Reliability Engineering and System Safety 254 (2025) 110636

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

Investigation of the risk influential factors of maritime accidents: A novel topology and robustness analytical framework

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ARTICLE INFO

Keywords:
Maritime transportation
Maritime safety
Maritime accident
Association rule
Complex network

ABSTRACT

This study aims to develop a novel and fully data-driven approach to analyse the maritime accidents risk influential factors (RIFs) by integrating Association Rule Mining (ARM) and Complex Network (CN) modelling. Firstly, a comprehensive dataset comprising 21,206 maritime accident records from Marine Accident Investigation Branch and Transportation Safety Board is collected and processed to serve as the foundational data source supporting the development of the new approach. Secondly, a novel Combined Association Rule Mining method is proposed to extract the interconnections among RIFs, with the mined results mapped into a CN framework. Finally, two importance ranking algorithms, namely the PageRank-Information-Entropy algorithm and edge betweenness centrality, are applied to identify the key RIFs and their information transmission paths. By simulating deliberate and random attacks within networks, a robustness analysis is conducted to further explore the evolution of RIFs. The findings reveal that ship-related factors demonstrate greater centrality and connectivity, exerting a more substantial influence on information propagation within the network structure. The robustness analysis illustrates that strategic node and edge removals are effective in preventing risk propagation. It therefore makes contributions to the development of a theoretical basis for stakeholders to develop cost-effective preventive measures against specific RIFs, ultimately enhancing maritime safety.

1. Introduction

In recent years, the rising volumes of maritime trade have exposed this sector to a heightened risk of maritime accidents. According to data from the European Maritime Safety Agency (EMSA), the period spanning 2014 to 2021 witnessed a total of 21,173 reported maritime casualties and accidents, resulting in substantial human and property losses [1].

Despite extensive efforts made by various stakeholders in this domain, the state of maritime safety remains critical due to many uncertainties. In essence, maritime accidents arise from a complex interplay of multiple Risk Influential Factors (RIFs) including, but not limited to ship conditions [2], weather conditions [3], geographical factors [4], navigational elements [5], and more recently, emerging cyber risks [6]. These factors mutually influence each other, leading to a sequence of events that ultimately result in an accident. Although maritime safety authorities and global shipping companies have dedicated considerable resources to enhance safety standards and service quality (e.g., increasing automation on board ships and coordinating with relevant organisations to strengthen regulations and emergency responses), accidents still occur [7]. The occurrence of an accident necessitates a thorough investigation, which involves collecting facts and data, analysing gathered information, determining root causes, prioritizing contributing factors, and formulating conclusions and recommendations [8]. Key to the success of any such accident investigation is the identification of the key RIFs, given their high degree of interdependence and dynamic nature. Therefore, the primary aim of this study is to develop a novel data-driven approach to enable effective assessment of key RIFs of maritime accidents, addressing today's fast-changing shipping operations of high uncertainty. This study analyses maritime accident RIFs from a global systematic perspective with a focus on the interactive network features of the RIFs and hence, differs from previous analyses in the literature that tends to focus on local independent considerations.

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https://doi.org/10.1016/j.ress.2024.110636
Received 12 February 2024; Received in revised form 19 October 2024; Accepted 5 November 2024
Available online 6 November 2024
0951-8320/

Furthermore, the novelty of this study lies in the systematic analysis of comprehensive accident data that supports the development of new approaches.

This study's structure is organised as follows: Section 2 critically assesses the literature on both maritime accident RIFs studies and data-driven approaches to accident analysis. In Section 3, research data is methodically presented, and a hybrid approach using Association Rule Mining (ARM) and Complex Network (CN) modelling is also proposed. Based on the topological and robustness analysis from the analytical framework, the results are demonstrated in Section 4. Section 5 discusses the results and presents implications. Finally, the conclusions are presented in Section 6.

2. Literature review

2.1. Research on RIFs in maritime safety

The evolution of maritime safety research has refined the identification of RIFs contributing to maritime accidents. Table 1 outlines the main findings from an in-depth literature review, based upon representative research papers corresponding to different RIFs and their respective findings.

The critical review results reveal that the primary data sources in the above papers are the accident investigation statistics from worldwide maritime authorities, which typically contain detailed explicit information such as the condition of the vessels involved, environmental factors at the time of the accidents, and the consequences. Based on these contents, researchers can summarise these accidents and extract relevant RIFs.

From a systematic review, current research on this topic can be further categorised into studies with and without human factors based on the RIFs involved. On the one hand, human factors are recognised as critical contributors to maritime accidents. However, analysing the influence of human factors in the evolution of an accident requires an in-depth survey during the accident investigation phase, which is sometimes challenging due to their complication and qualitative features. Often, human-related data mainly exist in textual form in the accident investigation reports and is challenging to conduct any in-depth quantitative analysis due to lacking an uniform statistical standard. Consequently, some studies attempted to manually extract human information from accident investigation reports to address the incompleteness of such data [10,21,22]. Although the manual extraction manner based on expert experience and surveys can reflect real-world scenarios to a certain extent, it inherently introduces subjectivity and further uncertainty into the analysis.

Table 1
Relevant papers related to different RIFs.

RIFs	Refs.	Findings
Ship type	[3,9,10]	Due to a lack of resistance and resilience to hazardous situations, fishing vessels are generally recognised to be vulnerable. Furthermore, ships carrying special and hazardous goods are more susceptible to fires, explosions and cargo leakages during accidents than other types, hence being easier to cause serious environmental pollution and loss of human lives.
Ship parameter	[2,9,11,12]	Parameters such as ship size, engine power and gross tonnage show a correlation with maritime accidents.
Accident type	[13–15]	In general, sinking is considered as the type of accident that results in the most casualties. While issues like cargo or fuel leakage due to collisions, explosions or mechanical damages are equally critical.
Weather and climate	[16–18]	Severe wind and wave conditions increase the probability of maritime accidents and exacerbate their severity.
Channel condition	[4,19,20]	Channel conditions, such as navigational density, channel width and depth, increase the risk of collisions and contact between ships, especially in port areas and inland waterways.

On the other hand, studies on objective factors serves as an effective approach to exploring the representative and independent RIFs in maritime accidents, based on historical data [15,23,24]. The rationale behind this approach is that known statistics can provide valid and objective validation and support for the introduction of new methods. A data-driven approach relies on actual data than subjective judgement, reducing personal or cultural biases in the analysis process. At the same time, it improves the reproducibility and credibility of the research. Despite these advancements, it still has a discernible limitation in the absence of a global analysis of the interactive and dynamic effects resulting from multiple RIFs. Therefore, these highlight the need to explore maritime accident RIFs from the dynamic and objective perspectives.

2.2. Research on modelling methods of maritime accident analysis

A diverse range of methods has been applied in the literatures of modelling accident analysis, including both traditional and emerging methods. These are reviewed below in turn.

2.2.1. Traditional methods

Traditional maritime accident analysis methods typically explore the causes of accidents through qualitative or subjective evaluations. Such methods include Human Factors Analysis and Classification System (HFACS) [25], Analytic Hierarchy Process (AHP) [26], Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [27] and fuzzy theory [28]. These methods have proven effective in incorporating expert knowledge, leading to results that align with real-world scenarios. The underlying mechanisms and processes of these methods are generally identifiable. For instance, an innovative study demonstrated the adaptability of the modified HFACS for Passenger Vessel collisions (HFACS-PV) analysis [29]. Wu et al. [30] proposed a fuzzy-TOPSIS framework to assess safety control measures under complex navigation conditions. Oraith et al. [31] analysed the human factors affecting pilot operations using AHP, and the hierarchical structure of the study was established mainly through the utilization of questionnaires and expert knowledge.

Despite the valuable contributions of such traditional methods, they suffer from a notable limitation due to their reliance on expert judgment for determining structural elements or weighting factors. It is important to acknowledge that variations in preferences among different experts will lead to disparate outcomes. This inherent drawback can impact the accuracy of assessments, leading to the need for novel solutions.

2.2.2. Emerging methods

To improve the objectivity, accuracy, and capability to predict potential risks, data-driven approaches have emerged, attracting increasing attention [32]. Contemporary maritime safety research has applied different approaches, such as regression analysis (e.g., linear regression and logic regression), cluster analysis (e.g., K-means), tree-structured algorithms (e.g., accident trees and decision trees), network-structured algorithms (e.g., Bayesian networks and CN) and mining algorithms (e.g., text mining and ARM) to comprehensively assess risks during ship navigation [28]. To facilitate comparative analysis, Table 2 summarises different data-driven methods, highlighting their strengths and weaknesses, especially in light of their performance of the target methods.

Research on maritime accidents can benefit to some extent from the analysis of accidents in other transport modes, including railways [43] and aviation [44]. These studies have adeptly incorporated CN to the research on transport safety by abstracting real accident causation and relationships into nodes and edges within networks. This abstraction allows for the application of CN theory to enhance the explanatory

Table 2
Relevant papers based on different data-driven methods.

Refs.	Methods	Application	Advantage	Disadvantage
[9]	Ordered logistic regression (OLR)	A regression technique to evaluate the relationship between maritime accident severity and RIFs.	Applicable to ordered categorical dependent variables (e.g., severity), highly interpretable and does not require the linearity assumption.	Multiple covariance issues between RIFs, and high data quality requirement.
[33]	HFACS and Bayesian network (BN)	A hybrid methodology to investigate human and organizational factors in collision accidents.	Ability to incorporate the hierarchical framework with quantitative analysis.	Model validation issues and sensitive to missing data.
[34]	Object-oriented BN	A quantitative risk assessment of navigational accidents in ice-covered Arctic waters	Ability to reflect relationships between RIFs and quantify their impacts.	Additional decision-making methods are needed to evaluate the effectiveness.
[35]	Text mining	An algorithm capable of extracting keywords from accident reports.	Ability to extract information from unstructured data.	Computationally complex, data quality issues and limited explicability.
[36, 37]	ARM	A comparative analysis between two ARM algorithms.	Suitable for large-scale data and discovering implicit relationships.	Difficult to explain results based solely on model parameters.
[38]	ARM	An algorithm to mine the critical factors of ship total loss accidents.	Ideal for initial exploration and discovering implicit relationships.	Complexity increases with data volume and variety.
[24]	BN	A data-driven model to analyse the RIFs of maritime accidents.	Strong predictability and explainability.	Computationally complex for a large network, expert/manual intervention.
[39]	A Direction-Constrained Space-Time Prism (DC-STP) approach	An approach for examining moving objects with respect to space and time, modelling collision risk.	Applicable to multi-ship involved risk evaluation	Computational efficiency for a more complex scenario needs to be improved.
[40]	Least Absolute Shrinkage and Selection Operator (LASSO) and BN	A data-driven combined method to investigate the human fatigue.	Strong explainability and easy to handle multiple data types.	Limited data and sensitive to missing data.
[41]	CN	A framework to evaluate marine traffic situation.	Ability to visualise and model complex relationships and couple with other models.	Lacks a basis for network establishment and systematic dynamic evaluation.
[42]	CN	A comprehensive framework to investigate key factors in collision accidents.	Ability to model and visualise complex relationships.	Lacks systematic topological analysis and dynamic evaluation.

power of risk analysis.

In the maritime safety research domain, although Sui et al. [41] and Sui et al. [45] have explored the topological characteristics of maritime traffic situational awareness by employing CN, the process of establishing CN remains unclear in terms of data quality and quantity, parameter setting and model validation. These drawbacks are inherent in the CN method. To address these issues, Lan et al. [42] utilised the rule mining capability of ARM to improve the evidence of the CN structure. ARM, a common data mining technique in unsupervised learning, exhibits capacities to uncover relationships between data to extract valuable insights. Hence ARM can assist in identifying contributing factors and exploring links within accident investigation, mitigating certain limitations of CN as a foundational modelling approach [37]. However, the main objective of Lan et al. [42] was to predict the severity of accidents through a subsequent random forest approach. Consequently, the topological analysis of that study was primarily discussed from the perspective of node degree, making it leaving research rooms of fully capturing a comprehensive global topology pattern and the evolution of robustness.

