200–1600, 1600–2000, 2000-2400 | 1,2,3,4,5,6 |
| Human | Physical & Psychological state | PPS | poor, good | 1,2 |
| | Education background | EB | poor, good | 1,2 |
| | Time at sea | TAS | $<5$ years, $5\leq$ time $<10$ years, $\geq 10$ years | 1,2,3 |
| | Time in present rank | TIR | $<1$ year, $1 \leq$ time $<5$ years, $\geq 5$ years | 1,2,3 |
| | Communication problem | C | yes, no | 1,2 |
| | Operational error | OE | yes, no, unknown | 1,2,3 |
| | Violation operation | VO | yes, no, unknown | 1,2,3 |
| Ship | Age | SA | 0–10 years, 10–20 years, 20–30 years, $\geq 30$ years | 1,2,3,4 |
| | Gross tonnage | GT | $<500$ t, 500–3000 t, $\geq 3000$t | 1,2,3 |
| | Engine power | EP | $<750$ KW, 750–3000 KW, $\geq 3000$ KW | 1,2,3 |
| | Flag state | FS | Flag of convenience, Not flag of convenience | 1,2 |
| | Ship's certificates | SC | complete and valid, incomplete or invalid | 1,2 |
| | Ship manning | SM | adequate, inadequate | 1,2 |
| | Seafarers' certificates | SFC | complete and valid, incomplete or invalid | 1,2 |
| | Seaworthiness | SEA | yes, no | 1,2 |
| | PSC/FSC inspection | PF | unsure, sure | 1,2 |
| Environment | Location | L | Inland waters, Port, Coastal waters, Open Sea | 1,2,3,4 |
| | Visibility | V | very poor - Vis $<0.5$ nm, Poor - $0.5 \leq$ Vis $<2$ nm, Moderate - $2 \leq$Vis $<5$ nm, Good and very good - Vis $\geq 5$ nm | 1,2,3,4 |
| | Wind force | WF | 0-5, 6–7, 8–9, 10-12 | 1,2,3,4 |
| | Sea state | SS | 0-3, 4–5, 6–7, 8-9 | 1,2,3,4 |
| | Current speed | CS | $<2$kn, 2-4kn, $\geq 4$kn | 1,2,3 |
| | Traffic density | TD | low, high | 1,2 |
| | Fairway width/ship length | WL | $w/l < 1$, $1 \leq w/l < 2$, $w/l \geq 2$ | 1,2,3 |
| | Depth-draft ratio (h/d) | DDR | $h/d < 1.2$, $1.2 \leq h/d < 1.5$, $1.5 \leq h/d < 3$, $h/d \geq 3$ | 1,2,3,4 |
| Management | Regulation | R | inadequate, adequate | 1,2 |
| | Supervision | SUP | inadequate, adequate | 1,2 |
| | Violation in supervision | VIS | yes, no | 1,2 |
| | Safety management system | SFS | defective, non-defective | 1,2 |
| | Safety management | SFM | inadequate, adequate | 1,2 |
| | Rectification of problems | ROP | unresponsive, responsive | 1,2 |
| | Company safety culture | CC | poor, good | 1,2 |
| | Training | TRA | inadequate, adequate | 1,2 |
| | Drill | D | off schedule, stick to the schedule | 1,2 |

Note: The unit of wind rating is "Beaufort scale"; The unit of the sea state class is the "Douglas scale.

