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Research paper

Dynamic evolution of maritime accidents: Comparative analysis through data-driven Bayesian Networks

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ABSTRACT

Maritime accident research has primarily focused on characteristics and risk analysis, which often overlooks the evolution of the associated risk patterns over time. This study aims to investigate the dynamic changes in maritime accidents from 2012 to 2021 by employing a data-driven Bayesian Network (BN) model and conducting a systematic dynamic pattern comparison. It presents two-stage models for two databases and five models against different timeframes to capture the evolving characteristics of global maritime accidents. Furthermore, within the context of the accident investigation, this study pioneers the analysis of the effectiveness of two network structures, namely a layered BN model and a Tree-Augmented Naive Bayesian (TAN) network, in terms of the accuracy of predicting the accident severity. The key findings regarding the changes in maritime accidents in the past decade include: (1) a significant rise in maritime risks linked to large ships (30.8%), port areas (11.67%), anchoring (11.82%), and manoeuvering operations (3.8%); (2) a connection between poor anchoring practices on fishing boats and 'overboard' accidents, and between inadequate equipment on tankers or chemical ships and 'fire/explosion' accidents; (3) the TAN model's superior performance in forecasting accident severity compared to the layered BN model; and (4) the probability of 'very serious' accidents in terms of ship-related factors is 74.7%, which is for the layered BN network, significantly lower than the TAN network's 99.4%. This study reveals shifts in accident patterns over time and underscores the importance of continuous monitoring and analysis for effective safety and risk management.

1. Introduction

Maritime transportation is indispensable to international trade and related supply chains, representing in excess of 90% of the worldwide trade volume (Jiang et al., 2020; Li et al., 2022; Xin et al., 2023). However, the rapid growth of the shipping industry, alongside unaddressed inherent challenges in ensuring maritime safety, require urgent solutions. Maritime accidents can have far-reaching and severe consequences on assets, environment, and personnel, including casualties, economic losses, channel blockage, and environmental pollution (Zhang et al., 2013; Chen et al., 2022; Sepehri et al., 2022; Khan et al., 2023). Given the essential role of maritime transportation in global trade, it becomes paramount to address the challenges associated with maritime safety (Cao et al., 2023a). Efforts are continuously made by all stakeholders, ranging from international organisations, governments, and shipping companies to researchers, to enhance safety measures, promote effective regulations, and develop advanced technologies and practices to prevent accidents and minimise their consequences (Cao et al., 2023b; Li et al., 2023; Li and Yang, 2023; Zhou et al., 2024).

Risk analysis plays a crucial role in identifying risk factors and root causes of different types of accidents. This enables the formulation of relevant measures to effectively prevent maritime accidents (Wang et al., 2023; Lan et al., 2023; Fu et al., 2022; Trucco et al., 2008). Qualitative methods like Functional Resonance Analysis Method (FRAM), Root Cause Analysis (RCA), and risk rating scales offer systematic risk assessment but lack reliability due to subjective interpretation. In contrast, quantitative methods such as Fault Tree Analysis (FTA), Bayesian Network (BN), Event Tree Analysis (ETA), and Evidence Reasoning (ER) provide data-driven approaches. Among these, BN stands out for its ability to model causal relationships between factors,

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handle multiple variables, and integrate various factors.

In maritime risk analysis, conventional approaches heavily rely on historical accident data and expert knowledge (Luo and Shin, 2019; Demirci et al., 2023). However, pure statistical or expert judgment-based analyses could possibly introduce biases to the results. Consequently, there is a need for advanced methods to address the inherent uncertainty in risk data. The combination of BN and real maritime accident data has emerged as a prominent solution due to its prized capability to effectively capture and model causal factors and their interrelationships (Fan et al., 2020a; Hossain et al., 2022; Zhou et al., 2023; Li et al., 2023a; Meng et al., 2022). The application of BN in maritime risk analysis allows for a systematic and probabilistic approach to understand and evaluate the complex factors contributing to accidents. While the accident analysis of 2012–2017 exists in the literature, there is an urgent need for a comprehensive investigation of the accident characteristics by using the latest five-year period (2017–2021) as a reference to detecting the dynamic pattern of maritime accident changes. This is particularly important and insightful as the world continuous to experience impactful changes to international shipping from events like the COVID-19 pandemic, the Russia-Ukraine conflict, and the rise of international trade protection. It is also necessary to see how such new data will train different BN-based maritime risk models that can best reflect the current maritime safe operation environment.

Furthermore, a detailed comparison of the accident analysis between the latest five-year period and the previous six-year period (2012–2017) will benefit the stakeholders to better understand the trends in accident development to devise new prevention measures. Due to the fact that the methodology of developing the data-driven BN risk model is generic, the effect of any specific shocking event on maritime safety could be investigated when the associated data from before, during, and after the occurrence of the event are obtained. The comparison between the analysis results of two databases (i.e., 2012-2017 and 2017–2021[1]) will enable an investigation of the evolution of maritime accident characteristics from a global perspective. This will provide new findings on maritime accidents in recent years and insights into changes in their characteristics over time.

This study further screened maritime accident data from 2017 to 2021, ensuring consistency with the data from 2012 to 2017 regarding the consistency of accident types. It included both the original accident data from the International Maritime Organization (IMO) Global Integrated Shipping Information System (GISIS) and the supplementary ship-normalised data provided by Lloyd's Register Fairplay (LRF). More specifically, the primary contributions of this paper are as follows.

(1) Conduct a comparative analysis of dynamic risk characteristics by data-driven BN models.
(2) Investigate the evolutionary features of maritime accidents for risk analysis and future prediction.
(3) Evaluate the predictive performance of two risk models on various accident types using annual data to reveal their yearly evolution characteristics.
(4) Design different risk models for maritime accident severity and evaluate their predictive abilities.

The paper is organised as follows: Section 2 reviews existing literature on risk studies pertaining to maritime accidents and identifies the prevailing risk factors in the literature. Section 3 describes an overview of the dataset generation, spatial and temporal features extraction, the identification of Risk Influencing Factors (RIFs), and the construction of a novel BN model for maritime accident risk. In Section 4, sensitivity analysis is conducted to explore the significance of RIFs and their impact on maritime accident risk. The constructed model is validated from multiple perspectives. Section 5 provides an in-depth comparative analysis, uncovering the unique and valuable research insights obtained from this study. The implications of this study are listed in Section 6 to provide useful guidance. Finally, Section 7 summarises the conclusions and future development.

2. Literature review

2.1. Research in the field of maritime risk analysis

Maritime risk analysis is crucial to ensuring navigational safety (Demirci and Elçiçek, 2023). The IMO has developed the Formal Safety Assessment (FSA) framework to bolster the safety and sustainability of maritime activities by providing a systematic approach to risk assessment. Scholars have embraced both qualitative and quantitative analysis methods to assess accident risks and navigation safety. Qualitative evaluation methods such as Functional Resonance Analysis Method (FRAM), Root Cause Analysis (RCA), and risk rating scales offer systematic approaches to assessing risk in complex maritime systems (Goerlandt and Montewka, 2015; Marino et al., 2023). While these methods help identify underlying causes of accidents and prioritise risks, they are limited in their ability to quantify risks. The methods rely heavily on subjective interpretation and lack reliability and validity. Human Factors Analysis and Classification System (HFACS) and Accident Analysis Mapping (AcciMap) specifically focus on human factors in accidents, but they face similar limitations in quantifying risks based on subjective judgments. Qualitative analysis typically leverages subjective judgments and expert knowledge to evaluate the impact of risk factors. While these methods are valuable in identifying potential risks, they are inherently subjective and lack quantifiability. This often leads to questions about their reliability.

In contrast, Quantitative Risk Assessment (QRA) methods like FTA, BN, ETA, and ER provide advanced and data-driven approaches to assess maritime accident risks (Zhou et al., 2024; Chen et al., 2019). FTA helps identify potential failure pathways, while ETA visualizes accident sequences and their probabilities. ER incorporates diverse evidence sources to assess risk, but it may be computationally intensive. However, among these methods, BN stands out because of its powerful modelling capabilities, including its ability to explore causal relationships between influential factors, handle multiple-state variables and outputs, and integrate human and organizational factors with other RIFs. Quantitative methods, using statistical data and analytical techniques and aiming to objectively quantify risk factors and their relationships with maritime accidents, offer a more measurable approach to risk assessment (Fu et al., 2023). Various studies have employed sophisticated quantitative tools like Fuzzy Fault Tree Analysis (FFTA), real-time risk models, and advanced algorithms such as eXtreme Gradient Boosting (XGBoost) and BN for improved risk evaluations. These methods capitalise on quantitative data to mitigate the subjective biases inherent in qualitative analyses, which provide a more robust framework for maritime risk assessment. For example, Tunçel et al. (2023) used the FFTA to analyse the potential risks of maritime pilots during operations. Li et al. (2023b) established a regional real-time risk model for assessing ship collision risks using the random forest method. Zhang et al. (2022) employed the XGBoost algorithm to build a predictive model for maritime accidents related to preventive safety risks, achieving an accuracy rate of 97.14%. Li et al. (2014) innovatively integrated logistic regression and BN into maritime risk assessment based on different maritime accident data resources. Montewka et al. (2014) used Bayesian Belief Networks (BBN) to develop a systematic risk framework for evaluating maritime transport risks. Wan et al. (2019) integrated BN with fuzzy belief rule methods to construct a more accurate risk factor assessment model for maritime supply chains. Generally, BN analysis of maritime risks often relies on expert experience or objective maritime accident datasets. Yu et al. (2020) integrated ER with BN and incorporated expert judgments to develop a risk assessment model for ship-turbine collisions to protect

[1] The detailed data and reports from 2022 onwards are not available from the IMO database.

navigation safety near Offshore Wind Farms (OWFs). Zhang et al. (2021) carried out a risk assessment involving 945 collision accidents in the Jiangsu section of the Yangtze River spanning from 2012 to 2016, using a conjugate Bayesian updating method supported by expert knowledge. However, the subjectivity of expert experience often results in inaccuracies in the research results. To avoid this type of uncertainty in the risk assessment process, data-driven BN has been proposed. Fan et al. (2022) established a data-driven BN risk model for maritime accidents in restricted waters worldwide from 2005 to 2021 and provided valuable insights for the Suez Canal blockage accident. Jiang et al. (2020) developed a BN model for the analysis of maritime accident risks using accident reports from the Maritime Silk Road (MSR).