2.3. Research contributions

Both the in-depth reviews pertaining to the RIFs of maritime accidents and the modelling methods reveal a pressing need for a new analytical framework to address the issues such as the lack of a data-driven approach to objectively conduct the topological and robustness analysis of maritime accident RIFs. Therefore, this paper aspires to enrich the field of maritime accident investigation by harnessing cutting-edge methodologies, across the following distinct dimensions:

1. An up-to-date and comprehensive database is established. Maritime accident analysis suffers from incomplete and non-comprehensive databases, resulting in the existing results often biased [10,42]. A new maritime accident database containing 21,206 accidents from the Marine Accident Investigation Branch (MAIB) in UK and the Transportation Safety Board (TSB) of Canada spanning the period between 2010 and 2023 is established as the data source. A thorough data quality assessment is conducted to evaluate the reliability of the database.
2. Both the ARM's ability to uncover implicit relationships and the CN's prowess in visualising and analysing intricate relationships are explored simultaneously to enable their individual advantages incorporated in this new maritime accident research framework. A novel Combined Association Rule Mining (CARM) method is developed to identify associations at the factor level. Alongside state-level associations, this study addresses the prevailing uncertainties surrounding the causal factors and evolution mechanisms of maritime accidents from both macro- and micro- perspectives.
3. A comprehensive analytical framework encompassing model construction, topological analysis and robustness analysis is proposed. Six parameters are utilized to measure the topology within this framework. The innovative PageRank-Information-Entropy (PIE) algorithm and edge centrality metric are used to rank key nodes and edges, providing a theoretical basis of robustness analysis.
4. To facilitate a dynamic accident evolution assessment, the reachability matrix (RM) is developed as a novel criterion for evaluating robustness. The Monte Carlo simulation algorithm and the importance ranking results are applied to implement both random and deliberate attacks on nodes and edges for the first time. A comparison of the decrease in robustness using the PIE method versus existing methods demonstrates the superiority of the proposed framework in this study.

3. Methodology

Towards achieving a systematic exploration of maritime accident RIFs, the methodology of this study involves database development, as well as ARM and CN modelling. The methodological framework of this study is shown in Fig. 1.

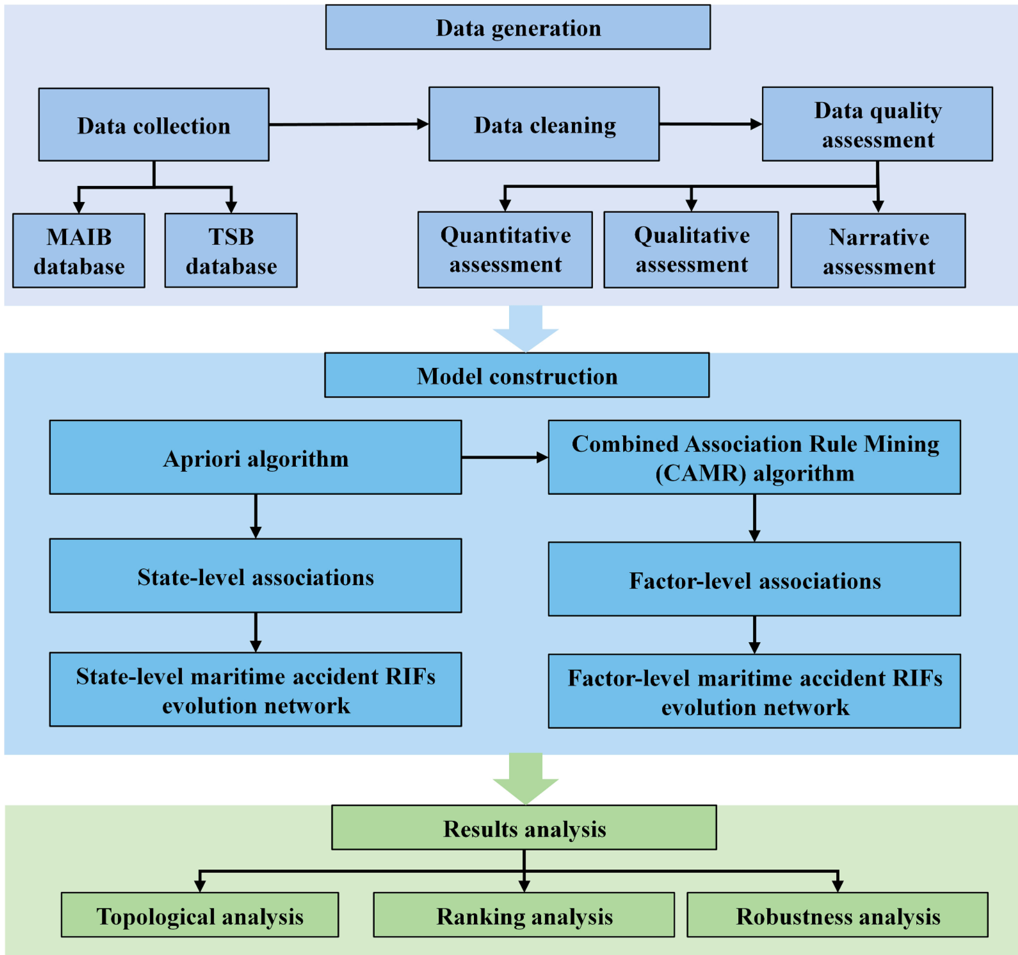

Fig. 1. The methodological framework.

3.1. Research data

The data used in this study are from two sources: the MAIB (https://www.gov.uk/government/organisations/marine-accident-investigation-branch) and the TSB (https://www.tsb.gc.ca/eng/stats/marine/data-6.html). Both authorities specialise in the investigation of transport accidents and maintain comprehensive datasets over an extended timeframe and encompassing a multitude of cases, which provides a sufficient sample size for this study. The reason of using both databases is to minimize data bias introduced by using only one database, and both databased apply similar statistical standards. Moreover, it needs to be recognised that the data used in this study is in CSV format, sourced directly from official maritime accident statistics. While both datasets record limited information on human errors, as such information is not mandatory in their investigation process. To keep the completeness of the developed database and develop an innovative data-driven framework, this study will focus on the evolution of objective factors that have been identified in both data sources during the accident process, which will provide an interesting view on accident prevention.

3.1.1. Data processing

The database released by the TSB contains all maritime accident data recorded by the Marine Safety Information System (MARSIS) from January 1995 to July 2023, with some exceptions and deletions due to protections of third party, personal and privileged information [46]. The database published by the MAIB contains maritime accident data recorded from January 2013 to December 2021. To ensure the relevance and timeliness of the study, as well as to avoid potential bias stemming from data processing, the databases are processed as follows:

(1) Data Selection: Accident data from 2010 onwards in the TSB database (due to the large amount of missing information in the previous data), and from 2013 onwards in the MAIB database, in total of 21,206 accidents, are selected for analysis. This dataset includes 17,923 accidents from TSB and 3283 accidents from MAIB. A visualisation of the distribution of the accident data is shown in Fig. 2, with red scatter points indicating the locations of accidents.
(2) RIFs Selection and Classification: In the original MAIB and TSB databases, each row represents an accident record, and each column represents a RIF. Considering the feasibility of the database and the desire to select the most comprehensive RIFs possible, this study, referring to relevant literature [10,47,48] and actual accident statistics, selects 13 RIFs in total. Meanwhile, a comprehensive maritime accident RIFs classification criterion is established in Appendix 1.

Specifically, the criterion contains two types of factors: internal and external. The former predominantly revolves around the inherent attributes of ships and the nature of accidents. Since the classification criteria for ship type and accident type from the MAIB and TSB are generally consistent, in addition to applying the official classification criteria, this study harmonizes related duplicated or synonymous items. Similarly, external factors primarily pertain to navigational conditions. Both the MAIB and TSB employ similar criteria and units for categorising natural light,

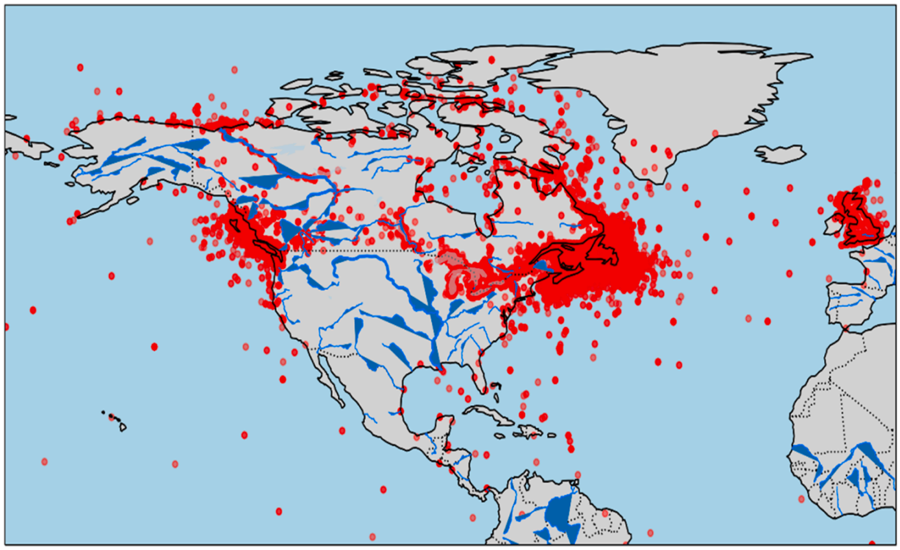

Fig. 2. Distribution of maritime accidents recorded by MAIB and TSB.

sea state, wind and visibility, and therefore, the original categorisation is retained.

(3) Handling Missing Data: The original databases contain missing items. To avoid bias arising from data processing methods, such as data deletion or imputation, the missing data is tackled through the ARM approach (see Section 3.2 for a detailed description). Data cleaning is then executed on the remaining data according to the classification system established in Appendix 1, to obtain the maritime accident database used for analysis.

3.1.2. Data quality assessment

Assessing the data is essential to validate its reliability and quality. This study makes use of the following data quality assessment (DQA) from the perspectives of quantitative [49–51], qualitative [49,52,53], and narrative assessments [52]. The specific dimensions of each assessment are shown in Section 4.1, with specific descriptions and formulas provided in Appendix 2.

3.2. Association rule mining (ARM)

ARM is an algorithm for mining potential relationships in the data. Similar to other machine learning methods (e.g., the TAN-BN model), ARM learns and identifies patterns to reveal insights hidden behind large datasets that may be difficult to discover intuitively by manual analysis. Commonly used ARM algorithms include FP-Growth [54], Apriori [36, 55] and Eclat [38]. Although these different algorithms exhibit slight variations in terms of their runtime and mining patterns, they consistently produce identical outcomes. According to the literature [56], the Apriori algorithm has demonstrated excellent performance in various simulations and hence will be chosen to mine association rules among RIFs in this study.

Specifically, an association rule (AR) contains items A_i and B_j in this study, representing different states of the different RIFs, respectively. In the ARM method, there are three parameters that correspond to the patterns of the RIFs namely: support, confidence and lift, see Eqs. (1)–(3) [38]. The Apriori algorithm is an iterative algorithm that searches for the frequent item sets by examining them layer by layer. The search process depends on the thresholds of minimum support and minimum confidence.