## Appendix B. The RINs for marine accidents involving Container ship, Fishing vessels and Oil tanker

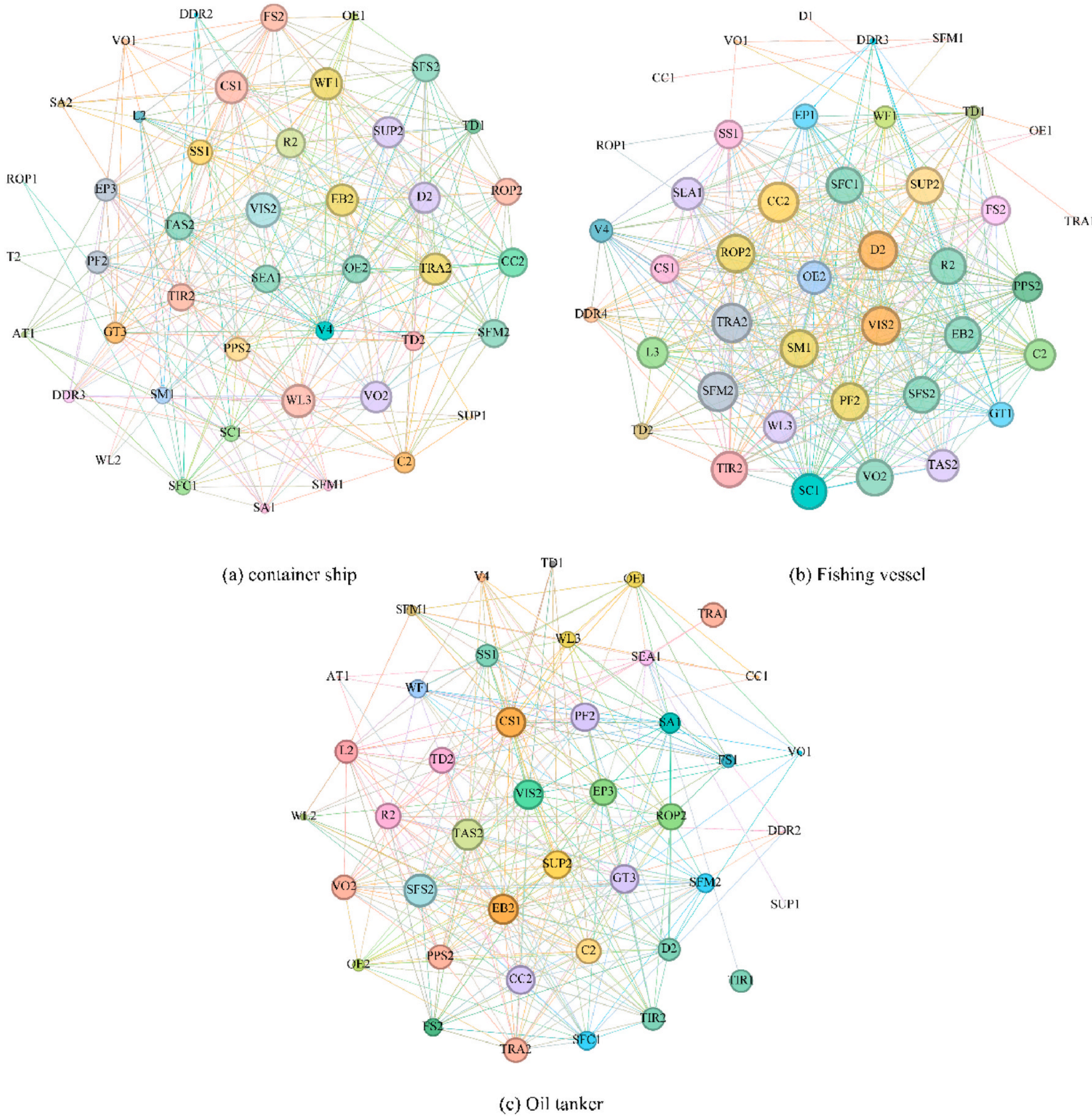


**Fig. B1.** Interactive network of RIFs for marine accidents.

## Appendix C. Comparison analysis with BN model

To effectively present the results, this study draws on previous studies (Cao et al., 2023a; Fan et al., 2020; Feng et al., 2024a) and uses "accident severity" and mutual information between RIFs as the core metrics for evaluation. The objective of this section is to demonstrate that the proposed model offers enhanced reasonableness, accuracy, and capability in marine risk analysis. Information on the establishment procedure of BN model is available in previous studies (Cao et al., 2023a; Fan et al., 2020).

Using marine accidents involving fishing vessel as an example, Figure C1 of Appendix C illustrates the BN model results for these accidents, with the mutual information between "Accident Severity" and RIFs presented in Table C1 of Appendix C. The CWA model and the BN model exhibit a high degree of consistency in identifying key RIFs, such as vessel attributes, environmental conditions, and crew-related factors. Specifically, the CWA model identifies RIFs like PF2, SM1, VIS2, CC2, SFC1, R2, SC1, TRA2, EB2, and SEA1 as having significant impacts on fishing vessel accidents. Among these, PF2 pertains to vessel attributes, while SM1, SFC1, SC1, and EB2 are related to crew factors, and SEA1 corresponds to environmental factors. The BN model also identifies these RIFs as key. However, the CWA model offers deeper insights into these complex RIFs. In addition to vessel, environmental, and crew factors, the CWA model highlights the critical roles of safety culture and management oversight, such as RIFs VIS2 and CC2, which are essential for accident prevention and management. In contrast, while the BN model identifies a broad range of RIFs, it lacks the systematic analysis and depth of understanding concerning hierarchical structural. By transitioning from static analysis to dynamic, hierarchical structural parsing, the CWA model provides greater comprehensiveness and depth, effectively revealing complex accident causes and offering strong support for developing comprehensive risk management strategies.

**Table C1**
Mutual information shared with "Accident Severity".

| Node | Mutual Information | Node | Mutual Information |
|---|---|---|---|
| Engine power | 0.04543 | Company safety culture | 0.01858 |
| Fairway width/ship length | 0.04307 | Current speed | 0.01844 |
| Ship manning | 0.04206 | Operational error | 0.01676 |
| Location | 0.04098 | Depth-draft ratio | 0.01615 |
| Gross tonnage | 0.03895 | Seaworthiness | 0.01598 |
| Physical & Psychological state | 0.03611 | Seafarers certificates | 0.01595 |
| Month | 0.03589 | Wind force | 0.01554 |
| Violation operation | 0.03542 | Training | 0.01547 |
| PSC/FSC inspection | 0.03403 | Time in present rank | 0.01409 |
| Accident type | 0.03356 | Time at sea | 0.01105 |
| Visibility | 0.03284 | Regulation | 0.00837 |
| Safety management | 0.02852 | Drill | 0.00764 |
| Supervision | 0.02566 | Traffic density | 0.0073 |
| Violation in supervision | 0.02533 | Education background | 0.00394 |
| Ship's certificates | 0.02419 | Ship age | 0.0032 |
| Communication problem | 0.02395 | Flag state | 0.00152 |
| Sea state | 0.02332 | Time | 0.00152 |
| Safety management system | 0.02204 | Rectification of problem | 0.00134 |