BN, in particular, has gained prominence for its comprehensive modelling capabilities, incorporating the probabilistic relationships between risk factors and accident outcomes. Its capacity to provide bi-directional risk analysis and accommodate various types of risk factors makes it invaluable for understanding the complex dynamics of maritime accidents. While constructing and interpreting BN requires specialized knowledge and could be data-intensive, its holistic perspective on accident risks significantly enhances maritime safety practices. BN serves as a dynamic tool for maritime risk analysis, offering insights into various aspects of accident dynamics by assessing accident likelihood, severity, and the influence of risk factors with versatility.

Maritime accident analysis using BN can be divided into three categories, namely: accident likelihood assessment, accident severity evaluation, and influence of risk factors analysis.

The first type explores the probability or frequency of maritime accidents. For example, Pristrom et al. (2016) employed data obtained from the GISIS and expert judgment to develop a BN model to evaluate the likelihood of a vessel being hijacked in the West Indies or East Africa. Sakar et al. (2021) applied a combination of BN and FTA to explore the influence of various influencing factors on the likelihood of grounding accidents. The second type focuses on the severity or consequences of maritime accidents. Wang et al. (Wang and Yang, 2018) applied the Augmented Naïve Network (ABN) model to examine the pivotal risk factors influencing the severity of waterway accidents. Liu et al. (2021) used BN to explore the factors impacting the severity of accidents in China's coastal waters. The third type concentrates on exploring how risk factors influence various categories of maritime accidents. However, the reliance on expert opinions and the challenge of integrating subjective experiences into BN models have prompted the development of data-driven approaches to enhance objectivity and reliability.

Despite these advancements, the field still faces challenges like data scarcity, outdated information, and regional research limitations, hindering a global perspective on maritime risk evolution. This study seeks to bridge these gaps by offering a comparative analysis of maritime accidents over time, using the latest data to understand global trends in accident characteristics.

Moreover, while secondary databases provide valuable accident statistics, detailed accident reports offer richer insights into the causes, conditions, and outcomes of maritime incidents. For instance, Fan et al. (2020a) used the Naive Bayesian Network (NBN) to quantify the degree of influence of different factors on various types of maritime accidents based on 161 maritime accident reports from 2012 to 2017. Khan et al. (2020) investigated the risks associated with different types of accidents in Hong Kong waters based on 331 accident reports spanning from 1999 to 2017. The research findings provided insights that might not be fully valid and representative at a global scale due to the data constraints from temporal and spatial perspectives. Cakir et al. (2021) explored the severity of oil spillage in potential ship accidents by analysing the U.S. Coast Guard (USCG) database from 2002 to 2015. Antao et al. (2023) assessed the impact of RIFs on collision accidents using 936 collision accidents in the GISIS database from 2005 to 2017. Fan et al. (2020b) explored the impact of human factors on maritime transportation based on accident reports from the Transportation Safety Board of Canada (TSB) and the Marine Accident Investigation Branch (MAIB) from 2012 to 2017. Ma et al. (2022) identified influencing factors and quantitatively assessed the accident risks associated with transporting maritime dangerous goods using 22 maritime accident reports from China. Fu et al. (2022) determined potential risk factors for grounding accidents in the Arctic region by examining 322 maritime accident investigation reports and introduced a framework for quantitatively analysing the causes of grounding accidents. A comprehensive recognition and state definition of RIFs can greatly facilitate the development of targeted risk management strategies. However, global studies on the factors and states of maritime accidents are limited due to the need for extensive global data support. Yu et al. (2021) established static and dynamic risk assessment models for ships using BN, based on 8 RIFs and 13 RIFs, respectively. These are followed by the identification of 'ship area', 'ship types', and 'ship off route' as the most important RIFs. Wu et al. (2021a) identified 6 RIFs by analysing 132 records of electric vehicles' fire accidents and suggested that RoPax ships should avoid electric vehicle charging during transportation. It is observed that previous research had issues such as insufficient RIFs, oversimplified state definitions, and limited application scenarios. However, extracting this information is labour-intensive and subject to interpretive variability, underscoring the need for comprehensive databases that amalgamate broad datasets like the IMO GISIS and LRF, improving the identification and analysis of RIFs.

As technologies advance and the maritime navigation environment continues to evolve, there is a growing need and advantage in undertaking an extensive and adaptable analysis of maritime accident evolution that reflects global trends, using the latest data on maritime incidents by integrating the IMO GISIS and LRF data. This research fills the gaps in understanding how maritime accident characteristics evolve over time by comparing and analysing the risk models and findings from earlier studies.

2.2. Research on maritime accident evolution analysis

Maritime accidents are influenced by a multitude of factors. To explore the intricate relationships among these factors, a comparative literature review is undertaken. This review aims to assess the effectiveness of different RIFs and update the latest advancements in maritime risk analysis. The keywords 'Bayesian network' and 'Maritime risk analysis' are used to search for the relevant papers on the Web of Science (WoS), focusing on journal articles. From an initial set of 238 journal articles related to maritime accident risk analysis, 23 papers are selected based on their detailed descriptions of RIFs, as determined by analysis of their titles, abstracts, and research content. A quantitative analysis was conducted on all RIFs found in the 23 selected papers, resulting in 22 high-frequency RIFs that were further analysed. The occurrence frequency of these 22 RIFs is illustrated in Fig. 1. As depicted in Fig. 1, the

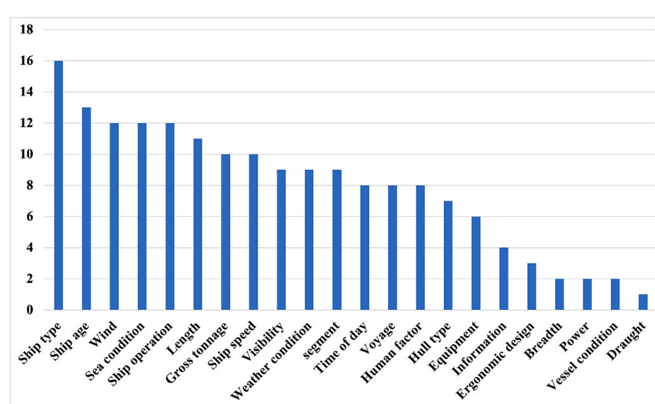

Fig. 1. The frequency of RIFs from the screened papers.

top eight RIFs are identified as 'ship type', 'ship age', 'wind', 'sea condition', 'ship operation', 'length', 'gross tonnage', and 'ship speed'.

Table 1 presents a macro-level analysis of the current state of research on maritime risk. It showcases the frequency and usage of different RIFs in various studies. The content presented in Table 1 underscores the predominant areas of research within the field of maritime accidents. Currently, the emphasis lies on conducting studies related to risk analysis, accident causation analysis, the assessment of accident severity, the analysis of collision accidents, and the examination of accidents involving fishing vessels. However, a noticeable gap in the literature exists on accident development.

Addressing this gap is important because it provides a deeper understanding of accident progression that can significantly improve maritime safety. The development of accident evolution comparative analysis, grounded in accident data, offers a promising avenue for improving maritime navigation safety practices and protocols. By dissecting and comparing how accidents unfold and progress, researchers and industry stakeholders can identify critical points of intervention and areas for preventative measures. This research could also lead to enhanced safety regulations, advanced navigational technologies, and improved training for maritime personnel. Despite progress in maritime accident analysis, there is a compelling need for focused studies on maritime accident evolution.

2.3. Research gaps

The research gaps have been identified through the literature review outlined above and are summarised below.

(1) The need for an extensive and adaptable analysis.

As maritime technologies and environments evolve, there is a crucial requirement for comprehensive analysis that incorporates global trends and the latest maritime incident data. This involves leveraging the IMO GISIS and LRF data to enhance the understanding of maritime accident evolution over time.

(2) Understanding the multifaceted causes of maritime accidents.

There is a gap in exploring the complex interplay of factors influencing maritime accidents, particularly during the period that involved many shocking events. A comparative literature review aimed at evaluating the effectiveness of different RIFs, update the current state of each RIF, and understand its impact on maritime safety changes.

(3) Deepening the understanding of accident progression.

A significant gap exists in the comparative analysis of accident development trends. Addressing this is essential for improving maritime safety by developing strategies based on understanding the accident progress mechanism and identifying intervention and preventative measures.

(4) Advancing maritime safe practices.