$Support(A_iB_j)$ signifies the probability of the co-occurrence of items A_i and B_j:

$$Support(A_iB_j) = \frac{N_{A_iB_j}}{N} \tag{1}$$

where:

A_iB_j represents the simultaneous occurrence of items A_i and B_j;
$N_{A_iB_j}$ represents the count of accidents where A_i and B_j co-occur;
N represents the total accidents count.

$Confidence(A_i \Rightarrow B_j)$ is the conditional probability of item B_j occurring when item A_i is observed.

$$Confidence(A_i \Rightarrow B_j) = \frac{Support(A_iB_j)}{Support(B_j)} \tag{2}$$

where $A_i \Rightarrow B_j$ represents the AR between item A_i and item B_j.

$Lift(A_i \Rightarrow B_j)$ is defined as the ratio of $Confidence(A_i \Rightarrow B_j)$ to $Support(B_j)$. A lift value greater than one signifies a strong positive association, a strong negative association is indicated by a value less than one and when the value equals 1, there is no discernible association between the RIFs.

$$Lift(A_i \Rightarrow B_j) = \frac{Confidence(A_i \Rightarrow B_j)}{Support(B_j)} \tag{3}$$

However, as previously noted, convectional ARM techniques primarily deliver results at a micro-level, i.e., items in the rules correspond to states of the different RIFs, and fail to capture associations at a higher, factor level. To overcome this limitation, this study introduces a novel algorithm, the Combined Association Rule Mining (CARM) method, which improves traditional ARM. The pseudocode for CARM is detailed in Table 3. Unlike traditional ARM outputs, CARM not only identifies but also elevates associations to the factor level. To quantify how antecedents influence consequences at this level, a new metric is proposed, the Joint Conviction (JC), which is defined as Eq. (4).

$$JC(A \Rightarrow B) = \sum_i \sum_j Conviction(A_i \Rightarrow B_j) \times \frac{Support(A_i \Rightarrow B_j)}{\sum_i \sum_j Support(A_i \Rightarrow B_j)} \tag{4}$$

where $Conviction(A_i \Rightarrow B_j) = 1 - Support(B_j)/1 - Confidence(A_i \Rightarrow B_j)$. Conviction measures the ratio between the occurrence frequency of A_i when B_j does not occur and the independent occurrence frequency of A_i and B_j when the rule is not applicable. It thus reflects the dependency of

Table 3
The pseudocode of CARM algorithm.

Algorithm 1: Combined Association Rule Mining algorithm
Input: Dataset, **DS**; Minimum support threshold, **min_sup**
Output: CARs
Begin
Calling Association Rule algorithm (Apriori)
Return association rules that satisfy **min_sup** and **lift > 1, AR**
Generate two matrices **C** and **S** with $Conviction(A_i \Rightarrow B_j)$ and $Support(A_i \Rightarrow B_j)$ as elements, respectively, based on the **AR**
Use Eq. (4) to perform scaling nodes operations are performed on C and S based on factors states to form new joint matrices, **JC**
Change the diagonal of **JC** to all Zeros, **CAR**
Transforming **CAR** matrix into association rule format
Return CARs
End

the consequent on the antecedent within an AR. A key attribute of conviction is its asymmetry concerning the support of the itemsets, implying that for the rules "$A_i \Rightarrow B_j$" and "$B_j \Rightarrow A_i$", despite identical support and confidence, their conviction values can differ significantly, thereby revealing deeper insights into rule evaluation.

In Eq. (4), A and B represent different RIFs, while A_i and B_j denote distinct states of these RIFs. The JC metric synthesizes these conviction values across all state pairs, weighting them by their occurrence probabilities to provide a comprehensive measure of influence at the factor level. This approach not only enhances interpretability by aggregating different state convictions into a unified metric but also ensures robustness against the influence of anomalous state pairs, offering a more stable measure of association.

3.3. Complex network

Based on the ARM and CARM methods, the ARs between the states of the RIFs and the CARs between the RIFs are obtained. In this section, antecedents, consequents and the relationships between them are extracted as nodes and edges in networks, respectively. The established CN models can reveal the network structure by explaining topological characteristics, identifying key nodes and edges within the network, and leading to a better understanding of accident evolution mechanisms.

3.3.1. Complex network development

In this study, a network can be expressed as $G = (N, E)$, where $N = \{n_1, n_2, \ldots, n_p\}$ represents the set of nodes (i.e., the states of RIFs or the RIFs), and $E = \{e_1, e_2, \ldots, e_q\}$ represents the set of edges. The network is considered as an adjacency matrix G. If there is a total of p nodes, there are $p \times p$ elements in the matrix G, as shown in Eq. (5):

$$G = \begin{bmatrix} g_{11} & \cdots & g_{1p} \\ \vdots & \ddots & \vdots \\ g_{p1} & \cdots & g_{pp} \end{bmatrix} \tag{5}$$

where $g_{A_iB_j} = w_{A_iB_j} \times e_{A_iB_j}$, $w_{A_iB_j}$ represents the weight of the directed edge from node A_i to node B_j, $e_{A_iB_j}$ represents the index of the AR from node A_i to node B_j, as illustrated in Eq. (6).

$$\begin{cases} e_{A_iB_j} = 1, \ \textit{If } A_i \Rightarrow B_j \textit{ exists} \\ e_{A_iB_j} = 0, \ \textit{otherwise} \end{cases} \tag{6}$$

The direction of the edges can in practice symbolize a chain reaction triggered by a change in the state of one RIF caused by another RIF. The realisation of this reaction relies on the abstract information transfer along the edges. Thus, the direction in the network model will be in line with the sequence of "antecedents" and "consequences" in the mined ARs and CARs. To enhance the theoretical basis for modelling complex network, this study also maps the ARM and CARM results to the CN model through weights, i.e., $w_{A_iB_j} = Confidence\ (A_i \Rightarrow B_j)$ and $w_{AB} = JC(A \Rightarrow B)$.

3.3.2. Network topological characteristics

In the field of accident investigation, the topological analysis of CN has proved effective in identifying key RIFs, and different values of parameters can effectively distinguish the functions of different RIFs [42]. In this study, parameters comprising degree, strength, centrality and the clustering coefficient are discussed in turn, to provide a comprehensive analysis of the RIFs network.

(1) The degree quantifies the number of edges connected to a node, which encompasses both incoming (i.e., in-degree) and outgoing (i.e., out-degree) links. Correspondingly, the algebraic sum of edge weights can be expressed by a parameter named strength, including both in-strength and out-strength. As basic statistical parameters among the network structure, both degree and strength characterise the activity level of a RIF in the network [43]. In practice, nodes with high degree and strength values tend to raise a more pronounced influence on other factors through changes in their own properties during accident evolution.
(2) Degree centrality (DC) serves as a direct index to measure the centrality, assisting in identifying critical RIFs in the network from the perspective of connectivity [57].
(3) Node closeness centrality (NCC) reflects the proximity of a node to other nodes, facilitating the detection of RIFs with high information dissemination rates [42].
(4) Node betweenness centrality (NBC) reflects the hubness and transitivity of a node, i.e., a series of changes that may be induced through a given condition. To compute NBC, it is necessary to compute node betweenness (NB) and subsequently normalise it.
(5) Clustering coefficient (CC) quantifies the likelihood of neighbouring nodes being connected to each other, which thereby can be used to measure the level of clustering in a network [43]. In conventional road traffic networks, the CC is typically used to assess congestion and traffic mobility [58,59]. While in the accident network established in this study, the function of the CC is to discover small-world structures and community structures, thus measuring the closeness of the network and discovering those RIFs that are prone to interact with each other.

3.3.3. Importance ranking of RIFs

To achieve a dynamic analysis of the information transmission of RIFs during the occurrence of maritime accidents, this study uses PageRank-Information-Entropy (PIE) algorithm and edge betweenness centrality (EBC) to further identify and rank key nodes and edges comprehensively.

(1) PageRank-Information-Entropy (PIE) algorithm

PageRank algorithm is a classical ranking method considering the global link structure to assess the importance of nodes [60]. Contrasts with other topological approaches (e.g. DC, NCC, NBC) which are only based on local neighbourhood information, the PageRank algorithm initiates by assigning the initial PageRank values to each node in the network, reflecting their initial importance or centrality within the network. Subsequently, the PageRank algorithm iteratively refines these values until they converge to stable values [61]. The PageRank value is calculated as shown in Eq. (7):

$$PR_i = \beta \sum_{j \in N} \frac{e_{ji}}{d_j^{out}} PR_j + \frac{1-\beta}{p} \tag{7}$$

where $\beta \in [0, 1)$ represents a damping factor to ensure the randomness in traversing nodes, e_{ji} represents the edge from node j to node i, d_j^{out} represents the out-degree of node j, PR_i represents the PageRank value of node i, and p represents the number of nodes.

The traditional PageRank algorithm exhibit its ranking ability in terms of computational efficiency and simplicity. However, it assesses the importance of nodes in a single dimension, and which has certain limitations in the context of complex and dynamically changing network environments. Therefore, based on the traditional PageRank algorithm and inspired by the mutual information theory (a concept of calculating the information interaction between nodes [62]), this study proposes an innovative node importance ranking method, i.e., the PIE algorithm. The pseudocode for the PIE algorithm is detailed in Table 4.

Specifically, in the PIE algorithm, the PageRank value is treated as the initial information retained by each node. Then, a PageRank information matrix (PIM) is developed to achieve the weighted assignment of information, as shown in Eqs. (8) and (9):

$$PIM = \left(\gamma_{ij}\right)_{p\times p} \tag{8}$$

$$\gamma_{ij} = PR_i \times \frac{w_{ij}}{\sum_{k\in N} w_{ik}} \tag{9}$$

where k denotes a node connecting with node i, γ_{ij} denotes information element between node i and node j, and w_{ij} denotes the edge weight between node i and node j.

Based on the PIM, the PageRank mutual information (PMI) between any two connected nodes can be calculated by Eq. (10):

$$PMI_{ij} = \ln\left(\frac{\sum_{k\in N}\gamma_{ij}}{\sum_{k\in N}\gamma_{kj}}\right) \tag{10}$$

Then, the PIE value of each node can be then calculated by Eq. (11):

$$PIE_i = \sum_k PMI_{ik} - \sum_k PMI_{ki} \tag{11}$$

Table 4
The pseudocode for the PIE algorithm.

Algorithm 2 PageRank-Information-Entropy algorithm

Require: A network $G = (N, E)$; a damping factor β; max iterations *maxiter*; convergence threshold *epsilon*.
Ensure: PageRank-Information-Entropy of each node *PIE*
Initialize the PageRank value for each node $PR_i = 1/p$
for iteration from 1 to *maxiter* **do**
  $pre\_PR = PR$
  for each node i **do**
    $sum = 0$
    for each node j **do**
      if $e_{ij} = 1$
      $sum += pre\_PR_j / d_j^{out}$
      end for
      $PR_i = (1-\beta)/p + \beta \times sum$
    end for
    $error = 0$
for each node i **do**
      $error += abs(PR_i - pre\_PR_i)$
    end for
    if $error < epsilon$
      break
end for
Calculate the PageRank mutual information:
$PIM = \left(\gamma_{ij}\right)_{p\times p}$; $\gamma_{ij} = PR_i \times \frac{w_{ij}}{\sum_{k\in N} w_{ik}}$
Initialize the PageRank mutual information between each pair of nodes $PMI_{ij} = 0$
for each node i **do**
  for each node j **do**
    if $i \neq j$ and there is a shortest path from node i to node j
      $PMI_{ij} = \ln\left(\sum_{k\in N}\gamma_{ij} / \sum_{k\in N}\gamma_{kj}\right)$
  end for
end for
Initialize the PageRank information entropy of each node PIE_i
for each node i **do**
  $PIE_i = \sum_k PMI_{ik} - \sum_k PMI_{ki}$
end for
return *PIE*

Therefore, the improved PIE algorithm introduces a multidimensional understanding of RIFs importance from different computational levels. The PIE algorithm combines the mutual information between nodes on the basis of calculating the PageRank value, which means that it not only takes into account the number and quality of edges, but also integrates the strength and direction of information transfer between nodes. This not only helps to identify nodes that are traditionally "important", but also nodes that play a key role in information transfer, network influence and structural stability. The superiority of the PIE algorithm over the traditional methods on importance rank is validated in the experimental section.