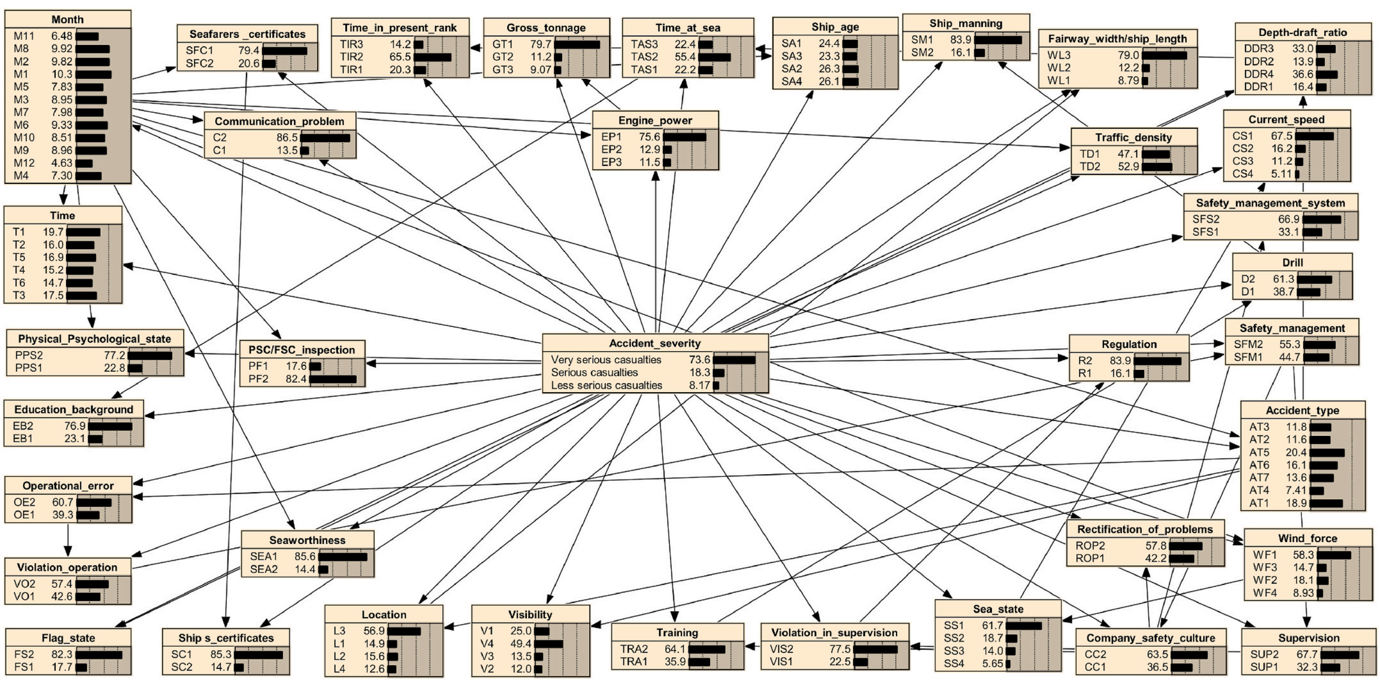


**Fig. C1.** Modelling results of BN.

## Appendix D. The results of hierarchy analysis

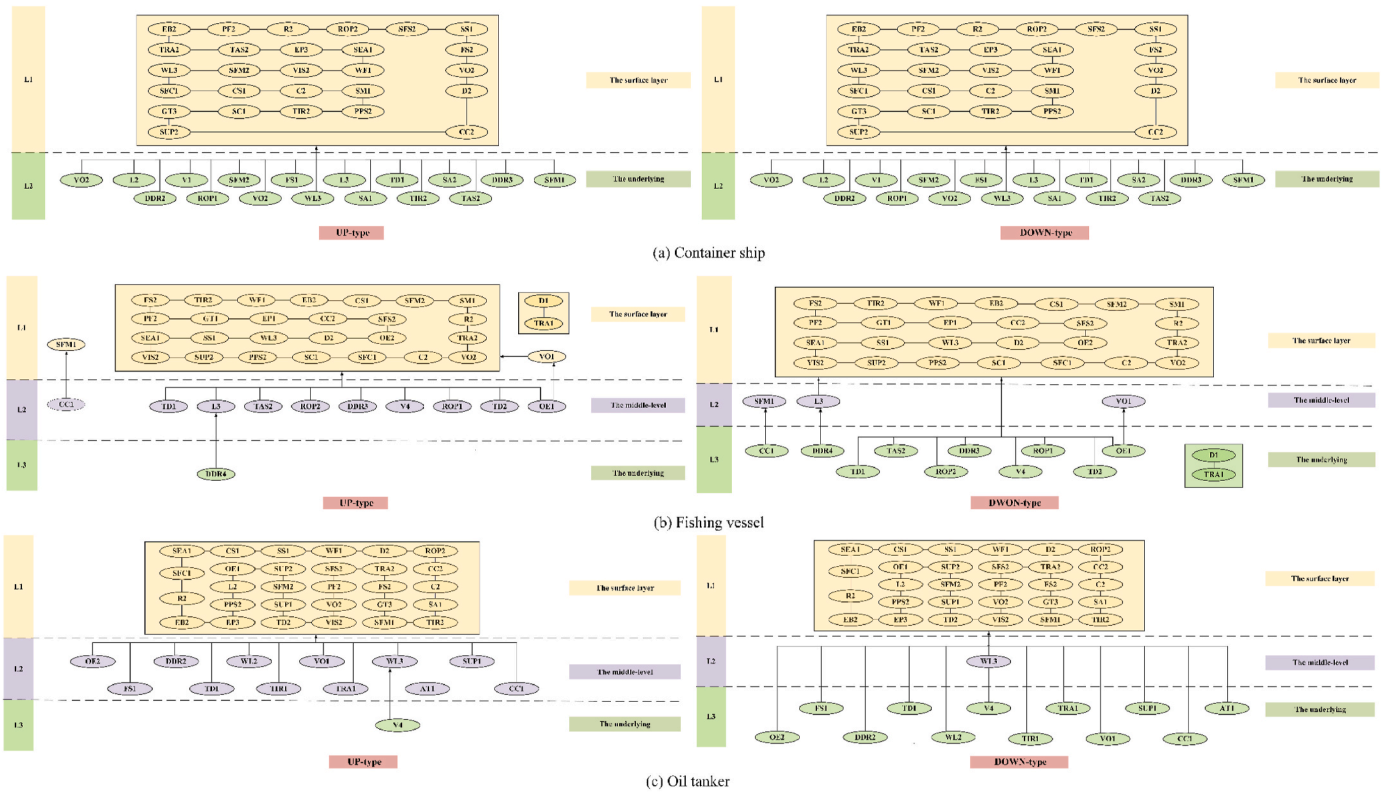


**Fig. D1.** Topological hierarchical structural model diagram.

**Table D1**
Results of adversarial hierarchy analysis.

| Ship type | Layer | Result Priority-UP Type | Effect Priority-DOWN Type |
|---|---|---|---|
| Bulk Carrier | Level 1 | ’SS1’, ’GT3’, ’SC1’, ’SM1’, ’ROP2’, ’SEA1’, ’PPS2’, ’SUP2’, ’WF1’, ’EB2’, ’C2’, ’FS2’, ’VIS2’, ’SFC1’, ’CC2’, ’D2’, ’CS1’, ’EP3’, ’PF2’, ’SFS2’, ’TRA2’, ’R2′ | ’SS1’, ’GT3’, ’SC1’, ’SM1’, ’ROP2’, ’SEA1’, ’PPS2’, ’SUP2’, ’WF1’, ’EB2’, ’C2’, ’FS2’, ’VIS2’, ’SFC1’, ’CC2’, ’D2’, ’CS1’, ’EP3’, ’PF2’, ’SFS2’, ’TRA2’, ’R2′ |
| | Level 2 | ’SFM1’, ’DDR3’, ’ROP1’, ’VO2’, ’WL3’, ’FS1’, ’SA2’, ’DDR2’, ’TIR2’, ’SFM2’, ’TD1’, ’SA1’, ’L3’, ’L2’, ’V1’, ’TAS2′ | ’L2’, ’SFM1’, ’VO2′ |
| | Level 3 | ’SUP1’, ’VO1’, ’TD2’, ’WL2’, ’OE1’, ’OE2′ | ’SUP1’, ’VO1’, ’SA2’, ’TIR2’, ’L3’, ’V1’, ’OE1’, ’DDR3’, ’TD1’, ’SA1’, ’TAS2’, ’ROP1’, ’WL3’, ’SFM2’, ’WL2’, ’FS1’, ’DDR2’, ’TD2’, ’OE2′ |