While knowledge of maritime accidents has grown, there remains a pressing demand for in-depth studies on accident progression. This area of research is critical to establishing more effective safety protocols,

Table 1
The comprehensive comparison of the screened papers.

Refs	Data resources	Years	Reports	Methods	RIFs	Accident types	Research content
(Li et al. (2023a))	GISIS and LRF	2017–2021	402	BN	23	11	Global accident risk analysis
(Fan et al. (2020c))	Maritime Accident Investigation Branch (MAIB), and the Transportation Safety Board of Canada (TSB)	2012–2017	161	BN and TOPSIS	25 (focus on human factors)	9	Prevention strategies in maritime accidents
(Zhang et al. (2016))	Tianjin Maritime Safety Administration (MSA)	2008–2013	234	BBN	10	7	Risk assessment and accident prevention
(Zhao et al. (2021))	China MSA	2013–2019	160	BN	20	5	Risk analysis for autonomous ships
(Wu et al. (2021b))	Accident in Yangtze River	2012–2016	942	BN and three-layer model	23	1	Anti-collision and decision-making
(Özaydın et al. (2022))	Turkish Accident Investigation Board	2000–2018	173	Expert judgement, BN, and Association Rule Mining (ARM)	21	1	Occupational accident analysis (fishing vessels >12 m)
(Uğurlu et al. (2020))	GISIS, MAIB, European Maritime Safety Agency (EMSA), Australian Transport Safety Bureau (ATSB), and TSB	2009–2018	226	BN and chi-square	15	5	Accident analysis of fishing vessels (>7 m)
(Kamal and Çakır (2022))	Main Search and Rescue Coordination Center (MSRCC)in Turkey	2016–2021	418	BN and C4.5 decision tree	12	9	Accident analysis in Istanbul strait
(Jiang and Lu (2020))	Remote Sensing Systems and Meteorological Center (RSSMC)	2007–2018	460	Dynamic Bayesian Network (DBN)	20	–	Risk analysis in sea lanes
(Ung (2021))	Ministry of Transportation and Communications (MOTC) marine accident database	2014–2019	583	BN	9	6	Navigational risk analysis
(Wang et al. (2021))	ATSB, Federal Bureau of Maritime Casualty Investigation (BSU), China MSA, National Transport Safety Board (NTSB), TSB, MAIB and Japan Transport Safety Board (JTSB)	2010–2019	1207	Classification of the accident severity levels	6	7	Maritime accident severity analysis
(Kelangath et al. (2012))	Lloyds database	1997–2009	7488	BN	10	2	Risk analysis of damaged ships
(Wu et al. (2020))	Jiangsu MSA	2006–2013	797	BN	13	–	Consequence estimation
(Fan et al. (2022))	MAIB, TSB, and GISIS	2012–2017, 2005–2021	61	BN	25	4	Accident analysis in restricted waters
(Zhou et al. (2024))	GISIS and LRF	2017–2021	402	BN	23	11	Maritime casualty analysis

pioneering navigational technology advancements, and improving training for maritime personnel.

3. Methodology

3.1. The proposed framework for maritime accident evolution analysis

In this study, a data-driven BN method is used to develop the global maritime accident risk model, serving as a fundamental basis for comparing the evolution of maritime accidents. The proposed framework is presented in Fig. 2 and consists of four parts. Firstly, a comprehensive accident dataset with the same accident types from the past six years (2012–2017) is constructed and generated based on the maritime accident records in the IMO GISIS database and ship static data from LRF (Li et al., 2023a). Subsequently, the accident dataset and the RIFs serve as input for building the accident model through a data-driven BN approach, where multiple methods are used for sensitivity analysis and model validation. Throughout this process, important RIFs with the greatest impact on various categories of maritime accidents and the overall impact of multiple RIFs are revealed. Concurrently, results from this study are compared with those of maritime accident risk analysis from the past six years (2012–2017). Multiple scenario analyses are conducted to reveal the latest characteristics of maritime risks and compare the evolution trends in maritime accidents. Finally, two different network structures, a layered BN model and a Tree-Augmented Naive (TAN) network, are implemented and compared to validate their performance in predicting accident severity.

3.2. Dataset generation

To create a standardised dataset of maritime accidents with the same accident types from the past six years (2012–2017), this study gathers accident information and reports from two authoritative maritime accident databases: GISIS and LRF.

Initially, maritime accident data was collected from the GISIS database for 2017 to 2021, resulting in a total of 1105 records. There are 948 records with accurate longitude and latitude.

Records of accidents lacking essential ship information and accident reports, such as IMO or MMSI numbers, were eliminated to maintain data quality. This resulted in 462 relevant accident records.

In the next step, missing ship details like hull structure, width, draft, speed, power, gross tonnage, and other important information were added from the LRF database for the remaining 428 accident records.

To maintain accuracy in maritime risk analysis, accident records with unclear descriptions of the accident process, causes, and consequences were excluded, leaving a dataset of 402 accident records.

Finally, accident records categorised as ‘occupational accident’ and ‘ship/equipment damage’ were removed to align with the accident types in existing literature (Fan et al., 2020a). This resulted in a final dataset comprising 362 maritime accident records.

3.3. Spatial and temporal feature analysis

This dataset with 948 records, including longitude and latitude, can be used for spatial and temporal pattern extraction and analysis. Fig. 3 depicts a series of world maps for 2017 to 2021, each showing the distribution of maritime accidents marked by purple dots. Over time, the distribution of these maritime accident points exhibits specific characteristics:

In 2017, maritime accidents were spread relatively sparsely across the globe, with notable concentrations in parts of North America, Europe, and East Asia.

In 2018, there appears to be a slight increase in the number of accidents, with more purple dots visible in the same regions that were affected in 2017, suggesting either an increase in accidents or better reporting in these areas.

By 2019, the distribution of purple dots remains consistent with the previous years, indicating a persistent pattern of accidents in the

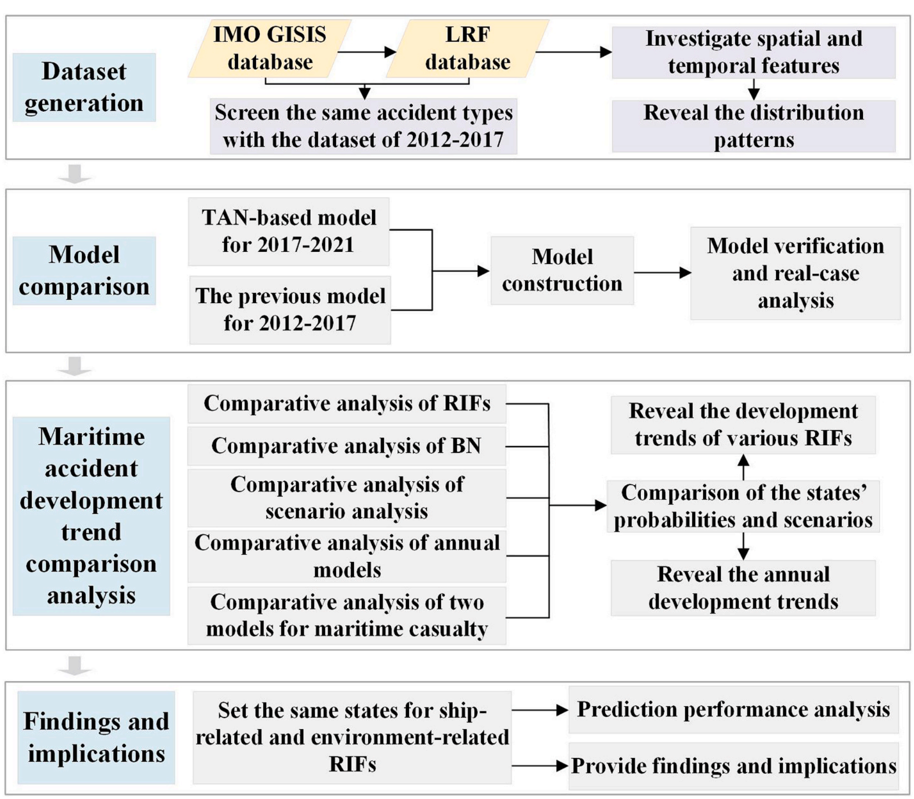

Fig. 2. The proposed framework.

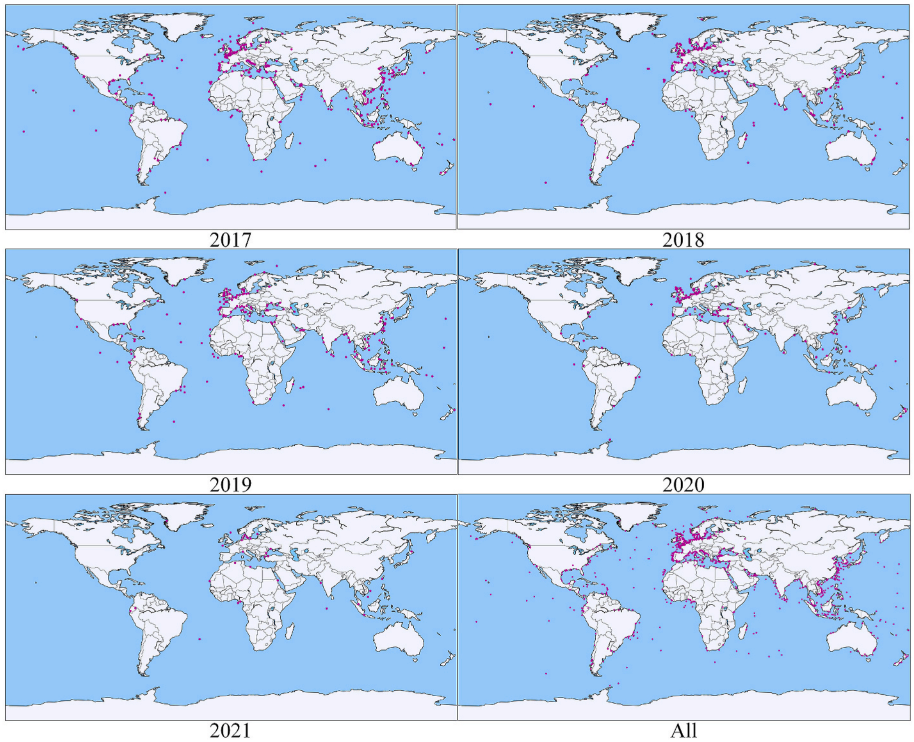

Fig. 3. The spatial and temporal patterns of maritime accidents.

aforementioned regions. There is no significant change in the overall global distribution.