(2) Edge betweenness centrality (EBC)

Correspondingly, key edges within the network bear increased responsibilities and act as connecting nodes. Therefore, the objective of edge identification is to reveal the paths in the network that are most critical for the transmission of abstract information, resources, or flows. Cutting off these key edges could potentially halt the ongoing evolution of accidents. Existing methods for ranking edges have their own focus, such as edge information centrality for evaluating the efficiency of communication networks, edge flow centrality for traffic network path identification and edge clustering coefficients for community detection. For the abstracted maritime accident evolution network, EBC can be used to identify bridges or bottleneck paths, which is in line with the aim of this study [63]. In general, calculating the EBC involves considering the frequency of occurrence of a particular edge in the information transfer process (i.e., the number of times that a particular edge lies on the shortest path between any two nodes) and this requires the computation of the edge betweenness (EB) first, followed by normalisation to obtain the EBC, as illustrated in Eqs. (12), (13):

$$EB_{e_v} = \sum_{\substack{i,j,v\in N \\ e_v\in E \\ i\neq j\neq v}} \frac{\sigma_{ij}(e_v)}{\sigma_{ij}} \tag{12}$$

$$EBC_v = \frac{EB_v}{(p-1)(p-2)} \tag{13}$$

where $\sigma_{ij}(e_v)$ represents the number of the shortest paths between node i to node j through edge e_v. σ_{ij} represents the total number of the shortest paths between node i to node j.

3.3.4. Robustness

Network robustness refers to the ability to retain functionality even when a portion of nodes or edges fails [63]. In the maritime accident RIFs network, a complete connecting path represents a complete chain of accident causation, leading to the occurrence of an accident. In this context, network robustness distinguishes itself from previous applications. This concept here represents the ability of the accident evolution network to resist external corrections. Such corrections can refer to manual control of corresponding RIFs within one accident causation chain so as to avoid further evolution of the accident. Therefore, a high robustness level in this study actually denotes a negative effect on mitigating accidents in reality. If the failure of a specific RIF in the network can effectively block the formation of an accident causal chain, the likelihood of an accident occurring should gradually decrease as the robustness diminishes. In this study, the reachability matrix (RM) is developed as a criterion for evaluating the robustness and defined as Eqs. (14) and (15):

$$RM = \begin{bmatrix} rm_{11} & \cdots & rm_{1p} \\ \vdots & \ddots & \vdots \\ rm_{p1} & \cdots & rm_{pp} \end{bmatrix} \tag{14}$$

$$rm_{ij} = \begin{cases} 1, RIF\ i\ can\ reach\ RIF\ j \\ 0, RIF\ i\ cannot\ reach\ RIF\ j \end{cases} \tag{15}$$

Subsequently, the RM calculates the reachability and the network robustness, as shown in Eqs. (16) and (17):

$$Reachability = (ones)_{1\times p}\cdot RM\cdot(ones)_{p\times 1} \tag{16}$$

$$Robustness = \frac{Reachability_{after}}{Reachability_{before}} \tag{17}$$

where $(ones)_{1\times p}$ represents a 1-row p-column matrix with all elements equal to 1, $(ones)_{p\times 1}$ represents a p-row 1-column matrix with all elements equal to 1. In this study, the failures in nodes and edges are simulated by random and deliberate attacks. Both random and deliberate attacks will be conducted on the nodes and edges within the network to assess changes in network robustness [64]. Therefore, in Eq. (17), $Reachability_{after}$ represents the reachability after attacks, and $Reachability_{before}$ represents the reachability before attacks.

During random attacks, the Monte Carlo simulation algorithm is used to randomly generate failed nodes and edges, respectively. The number of such failed nodes and edges is gradually increased from one to all, thereby spanning the entire network. The experiment is repeated 100 times to obtain the complex network robustness changes. While during deliberate attacks, nodes and edges of both networks are attacked based on the importance ranking results obtained from Section 3.3.3, respectively. Then, the attacked nodes or edges are removed from the network at each iteration, and the robustness of the network is calculated. Particularly, results from two other commonly used node ranking methods (i.e., the traditional PageRank algorithm and the Weight LeaderRank algorithm), together with the Monte Carlo random simulation are obtained and compared to validate the superiority of the PIE algorithm.

Distinguishing from realistic networks, such as transport networks or grid networks, this is an innovational attempt to measure the performance of maritime accident evolution networks by the reachability between nodes. In this study, the existence of a connection between two nodes indicates that the occurrence of one RIF causes another RIF, and a complete reachability path of RIFs represents a complete accident causation chain. As attack strategies are implemented (i.e., simulating the measures to be taken in practice), some connections may be severed or some nodes may be removed, both of which result in poorer network reachability, which in turn reduces robustness. Therefore, the robustness variations in this study demonstrate changes in the network performance before and after the attacks, thus revealing the impact of RIFs in the evolution of maritime accidents at the network science level.

4. Results

4.1. Data assessment results

The maritime accident RIFs database used in this study contains a total of 21,206 accidents. Specifically, the database records 13 RIFs with a total of 221,412 items. To assess the feasibility of the database, the results obtained through the DQA are presented in Table 5.

Overall, all quantitative assessments results exceed 50 %, and both qualitative and narrative assessments yield commendable results, thereby validating the overall reliability and suitability of the database.

Specifically, the values of consistency and relevance reach the values of 93.8 % and 87.9 % in the quantitative assessment, a testament to the alignment between the RIFs selected for this study and those found in the original TSB and MAIB databases. In addition, the completeness value is 79.8 % since there are 44,627 missing items and 221,412 known items in the entire database. As an acceptable result, this score ensures that this study is not biased due to the large amount of missing data. However, the accessibility value of the database is relatively low, primarily due to the selective extraction of the information from the original MAIB and TSB databases.

This extraction also affects the accuracy of qualitative analysis to some extent. Some RIFs are obtained by integrating a range of variables at different levels. For example, "ship type" in the original MAIB database has four sub-levels of categorisation, while this study integrates them into a single RIF. Furthermore, since the databases are sourced from the MAIB and the TSB, which are the official investigating organisations for maritime accidents in the UK and Canada respectively. The widely applied investigation system has been modified over decades and recognised by the academic community, carrying credentials and interpretability. Moreover, the maritime accident investigation reports are published or recorded on average 12.47 days after the accident. This also validates the timeliness and accuracy of these accident reports.

Table 5
The DQA results of research data.

Classifications	Dimension	Results
Quantitative assessment	Accessibility	61 %
	Consistency	93.8 %
	Completeness	79.8 %
	Relevance	87.9 %
Qualitative assessment	Accuracy	67.9 %
	Credentials	The source of the data comes from official accident investigation agencies (MAIB and TSB) and can therefore be considered reliable.
	Timeliness	12.47days
	Interpretability	Both the MAIB and the TSB provide corresponding explanatory documents, and the standards they use are internationally recognized and universal.
Narrative assessment	Narrative	Detailed

In addition, a 10 % data sample is randomly selected for narrative assessment. It is found that 76.8 % of the sample contains more than 50 words of narrative description of the relevant accident. The completeness of the data within the sample stands as 81.2 %, which is similar to the overall completeness value, further reinforcing its reliability.

In light of these findings, the maritime accident database established in this study can be considered reliable and feasible for the in-depth analysis. The analytical framework of this study is shown in Fig. 3.

4.2. Association rule results

After completing the DQA, the Apriori algorithm and the CARM algorithm are used to explore the association relationships among the states of RIFs and the RIFs. It is important to note that the results of both algorithms are influenced by the parameter settings. Optimal thresholds for support and confidence are crucial to strike a balance between capturing meaningful associations and avoiding noise. After several trials and with reference to a similar study [42], the minimum support and confidence thresholds are set to 0.1 and 0.3, respectively. The maximum restriction length is set to two, ensuring that each node represents only one RIF.

The association rules are programmed in Python. By calling "Apriori" package and running “CARM algorithm” and inputting the database, 115 ARs and 75 CARs are mined. The distribution of these ARs is visualized in Fig. 4, with the horizontal coordinate representing the support, the vertical coordinate representing the confidence, and the size of the scatter point indicating the lift. In addition, the top ten ARs and CARs ranked by the confidence and the JC values are shown in Tables 6 and 7, where the terms of "Antecedents" and "Consequents" represent the conditions and results in Eqs. (1)–(3).

Fig. 4 reveals that the ARs are centrally distributed within the support range of 0.1–0.25 and the confidence range of 0.3–0.65. By analysing the data in Table 6, it can be found that the top ten ARs are all related to internal factors. Specifically, one AR is related to "ship type", five ARs are associated with "gross tonnage", six ARs pertain to "hull materials", and eight ARs are connected to "length". This suggests a strong correlation between a ship’s inherent characteristics with the

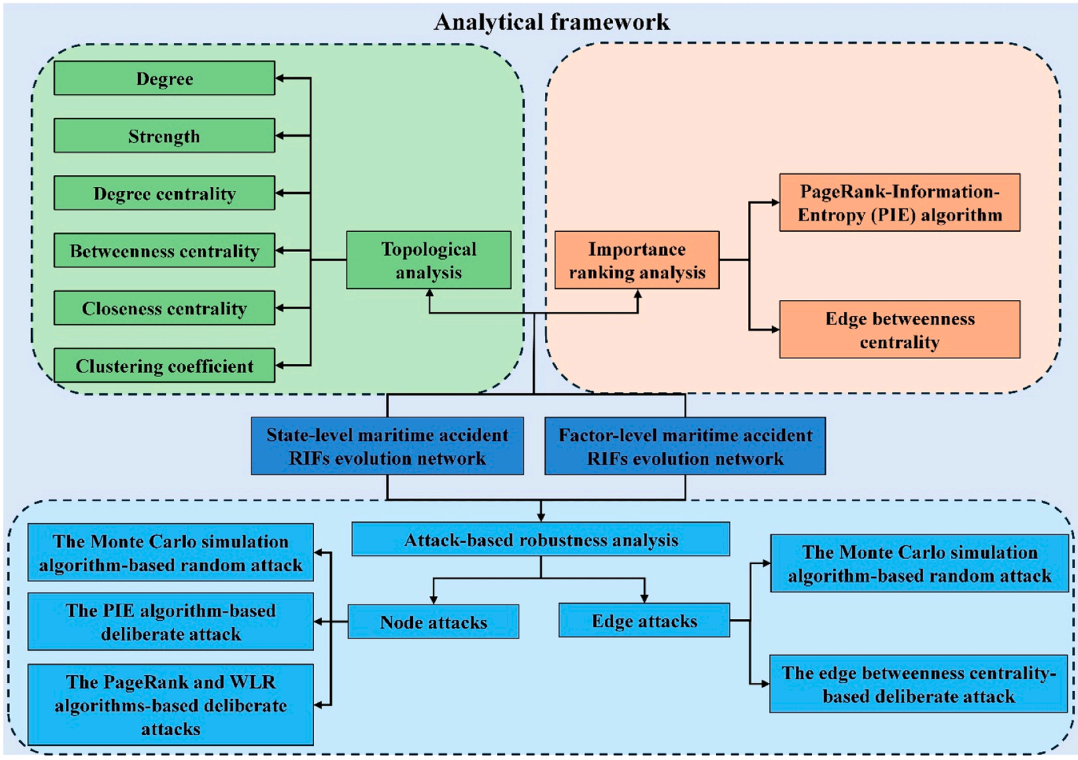

Fig. 3. The analytical framework.