| Container Ship | Level 1 | ’EB2’, ’PF2’, ’R2’, ’ROP2’, ’SFS2’, ’SS1’, ’FS2’, ’SEA1’, ’EP3’, ’TAS2’, ’TRA2’, ’WL3’, ’SFM2’, ’VIS2’, ’WF1’, ’VO2’, ’D2’, ’SM1’, ’C2’, ’CS1’, ’SFC1’, ’GT3’, ’SC1’, ’TIR2’, ’PPS2’, ’CC2’, ’SUP2′ | ’EB2’, ’PF2’, ’R2’, ’ROP2’, ’SFS2’, ’SS1’, ’FS2’, ’SEA1’, ’EP3’, ’TAS2’, ’TRA2’, ’WL3’, ’SFM2’, ’VIS2’, ’WF1’, ’VO2’, ’D2’, ’SM1’, ’C2’, ’CS1’, ’SFC1’, ’GT3’, ’SC1’, ’TIR2’, ’PPS2’, ’CC2’, ’SUP2′ |
| | Level 2 | ’DDR2’, ’ROP1’, ’OE2’, ’TD1’, ’WL2’, ’DDR3’, ’SFM1’, ’SUP1’, ’TD2’, ’VO1’, ’AT1’, ’V4’, ’OE1’, ’SA1’, ’L2’, ’SA2’, ’T2′ | ’DDR2’, ’ROP1’, ’OE2’, ’TD1’, ’WL2’, ’DDR3’, ’SFM1’, ’SUP1’, ’TD2’, ’VO1’, ’AT1’, ’V4’, ’OE1’, ’SA1’, ’L2’, ’SA2’, ’T2′ |
| Fishing Vessel | Level 1 | ’VIS2’, ’WF1’, ’C2’, ’VO1’, ’FS2’, ’EB2’, ’TRA1’, ’SUP2’, ’EP1’, ’PPS2’, ’CS1’, ’D1’, ’SFM2’, ’VO2’, ’SFS2’, ’WL3’, ’SFC1’, ’R2’, ’PF2’, ’SC1’, ’SFM1’, ’SS1’, ’D2’, ’TRA2’, ’OE2’, ’SEA1’, ’TIR2’, ’GT1’, ’SM1’, ’CC2′ | ’VIS2’, ’WF1’, ’C2’, ’FS2’, ’EB2’, ’SUP2’, ’EP1’, ’PPS2’, ’CS1’, ’SFM2’, ’VO2’, ’SFS2’, ’WL3’, ’SFC1’, ’R2’, ’PF2’, ’SC1’, ’SS1’, ’D2’, ’TRA2’, ’OE2’, ’SEA1’, ’TIR2’, ’GT1’, ’SM1’, ’CC2′ |
| | Level 2 | ’TAS2’, ’TD1’, ’ROP2’, ’CC1’, ’TD2’, ’V4’, ’L3’, ’OE1’, ’DDR3’, ’ROP1′ | ’SFM1’, ’L3’, ’VO1′ |
| | Level 3 | ’DDR4′ | ’TAS2’, ’TD1’, ’ROP2’, ’CC1’, ’TD2’, ’TRA1’, ’V4’, ’OE1’, ’DDR4’, ’D1’, ’DDR3’, ’ROP1′ |