In 2020, the pattern of purple dots again shows consistency with the earlier years, with no major shifts in the distribution. The concentration of accidents remains higher in North America, Europe, and East Asia.

The map for 2021 maintains the trend observed in the previous years, with no dramatic changes in the distribution of the purple dots. The same regions continue to have a higher density of accidents.

Overall, the distribution of the purple points over time suggests a consistent pattern, with certain regions consistently experiencing a higher frequency of these maritime accidents. There is no significant year-to-year variation in the global distribution of these events, indicating a possible ongoing issue that affects the same areas repeatedly.

3.4. RIF identification

To conduct a more accurate risk assessment and control of maritime accidents, 23 RIFs were identified by analysing the most frequently used RIFs in the existing literature and combining them with the risk factors recommended by the IMO. The comprehensive dataset on maritime accidents used in this study allowed for consideration of various RIFs, leading to an in-depth analysis of the risks connected with maritime accidents. Previous literature often simplifies the definition of RIF states to make data processing and classification less complex. However, such an approach results in the loss of granularity of accident information, making it difficult to uncover the intrinsic mechanisms of maritime accident risks. To address this deficiency, this study defines the states of the 23 RIFs in detail based on the constructed global maritime accident risk database and the IMO standards (Li et al., 2023a). Finally, the identified RIFs and their corresponding state definitions are listed clearly in Fig. 4.

The state definitions employed in this study encompass the most significant 11 types of 'ship type' and 'voyage segment' in the shipping industry. Moreover, the state definitions for 'ship age' and 'ship operation' are also exhaustive, including 6 and 8 classifications, respectively. These detailed definitions of RIFs enable a fine-grained assessment of maritime accident risk, adaptable to diverse risk analysis requirements. By using the RIFs and state definitions outlined in Fig. 4 for maritime accident risk analysis, new and compelling research findings can be uncovered, establishing a benchmark for future risk analysis.

3.5. Model construction

BN is a graphical model used for probabilistic modelling and inference, represented by a Directed Acyclic Graph (DAG). In the graph, nodes symbolise random variables, while edges signify conditional dependencies among these random variables. Due to its powerful capability to handle uncertainty and complex relationships among multiple variables, BN has been widely applied in maritime accident risk research.

In the past, most studies in the maritime safety field employed NBN to analyse the relationships between RIFs and target nodes. However, this approach assumes that all nodes are conditionally independent, given their parent nodes, disregarding the complex dependencies between nodes. Therefore, despite the simplicity and efficiency of NBN in computation, its modelling capability for complex probabilistic relationships is limited. To address this limitation, the study employs a TAN model to develop a maritime risk analysis model. TAN extends NBN by introducing additional edges to relax the assumption of conditional independence, thereby maintaining the simplicity of NBN while enhancing the expressive power of the model (Cao et al., 2023b). To construct the maritime risk analysis model, a data-driven approach is used based on TAN. Compared to the expert knowledge-based training methods used in previous studies (Yu et al., 2020; Zhang et al., 2016, 2021; Kaptan, 2022), the data-driven approach can adaptively and objectively learn the network structure and parameters from data, avoiding biases or errors that may result from expert knowledge.

Based on the new global maritime accident dataset, this study develops a purely data-driven TAN model for maritime risk analysis, consisting of 23 RIFs nodes. Then, the Conditional Probability Tables (CPTs) of each node in the model are obtained through parameter learning (Yang et al., 2018). The Bayesian rules are then used to

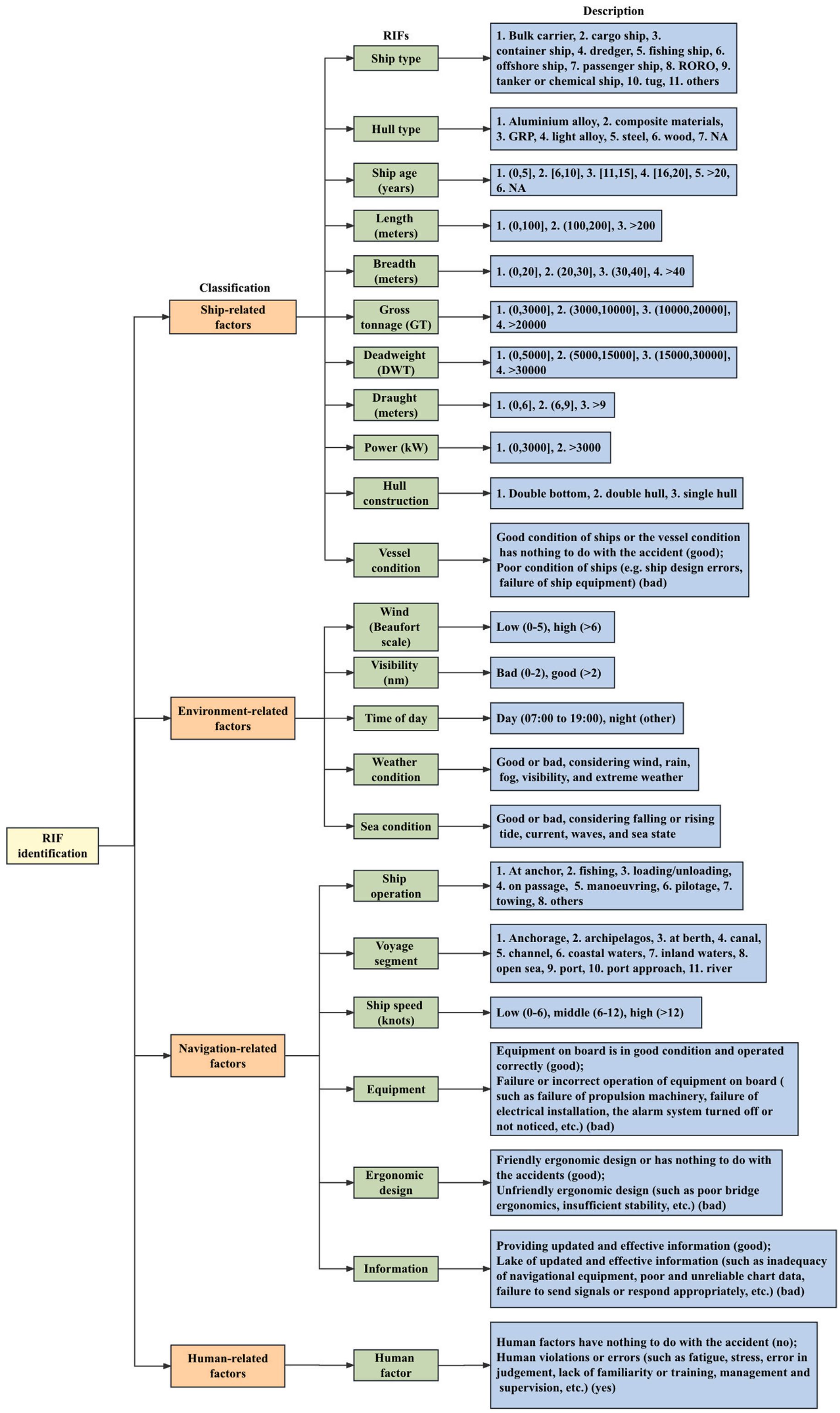

Fig. 4. Definition and states of RIFs.

calculate the marginal probabilities of each node upon the CPTs. This process can be simulated using Netica software, and the constructed TAN model is presented in Fig. 5.

Fig. 5 presents the probabilities of nine accident types obtained through the construction of the TAN model, which are as follows: 6.64%, 21.8%, 7.74%, 14.1%, 0.85%, 17.9%, 15.5%, 10.5%, and 4.99%. Subsequently, the proportions of the nine accident types are calculated using the original dataset, resulting in the following statistical outcomes: 6.62%, 21.8%, 7.73%, 14.1%, 0.83%, 17.95%, 15.5%, 10.5%, and 4.97%. It can be observed that the two sets of data exhibit a high degree of consistency in terms of probability values, providing preliminary evidence for the initial accuracy of the proposed model.