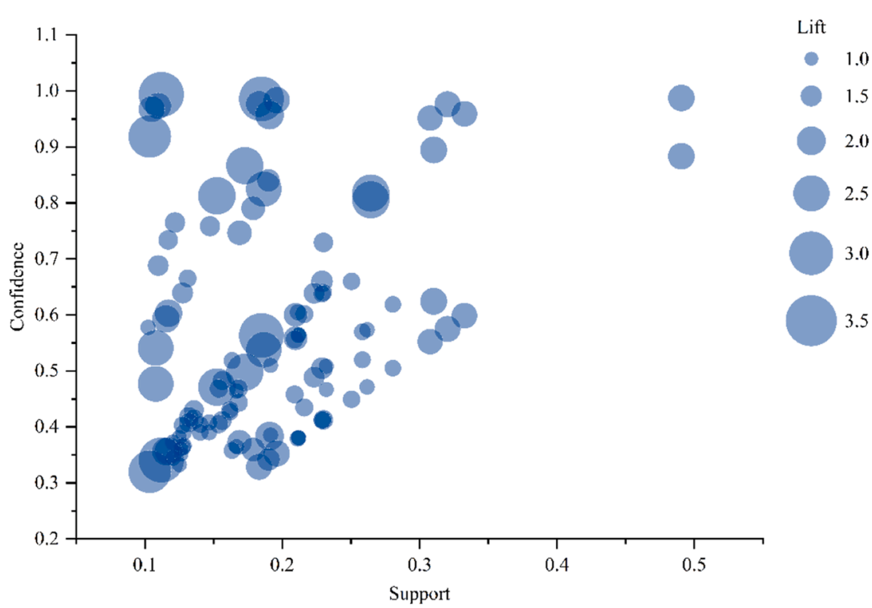

Fig. 4. The distribution of ARs.

occurrence of the accident. Particularly, both SL3 (length > 200 m) and GT2 (gross tonnage > 3000t) exhibit confidence exceeding 0.99. This observation aligns with the conventional perception that larger and longer ships generally have greater cargo carrying capacity [10]. Distinguished from the subjective experience, the ARM approach offers a theoretical basis to reveal these patterns. Moreover, the associations between the RIFs are highly coupled and cross-cutting, which likewise indicates potential accident evolution process. For example, from the results of ARs, an association chain can be integrated by multiple identified associations, e.g., from GT0 (gross tonnage < 500t) to SL0 (length < 50 m) to H2 (hull materials of GRP) to A3 (Hull/machinery damage). This may represent a practical scenario for a small ship with the hull material of GRP, which has a favourable risk to the accident type of hull/machinery damage based on the historical data.

4.3. Complex network development

Based on the ARM and CARM results, two directed weighted complex networks are built: Fig. 5 illustrates the established CN at the state level consisting of 22 nodes and 115 edges; and Fig. 6 illustrates the established CN at the factor level consisting of 10 nodes and 75 edges. The details of each node can be found in Appendix 1.

Table 6
Top 10 ARs at state level ranked by confidence.

Rank	Antecedents	Consequents	Support	Confidence	Lift
1	SL3	GT2	0.1119	0.9937	3.0286
2	GT0	SL0	0.4906	0.9875	1.7778
3	SL2	GT2	0.1848	0.9859	3.0048
4	H2	SL0	0.1959	0.9834	1.7705
5	SL2	H0	0.1831	0.9766	1.7530
6	GT2	H0	0.3203	0.9761	1.7522
7	SL3	H0	0.1095	0.9732	1.7469
8	SL1	H0	0.1048	0.9673	1.7364
9	ST0	SL0	0.3325	0.9591	1.7266
10	H2	GT0	0.1907	0.9569	1.9260

Table 7
Top 10 CARs at factor level ranked by JC.

Rank	Antecedent	Consequent	JC
1	SL	GT	0.9231
2	L	SL	0.8400
3	ST	GT	0.8319
4	GT	SL	0.7960
5	ST	H	0.7778
6	SL	H	0.7683
7	GT	H	0.7551
8	L	A	0.7466
9	ST	SL	0.7280
10	H	GT	0.7175

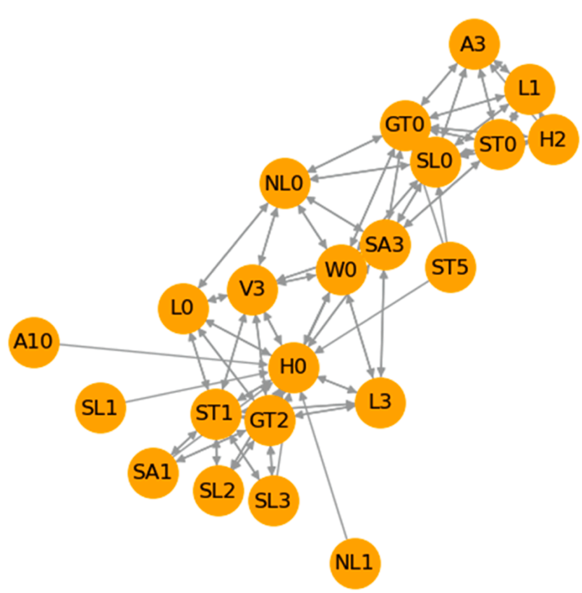

Fig. 5. The established CN at state level based on ARs.

Figs. 5 and 6 position nodes primarily based on their node degree, with nodes having higher node degree located at the centre of the network. An overall analysis of both networks exposes the interconnectivity of the maritime accident RIFs. There exists the information dissemination, energy exchange, interaction or other forms of connectivity among these RIFs. These abstract behaviours can in practice be responded to as a change in the state of one factor triggered by another. The information transfer efficiency of network in Fig. 5 is 0.484, significantly surpassing the transfer efficiency of a stochastic network of a similar size, which is approximately 0.26. This suggests that information in the network is more readily available, and nodes are more likely to swiftly influence each other quickly. Such a well-connected and efficiently propagated evolution network poses a great challenge in efforts to reduce the accident rates.

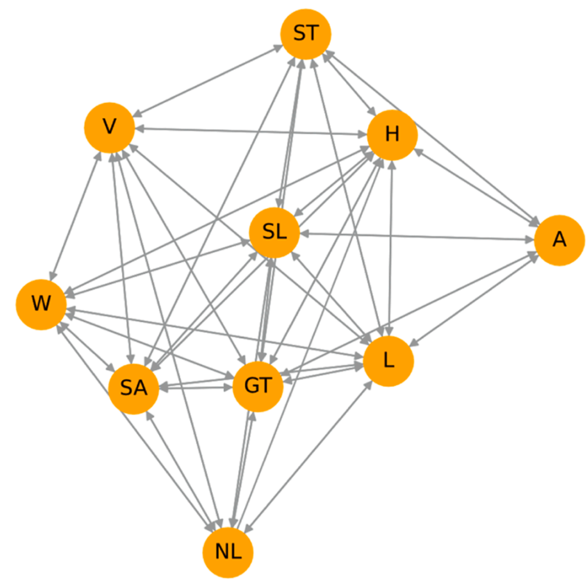

Fig. 6. The established CN at factor level based on ARs.

4.4. Topological analysis

Based on the established networks, this study further investigates six topological parameters for both the state-level network and the factor-level network, as visualised in Figs. 7 and 8 respectively. Topological analysis offers insights from a static network science theoretical perspective.

Specifically, node degree and node strength indicate the diversity of interactions between nodes. Although there are twice as many nodes for internal factors as external factors, the mean values of node degree for internal and external factors are similar, at 10.43 and 10.47 in Fig. 7, and at 15.17 and 14.75 in Fig. 8, respectively. This suggests that the two types of factors have comparable degrees of connectivity and interaction in both networks. Notably, the nodes with the largest degree and strength are H0 (hull materials with steel), followed by GT2 (gross tonnage > 3000t), GT0 (gross tonnage < 500t) and SL0 (length < 50 m) in Fig. 7. Similarly, in Fig. 8, GT (gross tonnage), L (location), H (hull materials) are the nodes with the largest degree and SL (length), GT and H have the largest strength. Conversely, the nodes with the smallest node degree are SL1 (50 m < length < 100 m), A10 (non-accidental events) and NL1 (nightlight), all of which are 1 and all have an in-degree value of 0. This suggests that these nodes only pass interaction information to other nodes without receiving information from other nodes. Both figures theoretically indicate that SL, GT, L and H are four RIFs which interact with most other nodes, and practically reveal that the reliable RIFs including a ship's inherent properties are the basis for its safe navigation.

Furthermore, from the perspective of centrality metrics, H0 (hull materials with steel) has the highest DC, NCC and NBC in Fig. 7. In Fig. 8, the nodes with highest DC, NCC and NBC are GT (gross tonnage) and L (location). Taking H0 as an example, as the central node of the whole network at state level, it not only has the highest degree of proximity to other nodes, but also services as a bridge that connects multiple nodes. Therefore, from the theoretical point of view, a change in the state of H0 significantly influences the efficiency of information transfer within the network, potentially affecting the stability of the network and accelerating the transfer of information about the risk of accidents. From a practical perspective, such changes can make it more difficult for the ship to respond to emergencies, potentially leading to maritime accidents. Hence, regardless of the ship's scenario or characteristics, any alteration in the state of the steel hull (e.g., damage) can impact the ship's stability and manoeuvrability.

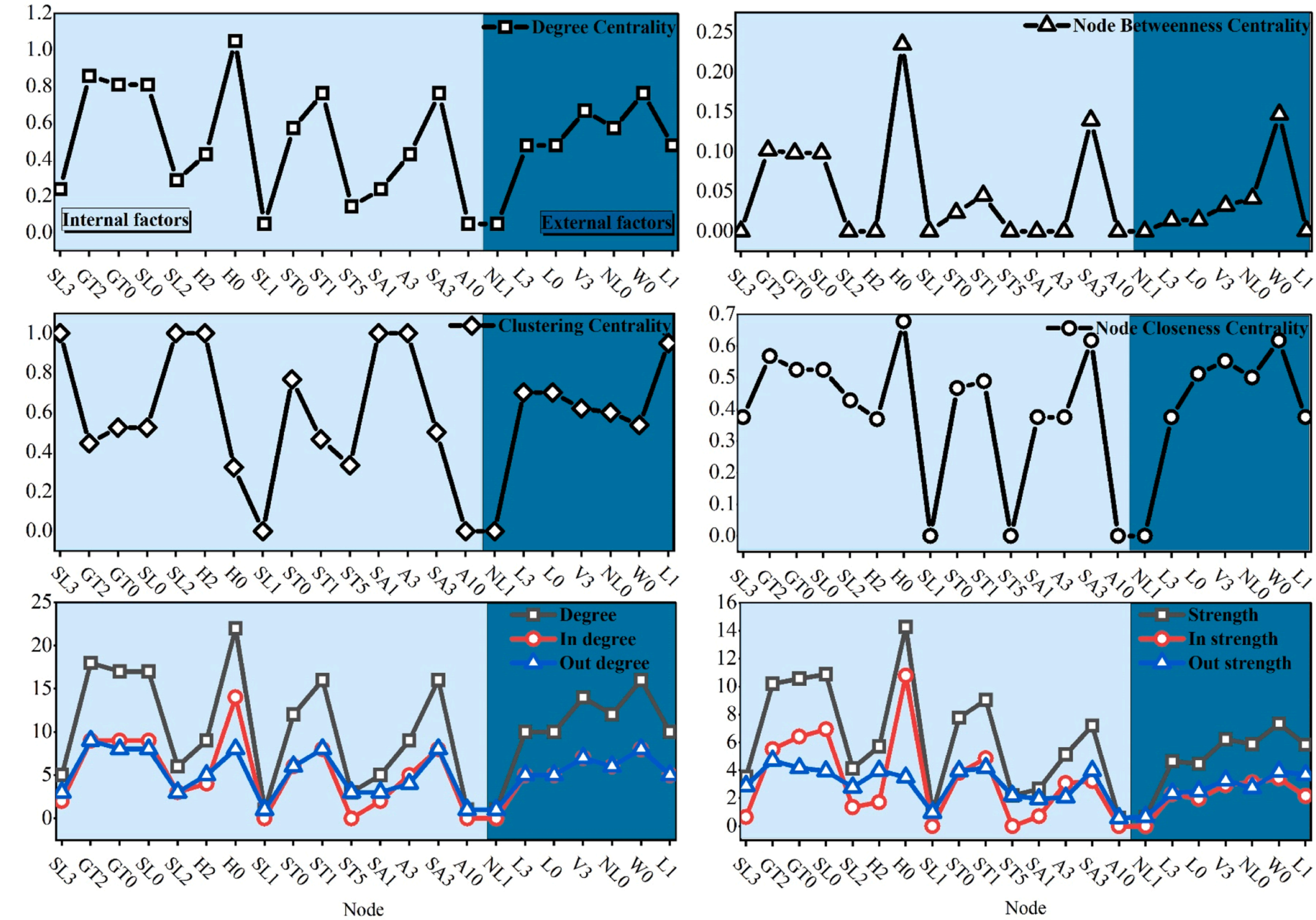

Fig. 7. Topological analysis at state level.