| Oil Tanker | Level 1 | ’GT3’, ’TAS2’, ’L2’, ’OE1’, ’VIS2’, ’SFM2’, ’VO2’, ’R2’, ’SA1’, ’PPS2’, ’FS2’, ’SFS2’, ’SFM1’, ’SS1’, ’CC2’, ’SEA1’, ’PF2’, ’TD2’, ’C2’, ’WF1’, ’TRA2’, ’ROP2’, ’EB2’, ’TIR2’, ’D2’, ’SFC1’, ’EP3’, ’CS1’, ’SUP2′ | ’GT3’, ’TAS2’, ’L2’, ’OE1’, ’VIS2’, ’SFM2’, ’VO2’, ’R2’, ’SA1’, ’PPS2’, ’FS2’, ’SFS2’, ’SFM1’, ’SS1’, ’CC2’, ’SEA1’, ’PF2’, ’TD2’, ’C2’, ’WF1’, ’TRA2’, ’ROP2’, ’EB2’, ’TIR2’, ’D2’, ’SFC1’, ’EP3’, ’CS1’, ’SUP2′ |
| | Level 2 | ’FS1’, ’DDR2’, ’CC1’, ’SUP1’, ’TRA1’, ’WL3’, ’OE2’, ’TIR1’, ’WL2’, ’AT1’, ’TD1’, ’VO1′ | ’WL3′ |
| | Level 3 | ’V4′ | ’FS1’, ’DDR2’, ’CC1’, ’SUP1’, ’TRA1’, ’OE2’, ’TIR1’, ’WL2’, ’V4’, ’AT1’, ’TD1’, ’VO1′ |

## References


Aljehani, S.S., Alotaibi, Y.A., 2024. Preserving privacy in association rule mining using metaheuristic-based algorithms: a systematic literature review. IEEE Access 12, 21217–21236. https://doi.org/10.1109/ACCESS.2024.3362907.

Callesen, F.G., Blinkenberg-Thrane, M., Taylor, J.R., Kozine, I., 2021. Container ships: fire-related risks. J. Mari. Eng. Technol. 20 (4), 262–277. https://doi.org/10.1080/20464177.2019.1571672.

Campanile, A., Piscopo, V., Scamardella, A., 2018. Comparative analysis among deterministic and stochastic collision damage models for oil tanker and bulk carrier reliability. Int. J. Nav. Archit. Ocean Eng. 10 (1), 21–36. https://doi.org/10.1016/j.ijnaoe.2017.03.010.