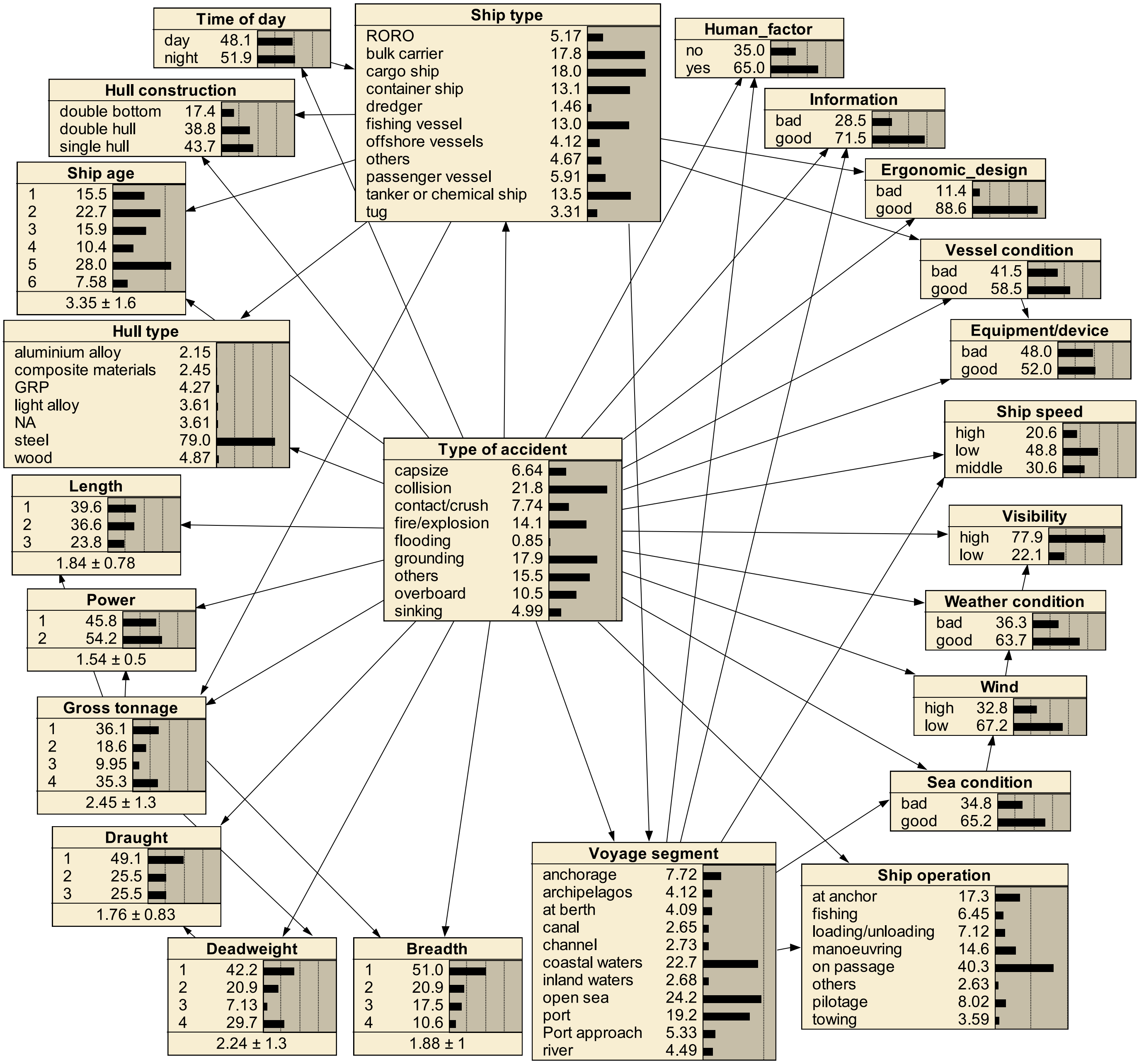

Fig. 5. The generated TAN model for the global maritime risk analysis.

4. Model validation

This study employs five validation methods for the constructed model. Firstly, sensitivity analysis is conducted to assess the dependence between RIFs and accident types based on Mutual Information (MI), joint probability, and True Risk Influence (TRI). Secondly, the correctness of the model is affirmed against two given axioms using the outcomes of the sensitivity analysis. Thirdly, a confusion matrix is constructed, with six derived metrics to measure the predictive performance of the model. Fourthly, the kappa coefficient is employed to ensure the model's consistency. Fifthly, a real-world maritime accident that occurred in 2023 serves as a case study for practical validation.

4.1. Sensitivity analysis

Sensitivity analysis is a methodology employed to evaluate the extent to which a model's outputs are affected by variations in its input variables. In maritime risk analysis, sensitivity analysis is used to identify important influencing factors of the model, which helps ensure its accuracy (Li et al., 2023a). In this paper, sensitivity analysis is conducted by MI, joint probability, and TRI to investigate the dependence of RIFs on accident types (Liang et al., 2022).

4.1.1. Mutual information

MI is a crucial indicator used to assess the correlation between two random variables and evaluate the degree of dependence between influencing factors and target nodes in maritime risk analysis. A larger MI value indicates a greater impact of the variable node on the target node. Table 2 presents the MI, entropy reduction percentage, and variance of beliefs of RIFs concerning the 'type of accident'. It can be observed from Table 2 that the parent node 'type of accident' is most significantly influenced by 'ship type'.

Table 2
MI shared with 'type of accident'.

Node	MI	Entropy Reduction Percent	Variance of Beliefs
Type of accident	2.8998	100	0.7298
Ship type	0.3321	11.5	0.0124
Ship operation	0.3138	10.8	0.0141
Voyage segment	0.2102	7.25	0.0068
Deadweight	0.1898	6.54	0.0045
Gross tonnage	0.1564	5.39	0.0036
Length	0.1535	5.29	0.0030
Power	0.1441	4.97	0.0026
Draught	0.1301	4.49	0.0030
Wind	0.1264	4.36	0.0034
Breadth	0.1213	4.18	0.0026
Sea condition	0.1172	4.04	0.0032
Human factor	0.1054	3.64	0.0025
Visibility	0.1052	3.63	0.0041
Ship age	0.1047	3.61	0.0035
Weather condition	0.1033	3.56	0.0026
Ship speed	0.1007	3.47	0.0029
Information	0.0910	3.14	0.0060
Hull construction	0.0886	3.05	0.0018
Hull type	0.0877	3.02	0.0023
Vessel condition	0.0788	2.72	0.0021
Equipment/device	0.0634	2.19	0.0018
Ergonomic design	0.0456	1.57	0.0014
Time of day	0.0426	1.47	0.0017

To identify the RIFs that considerably influence the 'type of accident', the arithmetic mean of the MI values of all RIFs is calculated. In Fig. 6, the blue bars represent the MI values of RIFs, and the orange horizontal dashed line represents the average MI value of all RIFs, serving as the baseline for filtering important RIFs. After calculation, the baseline represents an average MI value of 0.131, and the RIFs with MI values higher than 0.131 are selected as important RIFs. The results show that the first seven RIFs, namely ship type (0.3321), ship operation (0.3128), voyage segment (0.2102), deadweight (0.1898), gross tonnage (0.1564), length (0.1535), and power (0.1441), considerably impact the 'type of accident'.

4.1.2. Joint probability

After identifying the seven significant RIFs, further analysis is required to calculate the joint probabilities between the states of these RIFs and accident types, thereby refining the impact of RIFs on accident types. To obtain the updated probability values of accident types under a specific state, the probability of the important RIFs state is sequentially set to 100% while keeping the probabilities of other states constant. After completing the calculations for all states, Table 3 can be derived.

To simplify, let T1, T2, T3, T4, T5, T6, T7, T8, and T9 represent the nine accident types, namely capsize, collision, contact/crush, fire/explosion, flooding, grounding, others, overboard, and sinking,

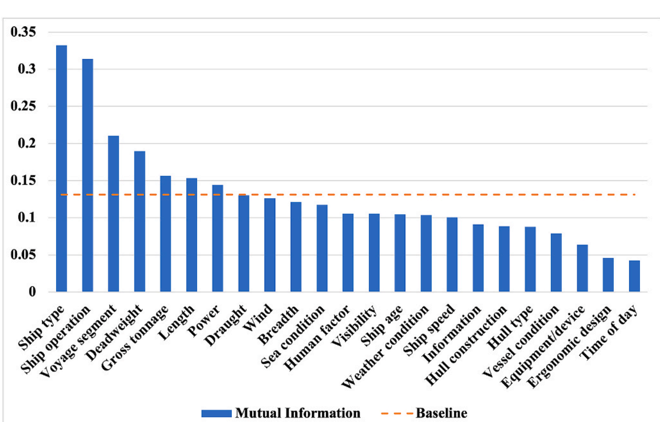

Fig. 6. Mutual information values of RIFs.

respectively. The bolded values in each column represent the maximum and minimum probabilities that significantly impact specific accident types. Some new findings can be revealed in Table 3. For instance, in terms of 'ship type', 'dredgers' are most likely to experience 'capsize' and 'sinking' accidents, while being least likely to have 'grounding' accidents. In contrast, 'bulk carriers' are less likely to experience 'capsize' accidents, and 'offshore vessels' are less likely to encounter 'grounding' accidents. Concerning 'voyage segments', 'port approach' is the most likely situation for 'collision' accidents, while 'at berth' is least likely. Additionally, 'channels' are more prone to experiencing 'grounding' accidents, while 'open sea' is the least likely. Regarding vessel characteristics, larger 'RORO' ships, specifically those with a deadweight range from (5000, 15,000], a gross tonnage falls in (10,000, 20,000], and a length exceeding 200 m, are more susceptible to 'fire/explosion' accidents. Conversely, smaller vessels with less weight and volume are less likely to experience 'fire/explosion' accidents.