The CC is a value between 0 and 1 and indicates how closely the nodes in the network are connected to each other's neighbours. In Figs. 7 and 8, SL3 (length > 200 m), SL2 (100 m < length < 200 m), H2 (hull materials with GRP), SA1 (10years < ship age < 20years), A3 (hull/machinery damage) and A (accident type) have a CC of 1, which indicates that the neighbouring nodes of these nodes are equally interconnected. The network in this study is structured as a functional network, and the high CC indicates that the nodes belong to the same functional module or community and have similar attributes. This concept can be verified from a practical standpoint. For example, GRP, also known as fibre reinforced plastics, is commonly used in the construction of small and medium-sized ships, such as sailboats and yachts. Although this material reduces the cost and weight of the ship and improves the manoeuvrability, it is still less reliable and stronger than steel. As the ship ages, the GRP hull structure becomes increasingly susceptible to deterioration, consequently elevating the likelihood of hull/machinery damage.

4.5. Ranking analysis

To stop the evolution of risk and to prevent accidents quickly and effectively, key nodes and edges in the network need to be analysed.

4.5.1. The identification of key nodes

The importance of each node is calculated based on the PIE algorithm as shown in Tables 8 and 9. Notably, in addition to L (location), the top five nodes in both tables are all internal factors, highlighting the pivotal role that the ship factors play in maritime accident RIFs network. In addition, W0 (clear weather), V3 (good visibility) and NL0 (daylight) are the top ten external factors in Table 8. This suggests that environmental factors also have a substantial influence on the occurrence of maritime accidents. Indeed, in the public's perception, bad weather is dangerous for ship navigation and it inevitably leads to heightened alertness among crews. Conversely, in good weather conditions, as demonstrated by W0 (clear weather), V3 (good visibility) and NL0 (daylight), it is still crucial to strengthen the safety management and enhance the vigilance of the crew, which can effectively delay the risk evolution and reduce the accident rate.

4.5.2. The identification of key edges

This study ranks the risk evolution paths (i.e., edges) in the network based on the EBC values. The top ten edges of both levels are shown in Tables 10 and 11. At state level, Table 10 indicates that the most important edges are: H0 (hull materials with steel) to SA3 (ship age > 30 years), W0 (clear weather) to GT2 (gross tonnage > 3000t) and H0 (hull materials with steel) to W0 (clear weather) and so on. While at factor level, the top five edges in terms of importance are all related to A (accident type), which reveals the impact of different RIFs on different types of accidents. It is worth noting that in CN structures, although edges do not account for real causal relationships between nodes, it can be assumed that they interact with each other by conveying abstract information. For example, it is hard to explain which specific interactions between the edges W0 (clear weather) and GT2 (gross tonnage > 3000t) will have in the event of a maritime accident. However, it is possible to mitigate the transfer of information when W0 and GT2 co-occur. In other words, taking precautions may reduce the

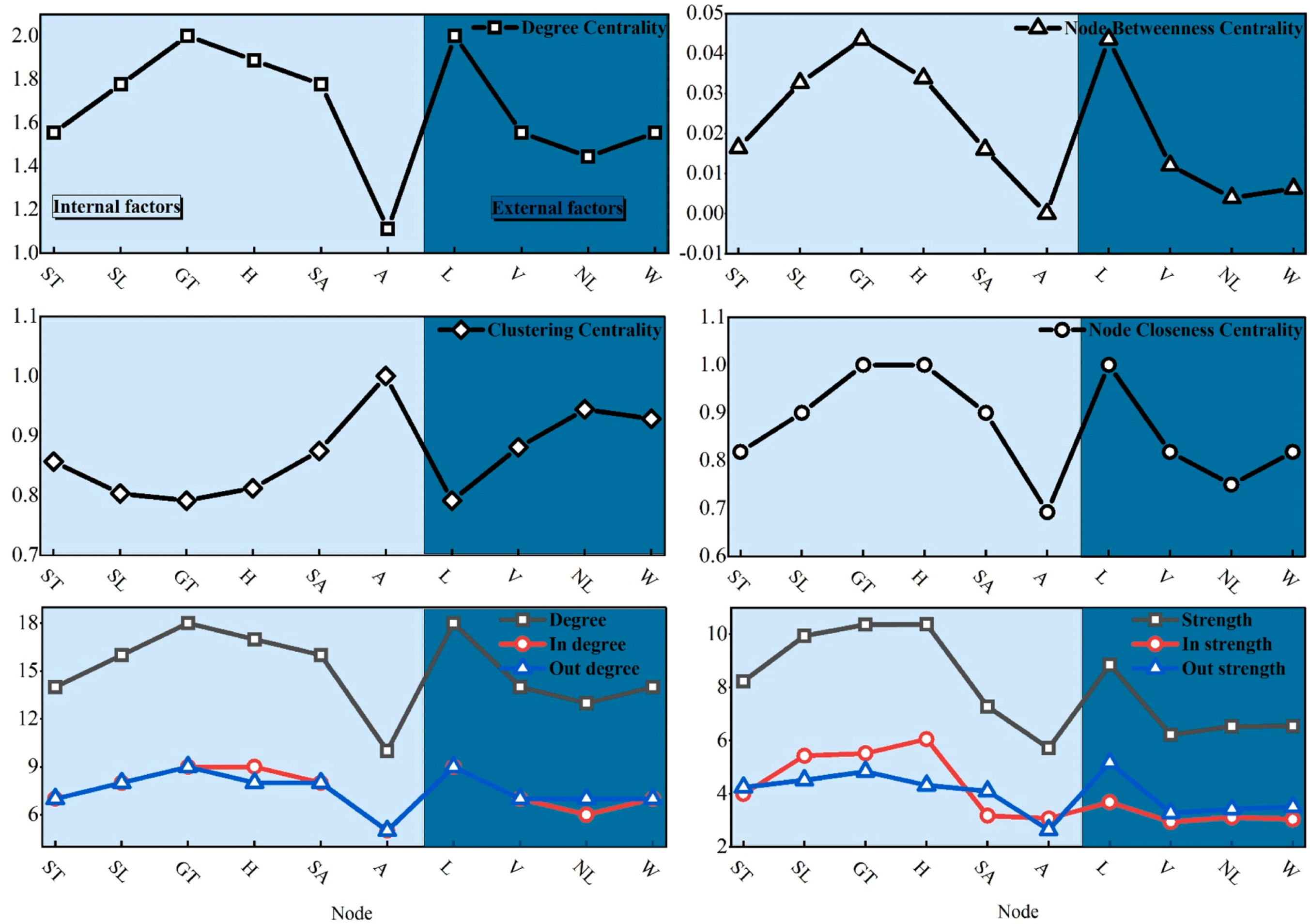

Fig. 8. Topological analysis at factor level.

Table 8
Nodes importance ranking at state level based on PIE values.

Rank	Nodes	PIE value	Rank	Nodes	PIE value
1	H0	34.8426	12	A3	−2.2148
2	SL0	27.3330	13	H2	−3.2483
3	GT0	26.5579	14	ST5	−4.8115
4	GT2	25.4225	15	L3	−6.2813
5	ST1	20.5494	16	L0	−8.7096
6	ST0	14.2072	17	SL2	−14.7766
7	W0	11.6229	18	SL1	−19.4954
8	SA3	10.5691	19	NL1	−26.2393
9	V3	5.1661	20	A10	−28.7740
10	NL0	3.2614	21	SL3	−30.0016
11	L1	0.3546	22	SA1	−35.3343

Table 9
Nodes importance ranking at factor level based on PIE values.

Rank	Nodes	PIE value
1	GT	5.6694
2	H	5.4458
3	SL	4.8041
4	L	2.2828
5	ST	1.0992
6	SA	−1.5149
7	NL	−3.5242
8	W	−3.5247
9	V	−4.5039
10	A	−6.2336

Table 10
Edges importance ranking at state level based on EBC.

Rank	Edges	EBC	Rank	Edges	EBC
1	('H0′, 'SA3′)	0.0757	6	('NL1′, 'H0′)	0.0390
2	('W0′, 'GT2′)	0.0510	7	('A10′, 'H0′)	0.0390
3	('H0′, 'W0′)	0.0466	8	('W0′, 'SL0′)	0.0376
4	('SA3′, 'ST0′)	0.0413	9	('W0′, 'GT0′)	0.0376
5	('SL1′, 'H0′)	0.0390	10	('GT0′, 'W0′)	0.0358

Table 11
Edges importance ranking at factor level based on EBC.

Rank	Edges	EBC	Rank	Edges	EBC
1	('A', 'GT')	0.0226	6	('SL', 'NL')	0.0205
2	('A', 'L')	0.0226	7	('A', 'SL')	0.0198
3	('GT', 'A')	0.0217	8	('ST', 'V')	0.0196
4	('H', 'A')	0.0217	9	('V', 'ST')	0.0192
5	('L', 'A')	0.0217	10	('SL', 'A')	0.0190

likelihood of accidents from occurring to some extent.

In addition, edges with higher EBC take more tasks as intermediaries in the network, which suggests that most information transmission flows through these edges. When these edges are blocked, the structure of the network changes significantly. Therefore, when certain factors cannot be directly prevented or controlled, the goal of preventing accidents can still be achieved by blocking the corresponding edges.

4.6. Robustness analysis

Maritime accidents occur as a result of a combination of multiple RIFs, which can be abstractly represented in the network structure as the successful transmission of information along a complete link that ultimately triggers a maritime accident. Therefore, disrupting the maritime accident RIFs network and reducing the stability of the network can stop the evolution of accidents to some extent. In this study, nodes and edges will be attacked respectively.

4.6.1. Node attacks

In this study, two strategies, random attacks with Monte Carlo simulation and deliberate attacks sorted by node importance are adopted to attack the established maritime accident RIFs evolution networks. To validate the effectiveness of the proposed PIE algorithm, deliberate attacks are conducted based on the ranking results from two other classical methods, i.e., the PageRank algorithm and the WLR algorithm. The changes of both networks' robustness are recorded, as shown in Fig. 9.