Cao, Y., Wang, X., Wang, Y., Fan, S., Wang, H., Yang, Z., Liu, Z., Wang, J., Shi, R., 2023a. Analysis of factors affecting the severity of marine accidents using a data-driven Bayesian network. Ocean Eng. 269, 113563. https://doi.org/10.1016/j.oceaneng.2022.113563.

Cao, Y., Wang, X., Yang, Z., Wang, J., Wang, H., Liu, Z., 2023b. Research in marine accidents: a bibliometric analysis, systematic review and future directions. Ocean Eng. 284, 115048. https://doi.org/10.1016/j.oceaneng.2023.115048.

Chan, J.P., Pazouki, K., Norman, R.A., 2023. An experimental study into the fault recognition of onboard systems by navigational officers. J. Mari. Eng. Technol. 22 (2), 101–110. https://doi.org/10.1080/20464177.2022.2143312.

Chen, H., Liu, S., Wanyan, X., Pang, L., Dang, Y., Zhu, K., Yu, X., 2023a. Influencing factors of novice pilot SA based on DEMATEL-AISM method: from pilots' view. Heliyon 9 (2), e13425. https://doi.org/10.1016/j.heliyon.2023.e13425.

Chen, J., Di, Z., Shi, J., Shu, Y., Wan, Z., Song, L., Zhang, W., 2020. Marine oil spill pollution causes and governance: a case study of Sanchi tanker collision and explosion. J. Clean. Prod. 273, 122978. https://doi.org/10.1016/j.jclepro.2020.122978.

Chen, X.-l., Lin, W.-D., Liu, C.-X., Yang, F.-Q., Guo, Y., Li, X., Yuan, S.-Q., Reniers, G., 2023b. An integrated EDIB model for probabilistic risk analysis of natural gas pipeline leakage accidents. J. Loss Prev. Process. Ind. 83, 105027. https://doi.org/10.1016/j.jlp.2023.105027.

Demirci, S.M.E., Canimoglu, R., Elcicek, H., 2023. Analysis of causal relations of marine accidents during ship navigation under pilotage: a DEMATEL approach. Proc. IME M J. Eng. Marit. Environ. 237 (2), 308–321. https://10.1177/14750902221127093.

Eisner, J., 2023. Time-and-Space-Efficient weighted deduction. Trans. Assoc. Comput. Lingu. 11, 960–973. https://doi.org/10.1162/tacl_a_00588.

European Maritime Safety Agency, 2023. The EU Maritime Profile - maritime safety. https://www.emsa.europa.eu/eumaritimeprofile/section-3-maritime-safety.html. Access on May 06, 2024.

Fan, S., Blanco-Davis, E., Yang, Z., Zhang, J., Yan, X., 2020. Incorporation of human factors into maritime accident analysis using a data-driven Bayesian network. Reliab. Eng. Syst. Saf. 203, 107070. https://doi.org/10.1016/j.ress.2020.107070.

Feng, J., Li, X., Mao, B., Xu, Q., Bai, Y., 2017. Weighted complex network analysis of the Beijing subway system: train and passenger flows. Phys. Stat. Mech. Appl. 474, 213–223. https://doi.org/10.1016/j.physa.2017.01.085.

Feng, Y., Wang, X., Chen, Q., Yang, Z., Wang, J., Li, H., Xia, G., Liu, Z., 2024a. Prediction of the severity of marine accidents using improved machine learning. Transport. Res. E Logist. Transport. Rev. 188, 103647. https://doi.org/10.1016/j.tre.2024.103647.

Feng, Y., Wang, X., Luan, J., Wang, H., Li, H., Li, H., Liu, Z., Yang, Z., 2024b. A novel method for ship carbon emissions prediction under the influence of emergency events. Transport. Res. C Emerg. Technol. 165, 104749. https://doi.org/10.1016/j.trc.2024.104749.

Feng, Y., Wang, Z., Dong, Q., 2021. How to Analyze the Urban Rail Transit Network in the Combination View of Complex Network and Clustering: Take Shenzhen as an Example, 15-17 Oct. 2021.

Feng, Y.W., Liu, Z.J., Jiang, Z.Y., Xia, G.Q., Cao, Y.H., Wang, X.J., Wang, H.X., 2023. Analysis of factors affecting ship collisions based on association rule mining and complex network theory. J. Dalian Marit. Univ. 49 (3), 31–44.

Feng, Y.W., Wang, H.X., Xia, G.Q., Cao, W.J., Li, T.Y., Wang, X.J., Liu, Z.J., 2024c. A machine learning-based data-driven method for risk analysis of marine accidents. J. Mari. Eng. Technol. https://doi.org/10.1080/20464177.2024.2368914.

Guan, W., Zhao, M.Y., Zhang, C.B., Xi, Z.Y., 2023. Generalized behavior decision-making model for ship collision avoidance via reinforcement learning method. J. Mar. Sci. Eng. 11 (2), 273. https://doi.org/10.3390/jmse11020273.

Jovanović, I., Perčić, M., BahooToroody, A., Fan, A., Vladimir, N., 2024. Review of research progress of autonomous and unmanned shipping and identification of future research directions. J. Mari. Eng. Technol. 1–16. https://doi.org/10.1080/20464177.2024.2302249.