Table 3 illustrates how accident types are affected when significant RIFs are in specific states. Moreover, the new maritime accident characteristics presented in Table 3 provide valuable insights for risk analysis and lay the foundation for later calculations of the TRI of significant RIFs on accident types.

4.1.3. True risk influence

TRI is a comprehensive evaluation metric proposed by Alyami et al. (2019), which can quantify the extent of the risk impact of a variable node on its parent node, taking into account the probabilities of each node state in the BN and the dependency relationships between nodes. TRI can quantify the importance of different RIFs on the accident types and provide a reliable basis for risk assessment in relevant decision-making (Li et al., 2023a).

The computation outcomes are displayed in Table 4. The last column of Table 4 displays the average TRI value of each important RIF for each accident type. It can be observed that 'ship type' has the most significant impact on accident types, while 'power' has the lowest impact. The impact level of these seven important RIFs can be ranked based on the values in this column, and the results are as follows:

Ship type > Ship operation > Voyage segment > Deadweight > Gross tonnage > Length > Power.

According to the results in Table 4, the influence levels of the important RIFs under different accident types are sorted in order from the largest to the smallest (represented by '1' and '7' respectively) in Table 5. It is observed that different RIFs have both similar and distinct impact levels on different accident types. For example, 'ship type' has the highest impact level on 'capsize', 'contact/crush', 'fire/explosion', 'grounding', and 'sinking', whereas 'power' has the lowest impact level on 'collision', 'fire/explosion', 'grounding', 'others', 'overboard', and 'sinking'. Furthermore, 'voyage segment' has the highest impact level on 'flooding' and 'overboard', but the lowest impact level on 'capsize'. Sorting the TRI values can provide valuable insights and is significant for improving the precision and dependability of risk evaluation.

4.2. Model correctness verification

It is essential to conduct an additional sensitivity analysis to validate the correctness of the model. This sensitivity analysis can assess the joint impact of various RIFs on accident types during the inference process. The inference process must adhere to the following two axioms (Jones et al., 2010; Yang et al., 2009).

Axiom 1. If the prior probability of each RIF changes slightly, the posterior probability of the target node should be adjusted accordingly.

Axiom 2. The total effect of integrating the probability variations of x parameters should be no smaller than the one from the set of y ($y \in x$) RIFs.

To verify the above two axioms, the extracted seven important RIFs

Table 3
The joint probability (100%).

	T1	T2	T3	T4	T5	T6	T7	T8	T9
Original	6.64	21.80	7.74	14.08	0.85	17.94	15.46	10.50	4.99
Ship type									
RORO	0.98	11.39	15.90	**46.95**	0.62	11.36	6.07	1.01	5.73
bulk carrier	**0.28**	33.57	1.74	9.25	**0.18**	16.82	25.84	10.64	1.67
cargo ship	4.51	19.68	13.09	4.73	**2.96**	23.99	13.56	8.98	8.50
container ship	2.34	18.81	6.19	18.51	0.24	16.63	**26.55**	10.35	**0.38**
dredger	**37.80**	3.68	3.52	3.63	2.20	**3.67**	21.55	3.59	**20.36**
fishing vessel	22.00	12.82	2.39	18.72	0.25	10.71	4.54	22.49	6.09
offshore vessels	1.23	**1.30**	13.68	14.12	0.78	**46.77**	**1.28**	7.65	13.19
others	22.63	29.99	**1.10**	**1.13**	0.69	29.86	6.88	6.66	1.06
passenger vessel	5.08	14.45	**35.62**	5.40	0.54	19.00	9.84	**0.88**	9.19
tanker or chemical ship	0.37	**34.24**	2.30	20.09	0.24	12.24	20.15	8.18	2.20
tug	16.82	17.79	1.55	17.58	0.97	9.71	1.60	**25.04**	8.95
Ship operation									
at anchor	**2.45**	**3.05**	8.78	13.52	0.96	28.46	13.79	**23.61**	5.38
fishing	**35.87**	4.33	3.61	18.86	1.10	7.98	7.39	17.65	3.22
loading/unloading	5.58	7.45	3.27	**22.75**	1.00	**3.90**	**49.70**	**3.43**	2.92
manoeuvring	5.82	**37.09**	20.41	4.97	**0.49**	21.64	**3.37**	4.79	**1.42**
on passage	3.14	32.26	**1.60**	17.76	0.65	12.59	18.74	6.67	6.59
others	15.13	10.63	8.87	10.19	**2.70**	10.56	10.00	18.05	**13.87**
pilotage	5.15	12.61	**20.75**	**3.34**	0.88	**39.85**	6.13	8.71	2.59
towing	16.13	21.33	6.49	13.63	1.98	14.35	7.31	12.99	5.79
Voyage segment									
anchorage	**1.91**	12.37	5.13	11.65	0.55	28.81	15.23	17.28	7.08
archipelagos	7.93	16.56	14.43	4.92	1.02	32.94	4.64	13.78	3.77
at berth	3.60	**5.28**	15.40	**27.33**	1.03	5.57	**28.69**	9.30	3.80
canal	5.55	27.10	**20.42**	7.65	1.59	17.90	7.21	6.73	5.86
channel	5.39	7.91	5.96	7.43	1.55	**43.23**	16.30	6.54	5.70
coastal waters	12.88	32.69	2.53	11.03	**0.19**	19.64	6.41	9.55	5.07
inland waters	**14.31**	8.06	14.79	7.57	1.57	8.50	7.14	**32.25**	5.80
open sea	3.38	25.49	**2.39**	24.49	0.71	**4.91**	25.47	7.39	5.77
port	4.60	12.04	13.75	11.28	0.90	23.52	21.24	10.39	**2.27**
port approach	10.52	**36.04**	11.77	**3.80**	**3.23**	21.18	**3.59**	**3.34**	6.53
river	3.28	21.12	13.24	9.88	0.94	20.85	4.26	19.08	**7.36**
Deadweight									
1	**13.38**	14.88	11.32	**11.00**	**1.39**	**24.81**	**3.45**	11.34	**8.43**
2	1.99	27.96	5.50	**20.04**	0.42	14.96	18.79	**5.88**	4.47
3	5.84	**9.65**	**12.87**	16.81	1.24	20.98	21.37	9.69	1.54
4	**0.53**	**30.20**	**3.01**	13.61	**0.30**	**9.55**	**28.76**	**12.74**	**1.30**
Gross tonnage									
1	**14.04**	**15.08**	9.54	**10.54**	**1.57**	**25.16**	**3.30**	**12.48**	**8.30**
2	6.15	**28.41**	7.58	12.52	0.52	16.79	16.78	**6.55**	4.70
3	2.14	15.68	**12.14**	**18.15**	0.96	20.82	15.60	9.94	4.57
4	**0.60**	26.91	**4.75**	17.38	**0.27**	**10.35**	**27.16**	10.70	**1.87**
Length									
1	**14.46**	**15.22**	**10.12**	**10.40**	**1.59**	**24.49**	**3.08**	**12.19**	**8.46**
2	1.98	24.37	7.00	16.11	**0.31**	15.46	21.98	9.41	3.38
3	**0.81**	**28.77**	**4.93**	**17.07**	0.47	**10.86**	**26.02**	**9.36**	**1.69**
Power									
1	**13.92**	**17.42**	**10.68**	**11.45**	**1.51**	**22.47**	**7.35**	**4.54**	**10.67**
2	**0.49**	**25.50**	**5.26**	**16.31**	**0.30**	**14.11**	**2.99**	**24.69**	**10.36**

Table 4
TRI of RIFs for all accident types (100%).

RIFs	TRI									
	T1	T2	T3	T4	T5	T6	T7	T8	T9	**Average**
Ship type	18.76	16.47	17.26	22.91	1.39	21.55	12.63	12.08	9.99	**14.78**
Ship operation	16.71	17.02	9.57	9.71	1.11	17.98	23.17	10.09	6.22	**12.40**
Voyage segment	6.20	15.38	9.02	11.76	1.52	19.16	12.55	14.45	2.55	**10.29**
Deadweight	6.42	10.28	4.93	4.52	0.55	7.63	12.66	3.43	3.56	**5.99**
Gross tonnage	6.72	6.67	3.69	3.81	0.65	7.40	11.93	2.97	3.21	**5.23**
Length	6.82	6.77	2.59	3.34	0.64	6.81	11.47	1.41	3.38	**4.80**
Power	6.71	4.04	2.71	2.43	0.61	4.18	10.07	0.15	2.18	**3.68**

are selected as variable nodes. Given the correlation between nodes in the TAN-based BN model and the mutual independence of each node's states, this study examines the overall impact on the 'type of accident' by modifying the specific states of the important RIFs. The detailed procedures are as follows: (1) Select 'Power' as the initial node and increase the probability value of the state that has the most significant impact on capsize by 2%, while decreasing the probability value of the state with the least impact by 2%; (2) Record this adjustment as '+2%' and document it in Table 6; (3) Repeat the same operation for the remaining important RIFs, and record the cumulative change values that affect 'capsize'; (4) Apply the above three steps to other states of 'type of accident' until all calculations are completed.

Table 5
The most important RIFs for all accident types.