From Fig. 9, it is evident that the network robustness gradually decreases with an increasing number of failed nodes, regardless of random attacks or deliberate attacks. A comparison of the two strategies reveals that deliberate attacks result in faster and more severe damage to the network than random attacks. Specifically, in deliberate attacks, the robustness of both networks drops faster to 0 according to the results of the PIE algorithm. It demonstrates that the importance ranking result based on the PIE algorithm is more reasonable and effective as accidents can be stopped by controlling fewer nodes in response to this result. For example, at the state level, once the number of failed nodes exceeds 12, the robustness of the entire network drops to 0 based on the PIE algorithm, while both deliberate attacks based on the PageRank algorithm and the WLR algorithm require 14 failed nodes and random attacks require 21 nodes. In practice, the result based on the PIE algorithm implies that when more than 12 nodes with higher importance are controlled, the ship will be in a relatively safe state, with a low occurrence probability of a maritime accident. Therefore, this highlights the effectiveness of targeted prevention and control of key RIFs in preventing maritime accidents from occurring.

4.6.2. Edge attacks

Similar to node attacks, this study also attacks the edges and records the robustness changes for both networks (see Fig. 10). It is re-emphasised here that the concept of network robustness represents the ability of the maritime accident evolution network to resist external corrections, and that a high robustness has a negative impact on mitigating accidents. From Fig. 10, at the state level, when the number of failed edges reaches 45, the network robustness decreases by 8.72 % for random attacks and 60.59 % for deliberate attacks. At this point, the network still maintains high robustness with random attacks, and the network robustness significantly decreases only when more than 70 edges are randomly attacked. At the factor level, although the rapid declines of robustness under random attacks and deliberate attacks appear with a same number of failed edges, the robustness level of deliberate attacks is always lower than that of random attacks when more than 20 edges failed. Therefore, deliberate attacks damage both networks faster than random attacks. Fig. 10 also highlights that although deliberate attacks can rapidly reduce network robustness, the robustness can only reach at 0 when all edges are attacked since it is based on network reachability as an indicator, and reachability is greater than 0 as long as any edges exist in the network.

In addition, the changes in network robustness with deliberate attacks exhibit a stepwise decrease, indicating that the network robustness remains stable within a certain range of failed edges. Only when the number of failed edges exceeds that range does network robustness decrease dramatically. To investigate changes in network structure when network robustness remains constant, this study calculates the change in the average shortest path length (AL) of the network during deliberate attacks (as shown in the red line in Fig. 10). Fig. 10 indicates that changes in AL of the network and changes in the network robustness are synchronised. However, when the network robustness remains constant, the AL of the network starts to increase, since deliberate attacks on edges are based on the order of magnitude of EBC, which is calculated based on the number of shortest paths through the edge. Therefore, edge failure directly changes the shortest path length between nodes, while the reachability between nodes in the network does not necessarily change immediately.

Although deliberate attacks on edges do not break the network directly, they can impede the interaction among RIFs. Consequently, edge attacks can reduce the probability of maritime accidents, especially when node attacks are challenging to implement directly. For example, at the state level, one of the interaction paths is as follows: NL1 (nightlight) → H0 (hull materials with steel) → W0 (fog weather) → GT0

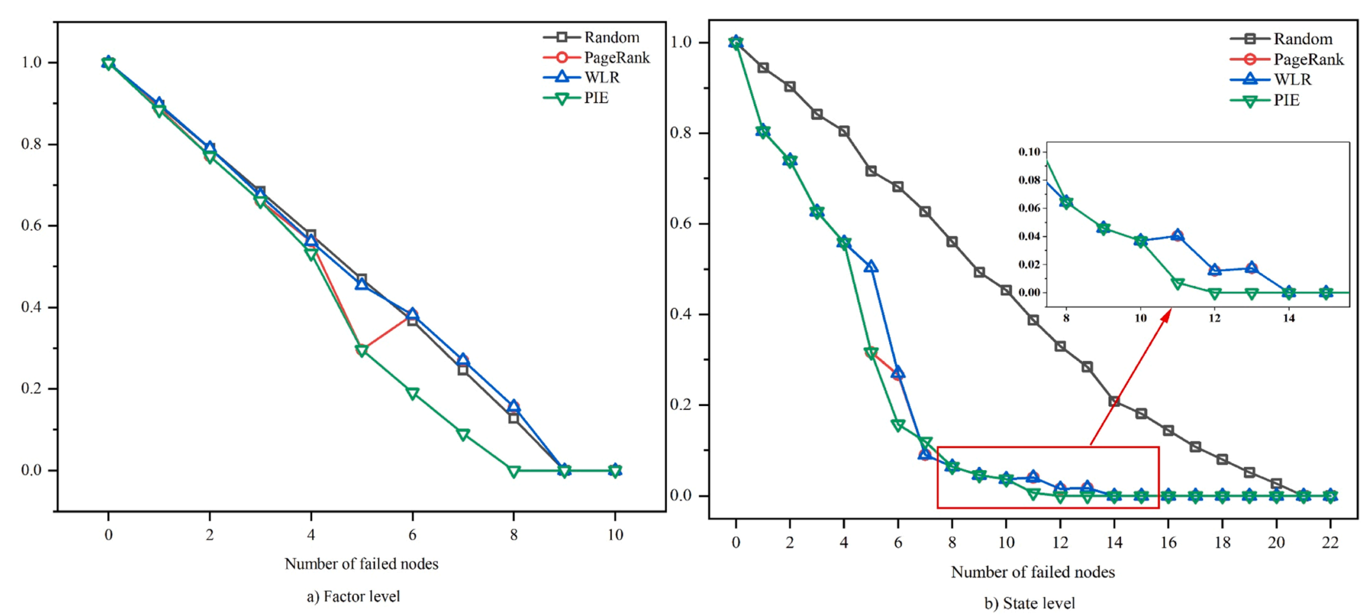

Fig. 9. Robustness based on attacks of network nodes.

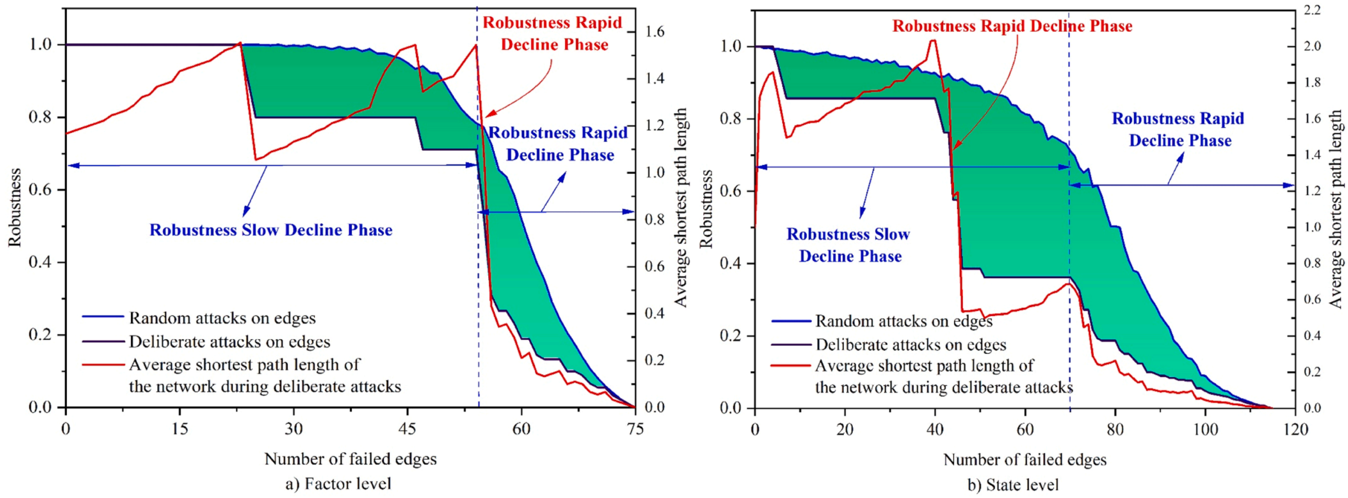

Fig. 10. Robustness based on attacks of network edges.

(gross tonnage <500t) →A3 (hull/machinery damage). In general, it is very difficult to take direct action on individual nodes to make them fail, since both weather conditions and ship parameters are objective. However, it is possible to stop the accident chain from evolving by taking practical measures to cut off W0 (fog weather) → GT0 (gross tonnage < 500t). More specifically, small ships with a gross tonnage of less than 500t may face challenges like limited visibility, navigation, or signal transmission in foggy weather, and most small ships are not equipped with radar or an Automatic identification System (AIS). This in turn can make it difficult to identify other ships, obstacles, or buoys. This may increase the risk of collision with other ships, docks, dykes, etc., leading to ship damage. Therefore, if ship operators and crews can take appropriate measures, such as using navigational equipment to help the ship navigate, slow down or pause, this will effectively stop the evolution of maritime accidents.

5. Discussion and implications

The findings from this study underscore the complexity and interconnectivity of risk factors in maritime accidents, as evidenced by the small-world characteristics of the maritime accident RIFs networks, cross-checking with findings from other studies [42,65], while they reveal new insights beyond the state of the art. Notably, both the network's average path length of 2.06 steps in the state level and a high aggregation coefficient suggest a tightly-knit structure that is prone to chain reactions leading to accidents. These properties underscore the critical need for reliability engineering strategies that address systemic vulnerabilities rather than isolated factors.

Specifically, both topological and ranking analyses highlight the role of ship-related factors—such as failures or specifications in hull materials, gross tonnage, and ship length—in contributing to the occurrence of accidents. For instance, GRP (Glass Reinforced Plastic)-constructed ships show a high risk for the occurrence of hull or machinery failure, demonstrated by identified associations. Through comparative analysis, the findings in this study are also consistent with several relevant studies in the maritime safety domain. For example, both studies of [47] and [10] considered ship parameters (e.g., GT) as one of the most critical RIFs. Particularly, these studies highlight the vulnerability of small ships (e.g., small fishing vessels), which are less resistant to the overall development of an accident, and where risks can rapidly evolve into an accident. Such scenarios include, but are not limited to high winds and waves, collisions or an emergency situation. This finding can be reflected in the importance ranking of GT (gross tonnage < 500t) and SL0 (ship length < 50 m) in this study. In response to these insights, it is essential to implement specific measures to mitigate risks accordingly. For example, shipowners should enhance preventive maintenance programs by conducting regular and comprehensive inspections, particularly for critical structural and mechanical components. Moreover, shipbuilders should adapt more robust materials and designs to meet the demands of tough operational environments that ships have to face. From a regulatory perspective, authorities should establish more rigorous construction and operational standards for small ships, enforce frequent safety inspections, and encourage the installation of advanced navigational aids and safety equipment on board. Additionally, crew members should undergo specialized training focused on emergency response procedures under high-risk scenarios, ensuring readiness to handle severe weather and collision risks.

Furthermore, the robustness analysis reveals that such nodes as ship age (SA3: ship age > 30 years) and environmental conditions (W0: clear weather), act as central hubs in the network, which is not yet the case with existing studies. These findings imply that failures of these nodes could significantly diminish the system's ability to propagate risk. As a result, implementing stricter safety protocols for aging vessels is crucial. This includes increasing the frequency of inspections beyond regulatory minimums, targeting critical areas such as the hull, machinery, and navigation systems. Additional operational restrictions, such as limiting the operation of aging vessels in high-risk weather conditions or busy shipping lanes, can reduce accident likelihood. Moreover, technological upgrades—such as retrofitting ships with modern monitoring systems—can provide early warnings for potential mechanical failures. Shipping companies could also consider gradually phasing out ships that exceed a certain age threshold to avoid elevated risks associated with older vessels. However, the influence of favourable weather conditions on accident occurrence seems to present a paradoxical risk factor. Despite the intuitive belief that poor weather increases accident risk, the analysis shows a higher occurrence of accidents in clear weather conditions, possibly due to reduced vigilance. This unexpected finding calls for heightened vigilance during routine operations in clear weather, emphasising the need for continuous safety protocols. Shipping companies should develop and enforce standard operating procedures (SOPs) that include maintaining high situational awareness, even in seemingly favourable conditions. This can be reinforced through regular drills and scenario-based training for crew members, where complacency risks are specifically addressed. Furthermore, adopting automated alert systems that monitor and report operational anomalies in real time can help mitigate human errors during periods of lower vigilance.