Kuzu, A.C., 2021. Risk analysis of break-in-two accident of ships using fuzzy DEMATEL method. Ocean Eng. 235, 109410. https://doi.org/10.1016/j.oceaneng.2021.109410.

Lan, H., Ma, X., Qiao, W., Deng, W., 2023. Determining the critical risk factors for predicting the severity of ship collision accidents using a data-driven approach. Reliab. Eng. Syst. Saf. 230, 108934. https://doi.org/10.1016/j.ress.2022.108934.

Lee, J.-S., Yu, Y.-U., 2023. Calculation of categorical route width according to maritime traffic flow data in the Republic of Korea. J. Mari. Eng. Technol. 22 (5), 222–232. https://doi.org/10.1080/20464177.2023.2223396.

Li, H., Yang, Z., 2023. Incorporation of AIS data-based machine learning into unsupervised route planning for maritime autonomous surface ships. Transport. Res. E Logist. Transport. Rev. 176, 103171. https://doi.org/10.1016/j.tre.2023.103171.

Li, Z., She, J., Guo, Z., Du, J., Zhou, Y., 2024. An evaluation of factors influencing the community emergency management under compounding risks perspective. Int. J. Disaster Risk Reduc. 100, 104179. https://doi.org/10.1016/j.ijdrr.2023.104179.

Liu, Y.Q., Jiang, J.Y., Zhang, Z.X., Huang, Q.L., Chen, L.H., Huang, Y.P., Zou, X.H., Nie, Y., Liu, M.Q., Zheng, Y.Z., 2024. Exploring the efficacy of Phyllanthus emblica L. based on association rule mining and multidimensional analysis. CyTA - J. Food 22 (1). https://doi.org/10.1080/19476337.2023.2293920.

Lutfi Tunçel, A., Bal Beşikçi, E., Akyuz, E., Arslan, O., 2023. Safety analysis of fire and explosion (F&E) accidents risk in bulk carrier ships under fuzzy fault tree approach. Saf. Sci. 158, 105972. https://doi.org/10.1016/j.ssci.2022.105972.

Ma, L., Ma, X., Lan, H., Liu, Y., Deng, W., 2022a. A data-driven method for modeling human factors in maritime accidents by integrating DEMATEL and FCM based on HFACS: a case of ship collisions. Ocean Eng. 266, 112699. https://doi.org/10.1016/j.oceaneng.2022.112699.

Ma, L., Ma, X., Lan, H., Liu, Y., Deng, W., 2022b. A methodology to assess the interrelationships between contributory factors to maritime transport accidents of dangerous goods in China. Ocean Eng. 266, 112769. https://doi.org/10.1016/j.oceaneng.2022.112769.

Ma, X., Deng, W., Qiao, W., Lan, H., 2022c. A methodology to quantify the risk propagation of hazardous events for ship grounding accidents based on directed CN. Reliab. Eng. Syst. Saf. 221, 108334. https://doi.org/10.1016/j.ress.2022.108334.

Olorvida, R.C., Bande, R.A., Ngalot, D., Lacaba, R., Codilla, J., Arcuino, L.A., Egloso, N., Aro, J.L., Maturan, F., Ocampo, L., 2023. Grey weighted influence non-linear gauge systems (WINGS) for evaluating consumption barriers of refurbished mobile phones for a circular economy. Cleaner Res. Consu. 8, 100091. https://doi.org/10.1016/j.clrc.2022.100091.

Özaydın, E., Fışkın, R., Uğurlu, Ö., Wang, J., 2022. A hybrid model for marine accident analysis based on Bayesian Network (BN) and Association Rule Mining (ARM). Ocean Eng. 247, 110705. https://doi.org/10.1016/j.oceaneng.2022.110705.

Pearce, D.J., 2016. A space-efficient algorithm for finding strongly connected components. Inf. Process. Lett. 116 (1), 47–52. https://doi.org/10.1016/j.ipl.2015.08.010.

Rezaee, S., Pelot, R., Ghasemi, A., 2016. The effect of extreme weather conditions on commercial fishing activities and vessel incidents in Atlantic Canada. Ocean Coast Manag. 130, 115–127. https://doi.org/10.1016/j.ocecoaman.2016.05.011.

Sakar, C., Toz, A.C., Buber, M., Koseoglu, B., 2021. Risk analysis of grounding accidents by mapping a Fault Tree into a bayesian network. Appl. Ocean Res. 113, 102764. https://doi.org/10.1016/j.apor.2021.102764.

Shi, J., Liu, Z., Feng, Y., Wang, X., Zhu, H., Yang, Z., Wang, J., Wang, H., 2024. Evolutionary model and risk analysis of ship collision accidents based on complex networks and DEMATEL. Ocean Eng. 305, 117965. https://doi.org/10.1016/j.oceaneng.2024.117965.

Sokukcu, M., Sakar, C., 2022. Risk analysis of collision accidents during underway STS berthing maneuver through integrating fault tree analysis (FTA) into Bayesian network (BN). Appl. Ocean Res. 126, 103290. https://doi.org/10.1016/j.apor.2022.103290.