	T1	T2	T3	T4	T5	T6	T7	T8	T9
Ship type	1	2	1	1	2	1	3	2	1
Ship operation	2	1	2	3	3	3	1	3	2
Voyage segment	7	3	3	2	1	2	4	1	6
Deadweight	6	4	4	4	7	4	2	4	3
Gross tonnage	4	6	5	5	4	5	5	5	5
Length	3	5	7	6	5	6	6	6	4
Power	5	7	6	7	6	7	7	7	7

The second column of Table 6 presents the occurrence probabilities of various accident types in the original data. As the inference process progresses, the following columns demonstrate how the cumulative probability of each accident category evolves in response to alterations in the prior probabilities of significant RIFs. It is worth noting that calculating cumulative probability changes for different accident types is independent.

Taking 'capsize' as an example, '6.64' represents the original probability value. Let the prior probability of the state in 'power' that has the maximum impact on 'capsize' increase by 2%, and the prior probability of the state in 'power' that has the minimum impact decrease by 2%. Then, the probability value of 'capsize' changes to '6.90'. Based on '6.90', set the prior probability of the states in 'length' with maximum and minimum impacts on 'capsize' increase and decrease by 2%, respectively. The probability value of 'capsize' is further updated to '6.91'. Then, the same operation is applied to the remaining important RIFs, including 'gross tonnage', 'deadweight', 'voyage segment', 'ship operation', and 'ship type'. After calculating the cumulative probability changes for the corresponding row of 'capsize', the identical inference process is applied to the remaining accident types until all calculations are completed.

From Tables 6 and it is evident that the posterior probability of the target node increases or decreases as the prior probability of the variable node set increases or decreases, thus confirming Axiom 1. Additionally, as the probability values of the variable node-set are continuously updated, the cumulative change in the target node also increases, thereby proving Axiom 2 and confirming the correctness of the BN model developed in this study.

4.3. Prediction performance verification

After completing the correctness test of the model, it is necessary to evaluate its predictive performance. To achieve this, 20% of the accident data (72 cases) from the dataset created in this study are randomly selected as the testing set. In addition, to comprehensively gauge the reliability of the constructed model, a confusion matrix and six evaluation indicators based on the confusion matrix are employed. The confusion matrix is a standard method to evaluate the performance of classification models and can offer a more profound comprehension of the model's effectiveness in predicting maritime risks. The representation of the confusion matrix is illustrated in Fig. 7.

Based on the four primary indicators in the confusion matrix, namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), four secondary indicators (i.e., Precision, Recall, Specificity, and False Positive Rate (FPR)) and two tertiary indexes (i.e., F-measure and Area Under Curve (AUC)) can be derived. The details of the six indicators are listed in Table 7.

Based on Fig. 7, the prediction outcomes of the test set are presented through a confusion matrix displayed in Table 8.

Table 8 shows that the model achieves an overall prediction accuracy of 91.67% (66/72), and the prediction accuracy for 'capsize', 'contact/crush', 'flooding', 'overboard', and 'sinking' is 100%, revealing the excellent predictive performance of the model. Furthermore, based on Table 8, the first five evaluation indicators are computed. Subsequently, the classification problem of this study is processed for binary classification to obtain AUC values for specific accident types. The computation results are presented in Table 9.

Table 9 indicates that the values of Precision, Recall, Specificity, and F-measure metrics are all above 0.8. For specific accident types (e.g., T1, T5, and T9), all four metrics mentioned above have the value of '1', highlighting the excellent predictive performance of the model. A lower FPR value indicates the model has a stronger ability to correctly classify negative samples as negative, reducing false alarms effectively. The FPR values of this model are all below 0.035, demonstrating good stability and accuracy. Moreover, the AUC values for all nine accident types are above 0.97, verifying the outstanding classification performance of the model.

4.4. Model consistency verification

The dataset created in this study has an uneven distribution of each accident type. For instance, 'collision' accounts for 21.8%, while

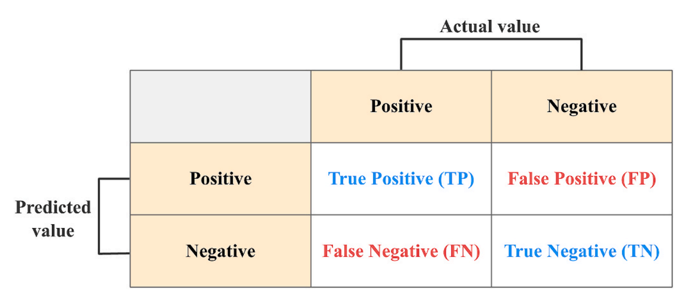

Fig. 7. The schematic representation of the confusion matrix.

Table 6
The combined influence of multiple variables.

Power		+2%	+2%	+2%	+2%	+2%	+2%	+2%
Length			+2%	+2%	+2%	+2%	+2%	+2%
Gross tonnage				+2%	+2%	+2%	+2%	+2%
Deadweight					+2%	+2%	+2%	+2%
Voyage segment						+2%	+2%	+2%
Ship operation							+2%	+2%
Ship type								+2%
T1	6.64	6.90	6.91	7.18	7.44	7.71	8.44	9.23
T2	21.80	21.96	22.07	22.34	22.76	23.40	24.13	24.85
T3	7.74	7.85	7.85	7.99	8.19	8.55	8.98	9.75
T4	14.08	14.18	14.21	14.37	14.56	15.04	15.45	16.43
T5	0.85	0.87	0.88	0.91	0.93	0.99	1.04	1.11
T6	17.94	18.11	18.21	18.51	18.81	19.59	20.39	20.86
T7	15.46	15.86	15.92	16.39	16.90	17.43	18.39	18.94
T8	10.50	10.51	10.56	10.67	10.81	11.39	11.80	12.31
T9	4.99	5.08	5.12	5.25	5.39	5.49	5.73	6.18

Table 7
The definitions of six indicators.

Six indicators	Definitions
$Precision = \frac{TP}{TP+FP}$	The proportion of true positive samples among all the samples predicted as positive.
$Recall = \frac{TP}{TP+FN}$	The ratio of true positive samples to the total number of positive samples.
$F-measure = \frac{2*Precision*Recall}{Precision+Recall}$	The weighted harmonic mean of Recall and Precision, which assesses the overall performance of the model
$Specificity = \frac{TN}{FP+TN}$	The proportion of true negative samples among the total number of negative samples
$FPR = \frac{FP}{FP+TN}$	The ratio of false positive samples to the total number of negative samples
AUC	AUC is the area under the Receiver Operating Characteristic (ROC) curve and ranges between 0.5 and 1. A higher AUC value indicates better classification performance of the model.

'flooding' only accounts for 0.85%. Therefore, the Kappa coefficient is used to test the model's consistency and offer a comprehensive assessment of the model's overall performance.

The Kappa coefficient, proposed by Cohen (1960), is a critical evaluation index for measuring the consistency of classification models, which is calculated by comparing the consistency between the model's predicted and actual observed results. The range of the Kappa coefficient is [−1,1], with higher values indicating better consistency of the model. When the Kappa value is greater than 0.75, it indicates that the consistency of the model is excellent and can be considered completely consistent. The formula of the kappa statistic is defined as follows:

$$k = \frac{p_o - p_e}{1 - p_e}, p_e = \frac{1}{n}\sum_{i=1}^{9} t_i \times p_i \tag{1}$$

where k is the kappa statistic, p_e indicates overall accuracy, and n is the total number of samples in the test dataset. The number of real samples of each accident type is $t_i, i = 1, \ldots, 9$ respectively, and the number of each accident type in the prediction result is p_i respectively.

By employing the relevant calculation formulas and confusion matrix, the Kappa coefficient is determined to have a value of 0.903, which demonstrates the remarkable consistency of the model constructed in this study (Li et al., 2023a).

4.5. Real case analysis

To validate the applicability of the BN model, a real collision accident from the China Maritime Safety Administration (CMSA) is selected for testing, which is not included in the dataset of 362 cases used in this study. On September 25, 2022, the bulk carrier 'Xin xx' had a collision with a fishing vessel about three nautical miles south of Dongshan Island in Zhangzhou. The accident details and corresponding RIFs states are reflected in Fig. 8. Among them, the information on 'draught', 'power', and 'hull construction' is not recorded in the accident report and thus is considered as 'NA'. Remarkably, despite the absence of three RIFs' states, the probability of the accident type 'collision' remains high at 99.1%, consistent with the actual situation. This result further confirms the reliability of the proposed model and its potential applicability in preventing specific types of accidents.

5. Comparison analysis and discussion

Maritime risk factors and characteristics may change over time. Thus, this study conducts a multidimensional comparison and analysis of the maritime accidents in the two periods of 2017–2021 and 2012–2017. The study in 2017–2021 is conducted using the above proposed BN model, while the findings in 2012–2017 are derived from a previous study (Fan et al., 2020a).

5.1. Comparative analysis of RIFs

This research takes into consideration the perspective of RIFs and incorporates eight new RIFs, namely 'hull construction', 'deadweight', 'breadth', 'draught', 'power', 'wind', 'visibility', and 'human factor', compared to the previous study. These eight RIFs cover three aspects: vessel characteristics (i.e., hull construction, deadweight, breadth, draught, and power), weather conditions (i.e., wind and visibility), and human factors (i.e., human factor). The vessel's characteristics directly influence its operational and safety performance, while the magnitude of wind and visibility affects the vessel's navigation. Moreover, human factors play a significant role in maritime risk. This research expands the number of RIFs from these three aspects, providing a multidimensional and comprehensive analysis of maritime risk and filling the gaps in previous studies.