Lastly, the comprehensive analytical framework employed in this study has been proven to be effective. In Section 2.2.2, this study has reviewed some studies that used ARM methods [36,38], CN methods [41,45] and coupled methods [42] to analyse maritime accidents. The convectional ARM technique delivers results at a micro-level, i.e., items in ARs are states of the different RIFs, while the newly proposed CARM algorithm improves the extraction of association rules to a macro-level (i.e., the factor level). Association rules for both dimensions are extracted and used to build the corresponding networks in this study. Without limiting to the traditional static topology analysis, this study innovatively applies the attack-based robustness analysis method from traffic networks [63] to the established maritime accident RIFs evolution networks. Compared with existing methods, the importance ranking results of the new PIE algorithm exhibit superiority, where corresponding node deliberate attacks can prevent accidents by controlling fewer RIFs. Therefore, the network analysis of maritime accidents in this study not only demonstrates the interdependencies among risk factors but also informs the development of targeted interventions. By concentrating on high-impact nodes and employing a holistic approach to risk management, maritime safety stakeholder groups can better interrupt potential pathways leading to accidents, thereby enhancing overall system safety and reliability.

6. Conclusion

The increasing volume of maritime trade has unfortunately been accompanied by a heightened risk of maritime accidents. Hence understanding the RIFs in reported maritime casualties and accidents is crucial for significantly improving maritime safety.

This study proposes an analytical framework to provide a comprehensive analysis of maritime accident RIFs and explore the evolutionary mechanisms of maritime accidents. Based on a critical literature review, the contributions of this study in the terms of data, objectives, models and analysis are highlighted. Subsequently, 21,206 accident reports for the last 10 years are introduced to the quantitative framework integrating ARM and CN. By conducting topological analysis, the maritime accident RIFs network has been recognised as an active, high connectivity and functional community network with rapid information transmission. Meanwhile, as a dynamic evolution process, targeted control and prevention have proven effective in mitigating accidents. Finally, building upon the discussions and implications, the risk control measures are developed.

In future, the limitations of this current study can be improved. Applying a larger scale global maritime accident dataset and including human factors will improve its universal acceptance. A text mining technique may help to extract human factor information from accident investigation reports and avoid human interventions. Furthermore, the established network model in this study is a benchmark in understanding the role of RIFs in maritime accidents. More detailed and accurate modelling can be undertaken by considering the engagement of more RIFs and the weight on edges. Nevertheless, the framework proposed in this study will prove invaluable to maritime regulators in order to improve safety and the authors recommend its incorporation into safety management systems.

CRediT authorship contribution statement

Yuhao Cao: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Manole Iulia:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization. **Arnab Majumdar:** Writing – review & editing, Supervision, Resources, Project administration, Conceptualization. **Yinwei Feng:** Writing – review & editing, Validation, Methodology, Formal analysis, Conceptualization. **Xuri Xin:** Writing – review & editing, Validation, Methodology, Formal analysis, Conceptualization. **Xinjian Wang:** Writing – review & editing, Validation, Methodology, Funding acquisition. **Huanxin Wang:** Writing – review & editing, Validation, Methodology, Funding acquisition. **Zaili Yang:** Writing – review & editing, Validation, Supervision, Funding acquisition.

Declaration of competing interest

We can confirm that there is no conflict of interest in publishing this submitted manuscript.

Acknowledgment

This research was funded by a European Research Council project under the European Union's Horizon 2020 research and innovation programme (TRUST CoG 2019 864724). The authors also gratefully acknowledge support from the National Natural Science Foundation of China (Grant No. 52101399), the Bolian Research Funds of Dalian Maritime University (Grant No. 3132023617) and the China Scholarship Council (Grant No. 202308060322).

Appendix 1

Maritime accident RIFs classification criteria

	Variables	Indexes	Statements	Indexes	Refs.
External factors	Month	M	1–12	M1-M12	NA
	Location	L	Port	L0	[66,67]
			Open sea	L1	
			Coastal water	L2	
			Inland water	L3	
	Nature light	NL	Daylight	NL0	[68] TSBM16P0362
			Nightlight	NL1	
			Twilight	NL2	
	Sea state	SS	0 Calm glassy (0 m)	SS0	MAIB 26–2017
			1 Calm rippled (0 – 0.1 m)	SS1	MAIB 22–2017
			2 Smooth (0.1 – 0.5 m)	SS2	
			3 Slight (0.5 – 1.25 m)	SS3	
			4 Moderate (1.25 – 2.5 m)	SS4	
			5 Rough (2.5 – 4 m)	SS5	
			6 Very rough (4.0 – 6.0 m)	SS6	
			7 High (6.0 – 9.0 m)	SS7	
			8 Very High (9.0 – 14.0 m)	SS8	
			9 Phenomenal (over 14 m)	SS9	

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(*continued*)

	Variables	Indexes	Statements	Indexes	Refs.
			Ice covered	SS10	
	Wind force	WF	0 Calm (0–1 knot or 0–1 m/s)	WF0	MAIB 26–2017
			1 Light air (1–3 knot or 1–2 m/s)	WF1	MAIB 22–2017
			2 Light Breeze (4–6 knot or 2–3 m/s)	WF2	MAIB 20–2017
			3 Gentle Breeze (7–10 knot or 4–5 m/s)	WF3	
			4 Moderate Breeze (11–16 knot or 6–8 m/s)	WF4	
			5 Fresh Breeze (17–21 knot or 9–11 m/s)	WF5	
			6 Strong Breeze (22–27 knot or 11–14 m/s)	WF6	
			7 Near Gale (28–33 knot or 14–17 m/s)	WF7	
			8 Gale (34–40 knot or 17–21 m/s)	WF8	
			9 Strong Gale (41–47 knot or 21–24 m/s)	WF9	
			10 Storm (48–55 knot or 25–28 m/s)	WF10	
			11 Violent Storm (56–63 knot or 29–32 m/s)	WF11	
			12 Hurricane (+64 knot or +33 m/s)	WF12	
	Visibility	V	Very poor - Vis < 0.5 nm	V0	MAIB 26–2017
			Poor - 0.5 ≤Vis < 2.0 nm	V1	MAIB 22–2017
			Moderate - 2.0 ≤Vis < 5.0 nm	V2	
			Good - 5.0 ≤ Vis < 25.0 nm	V3	
			Very good - Vis ≥ 25.0 nm	V4	
	Weather	W	Clear	W0	MAIB 26–2017
			Fog	W1	MAIB 22–2017
			Overcast	W2	
			Rain	W3	
			Snow	W4	
			Thunder/storm/lightning	W5	
Internal factors	Accident type	A	Capsizing / Listing	A0	[68,69]
			Collision	A1	
			Contact	A2	
			Hull/machinery damage	A3	
			Fire / Explosion	A4	
			Floating object	A5	
			Flooding / Foundering	A6	
			Grounding / Stranding	A7	
			Cargo/shift/loss/released	A8	
			Loss of control	A9	
			Non-accidental events	A10	
	Ship type	ST	Fishing ships	ST0	[10,47]
			Cargo ships	ST1	
			Navy ships	ST2	
			Passenger ships	ST3	
			Recreational ships	ST4	
			Service ships	ST5	
			Other ships	ST6	
	Length	SL	0–50m	SL0	[3,68]
			50–100m	SL1	
			100m-200m	SL2	
			200m+	SL3	
	Gross tonnage	GT	0–500t	GT0	[10,66]
			500–3000t	GT1	
			3000t+	GT2	
	Ship age	SA	0–10 years	SA0	[10,66]
			10–20 years	SA1	
			20–30 years	SA2	
			30 years+	SA3	
	Hull materials	H	Steel	H0	[3,68]
			Wood	H1	
			GRP (Glass Fiber Reinforced plastics)	H2	
			Aluminium alloy	H3	
			Composite materials	H4	
			Ferro cement	H5	
			Other materials	H6	

Appendix 2

Data quality assessment system

Categories	Dimension	Description	Formula
Quantitative assessment	Accessibility	Accessibility reflects the ease of access to the data. Assessing the accessibility of data quantifies the number of data without further modification.	$Accessibility = \frac{1 \times N_{explicit} + 0.8 \times N_{implicit} + 0.2 \times N_{inferred}}{N_{variables}} \times 100\%$ Where $N_{explicit}$ represents the number of existed variables, $N_{implicit}$ represents the

(*continued on next page*)

(*continued*)

Categories	Dimension	Description	Formula
			number of newly created variable, $N_{inferred}$ represents the number of modified variable, $N_{variables}$ represents the number of the total variables.
	Consistency	Consistency is concerned with the continuity of data collection, recording and updating. Assessing data consistency helps to estimate that accident data remains consistent in concept, value domain and format.	$Consistency = \frac{1 \times N_{consistent} + 0.8 \times N_{recoded} + 0.2 \times N_{newly\ coded}}{N'_{variables}} \times 100\%$ Where $N_{consistent}$ represents the variables with the same manner in each dataset, $N_{recoded}$ represents the number of recoded variables, $N_{newly\ coded}$ represents the number of newly coded variables. $N'_{variables}$ represents the number of used variables.
	Completeness	In the maritime accident database, assessing data completeness helps to investigate the usability of the data.	$Completeness = 1 - \overline{P}_{missing}$ Where $\overline{P}_{missing}$ represents the arithmetic average of missing values percentage.
	Relevance	Relevance reflects the degree to which the data are relevant to the objective of this study.	$Relevance = \frac{1}{N_{categories}} \sum_{i=1}^{N_{categories}} \frac{N_{relevant,\ i}}{N_{request,i}}$ Where $N_{categories}$ represents the number of categories in which the required (ideal) datasets are grouped, $N_{relevant,\ i}$ represents the number of relevant datasets in category i, $N_{request,i}$ represents the number of requested datasets in category i.
Qualitative assessment	Accuracy	The accuracy of data reflects the extent to which it is accurate, true and free from error.	$Accuracy = \frac{N_{accuracy}}{N_{variables}} \times 100\%$ Where $N_{accuracy}$ represents the number of variables that are accurate.
	Credentials	Credentials reflect the extent to which data is obtained from reliable data sources.	NA
	Interpretability	Assessing the interpretability of data requires that the data are clearly presented in terms of language, notation, units and definitions.	NA
	Timeliness	Timeliness reflects the extent to which data is up to date. Assessing the timeliness of data requires consideration of the time gap between the moment an accident occurs and the moment it is recorded.	$Timeliness = \frac{\sum_{i=1}^{N_{record}} \left(T_{report,\ i} - T_{occurrence,\ i}\right)}{N_{record}}$ Where $T_{report,\ i}$ represents the time of accident i reported, $T_{occurrence,\ i}$ represents the time of accident i occurred.
Narrative assessment	Narrative	In this study, 10% of the accident data will be selected as a sample for narrative assessment. This sample will be used to calculate narratives of more than 50 words and to check whether they provide information about the variables identified in the dataset (1 if yes, 0 if no).	$Narrative = \frac{1}{N_{variables}} \sum_{j=1}^{N_{variables}} \frac{N_{record,\ j}}{N_{record}} \times 100\%$ Where $N_{record,\ j}$ represents the number of accident statistics where variable j exists.

Data availability

Data will be made available on request.

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