Soner, O., 2021. Application of fuzzy DEMATEL method for analysing of accidents in enclosed spaces onboard ships. Ocean Eng. 220, 108507. https://doi.org/10.1016/j.oceaneng.2020.108507.

Tian, H., Liu, Y., Li, J.C., Xing, Q.W., Sun, H., Tian, Y.J., 2024. Satellite nighttime remote sensing promotes the spatially refined monitoring and assessment of offshore fishery. Intern. J. Dig. Earth 17 (1). https://doi.org/10.1080/17538947.2024.2322762.

Ung, S.T., 2019. Evaluation of human error contribution to oil tanker collision using fault tree analysis and modified fuzzy Bayesian Network based CREAM. Ocean Eng. 179, 159–172. https://doi.org/10.1016/j.oceaneng.2019.03.031.

Wang, H., Liu, Z., Wang, X., Huang, D., Cao, L., Wang, J., 2022. Analysis of the injury-severity outcomes of maritime accidents using a zero-inflated ordered probit model. Ocean Eng. 258, 111796. https://doi.org/10.1016/j.oceaneng.2022.111796.

Wan, C., Zhao, Y., Zhang, D., Fan, L., 2023. A system dynamics-based approach for risk analysis of waterway transportation in a mixed traffic environment. Maritime Pol. Manag. 51 (6), 1147–1169. https://doi.org/10.1080/03088839.2023.2224328.

Wang, H.X., Liu, Z.J., Wang, X.J., Graham, T., Wang, J., 2021. An analysis of factors affecting the severity of marine accidents. Reliab. Eng. Syst. Saf. 210, 107513. https://doi.org/10.1016/j.ress.2021.107513.

Wang, J., Wang, X., Feng, Y., Cao, Y., Guo, Z., Liu, Z., 2023a. Assessing the connectivity reliability of a maritime transport network: a case of imported crude oil in China. J. Mar. Sci. Eng. 11 (8), 1597. https://doi.org/10.3390/jmse11081597.

Wang, J., Zhou, Y., Zhuang, L., Shi, L., Zhang, S., 2023b. A model of maritime accidents prediction based on multi-factor time series analysis. J. Mari. Eng. Technol. 22 (3), 153–165. https://doi.org/10.1080/20464177.2023.2167269.

Wang, M., Tian, Y., Zhang, K., 2023c. The fuzzy weighted influence nonlinear gauge system method extended with D numbers and MICMAC. Compl. Intelli. Syst. 9 (1), 719–731. https://doi.org/10.1007/s40747-022-00832-4.

Wu, P., Chen, Q., Chen, Y., Chen, S., Zou, J., 2023. ISM-MICMAC based safety risk sources analysis and control measures for underground engineering of urban rail transit projects. J. Eng. Res. 11 (3), 40–50. https://doi.org/10.1016/j.jer.2023.100076.

Xin, X., Liu, K., Li, H., Yang, Z., 2024. Maritime traffic partitioning: An adaptive semi-supervised spectral regularization approach for leveraging multi-graph evolutionary traffic interactions. Transport. Res. Part C: Emerg. Technol. 164, 104670. https://doi.org/10.1016/j.trc.2024.104670.

Xing, M., Luo, X., Zan, Y., Yang, L., Jin, H., Luo, J., 2023a. Identification of factors affecting hoisting quality of large offshore structures and analysis of their coupling relationship based on grey-DEMATEL-ISM-MICMAC. Ocean Eng. 280, 114805. https://doi.org/10.1016/j.oceaneng.2023.114805.

Xing, Y., Meng, W., Zhou, J., Hu, F., Meng, L., 2023b. DEMATEL, AISM, and MICMAC-based research on causative factors of self-build housing fire accidents in rural areas of China. Fire 6 (5), 179. https://doi.org/10.3390/fire6050179.

Yan, K., Wang, Y., Wang, W., Qiao, C., Chen, B., Jia, L., 2023. A system-theory and complex network-fused approach to analyze vessel–wind turbine allisions in offshore wind farm waters. J. Mar. Sci. Eng. 11 (7), 1306. https://doi.org/10.3390/jmse11071306.

Zhang, M., Kujala, P., Hirdaris, S., 2022a. A machine learning method for the evaluation of ship grounding risk in real operational conditions. Reliab. Eng. Syst. Saf. 226, 108697. https://doi.org/10.1016/j.ress.2022.108697.

Zhang, Y.Q., Chang, Y., Wang, C.B., Fung, J.C.H., Lau, A.K.H., 2022b. Life-cycle energy and environmental emissions of cargo ships. J. Ind. Ecol. 26 (6), 2057–2068. https://doi.org/10.1111/jiec.13293.

Zhang, M., Taimuri, G., Zhang, J., Zhang, D., Yan, X., Kujala, P., Hirdaris, S., 2025. Systems driven intelligent decision support methods for ship collision and grounding prevention: Present status, possible solutions, and challenges. Reliabil. Eng. Syst. Safet. 253, 110489. https://doi.org/10.1016/j.ress.2024.110489.