From the perspective of important RIFs, the previous research

Table 8
Confusion matrix for the predicted outcomes.

Predicted	T1	T2	T3	T4	T5	T6	T7	T8	T9	Actual total	Accuracy rate (100%)
T1	**5**	0	0	0	0	0	0	0	0	5	100
T2	0	**15**	1	0	0	0	0	0	0	16	93.75
T3	0	0	**6**	0	0	0	0	0	0	6	100
T4	0	0	0	**8**	0	0	2	0	0	10	80
T5	0	0	0	0	**2**	0	0	0	0	2	100
T6	0	0	0	1	0	**11**	0	0	0	12	91.67
T7	0	1	0	0	0	0	**8**	1	0	10	80
T8	0	0	0	0	0	0	0	**7**	0	7	100
T9	0	0	0	0	0	0	0	0	**4**	4	100
Predicted total	5	16	7	9	2	11	10	8	4	72	91.67

Table 9
Performance metrics for each category of accidents.

	T1	T2	T3	T4	T5	T6	T7	T8	T9
Precision	1	0.938	0.857	0.889	1	1	0.8	0.875	1
Recall	1	0.938	1	0.8	1	0.917	0.8	1	1
Specificity	1	0.982	0.985	0.984	1	1	0.968	0.985	1
FPR	0	0.018	0.015	0.016	0	0	0.032	0.015	0
F-measure	1	0.938	0.923	0.842	1	0.957	0.8	0.933	1
AUC	1	0.986	0.979	0.985	1	0.979	0.977	0.999	0.996

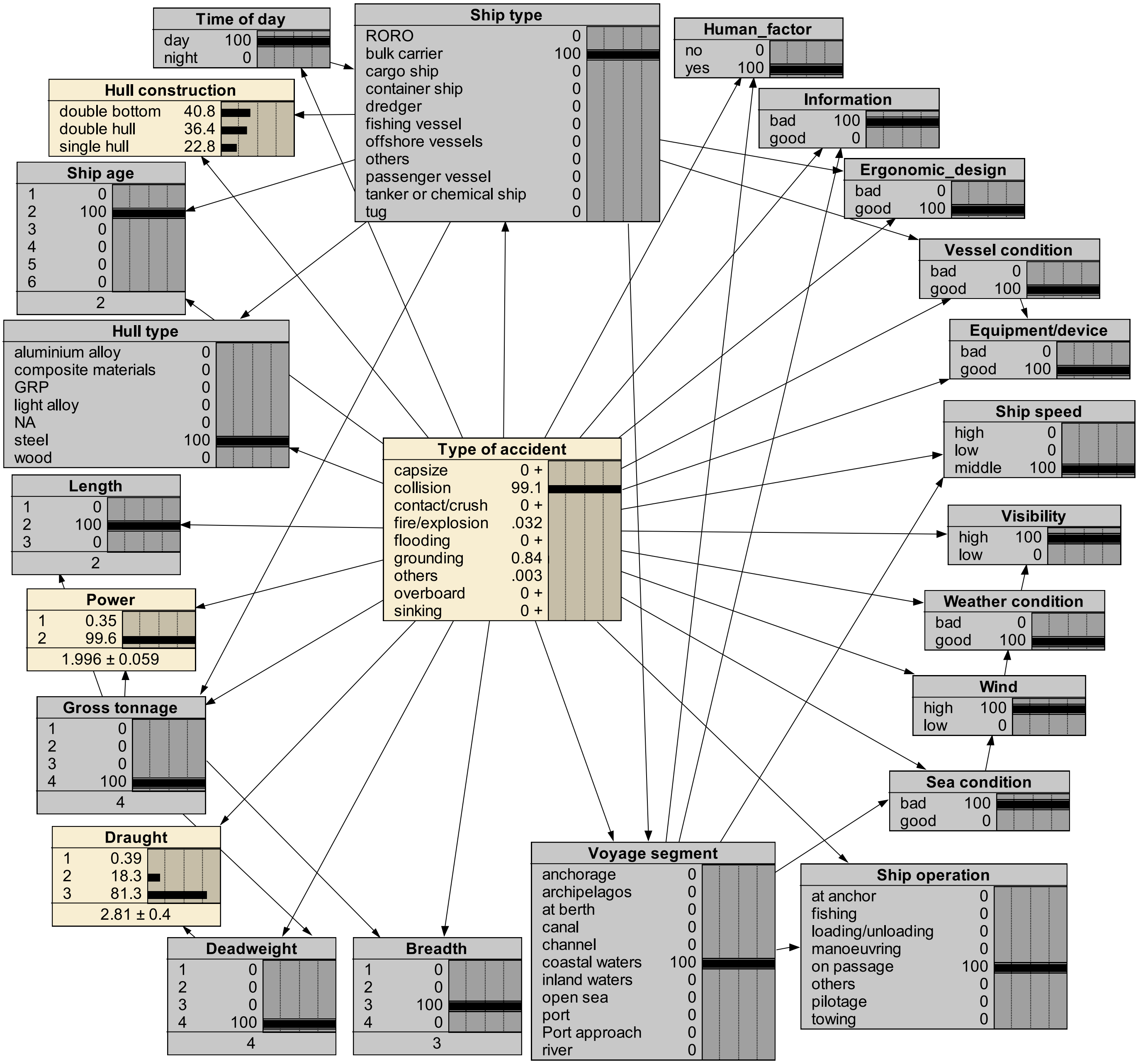

Fig. 8. A real case validation in 2022 by the constructed data-driven BN network.

identified the important RIFs and their ranking as follows:

Ship operation > Voyage segment > Ship type > Hull type > Gross tonnage > Information.

In comparison, the identified important RIFs in this study also include 'ship operation', 'voyage segment', 'ship type', and 'gross tonnage', similar to previous findings. However, this study has newly included 'deadweight', 'length', and 'power' as RIFs. This finding further supports the validity of considering deadweight and power as RIFs for maritime risk analysis. Moreover, it suggests that 'deadweight' and 'power' have a more pronounced influence on the types of maritime accidents compared to other ship characteristics. There are two main reasons for this: (1) the excessive or insufficient deadweight of a vessel can affect its stability, subsequently influencing the probability of maritime accidents; (2) the strength and reliability of a vessel's power system directly impact its manoeuvrability and control capabilities.

5.2. Comparative analysis of BN

5.2.1. Network structure and dataset

The previous study (Fan et al., 2020a) employed NBN to analyse maritime transportation risk using a dataset of 161 maritime accidents. However, NBN has limitations such as sensitivity to missing data and less precise modelling of dependencies among variables. Moreover, the small dataset used for model training may compromise the reliability and feasibility of the research findings.

In contrast to the previous study, this research employs TAN to construct a maritime risk analysis model that captures the dependencies among influencing factors more accurately. Furthermore, the TAN model is trained on a larger dataset of 362 global maritime accident data, ensuring objectivity and correctness of the research findings driven purely by data. Additionally, the TAN model incorporates more RIFs and a more comprehensive range of variable states, enabling multidimensional analysis of maritime accident risk and investigation of accident causes. By overcoming the limitations of the previous study, the TAN-based model developed in this research provides a more robust and accurate approach to maritime risk analysis.

5.2.2. The state change of common RIFs in constructed BN

According to the finalised BN model, a comparative analysis of changes in the state of common RIFs between this study and the previous one unveils valuable findings. To illustrate the changes in the state probabilities of common RIFs, representative state probability values from both studies are summarised in Table 10.

Based on the analysis of the 'gross tonnage', 'length', and 'speed' of ships, the proportion of large and high-speed ships in maritime accidents is rapidly increasing. Table 10 displays that in contrast to the results of the previous study, this study highlights the following changes: (1) the probability of gross tonnage less than '10,000' decreased by 13.1%, while the probability of gross tonnage greater than '20,000' increased to 35.3%; (2) the probability of length less than '100' decreased by 25.4%, while the probability of length greater than '100' increased by 30.8%; (3) the probability of ship speed being 'normal' decreased by 56.5%, while the probability of ship speed being 'fast' increased by 7.7%. The comparative analysis indicates that the trend towards the enlargement and high-speed operations of ships is inevitable, driven by the rapid development of the maritime transportation industry. However, it also increases the inertia and manoeuvring difficulty of ships, potentially elevating the risk of accidents. Consequently, maritime authorities are advised to devise effective management strategies and prioritise the safety of transportation for large ships to counteract the risks tied to this trend.

From an environmental standpoint, the rate of maritime accidents in unfavourable weather and sea conditions is declining. This suggests that the negative influence of external environments on maritime transportation safety is lessening. Table 10 shows that the probabilities of poor weather conditions and sea conditions in the past six years were 40.3% and 53.2%, respectively, while in this study, the probabilities of poor weather conditions and sea conditions were 36.3% and 34.8%, respectively. This finding indicates that as maritime meteorological warning technology continues to advance, ship owners can choose more appropriate weather conditions for maritime operations, thereby minimising accident risks. Additionally, with enhancements in ships' structural strength and stability, their capability to withstand adverse environments has also improved. From the perspective of 'voyage segments', maritime accidents occurring in ports have significantly increased. Table 10 indicates that the probability of accidents occurring in ports has increased from 7.53% to 19.2%. This finding highlights that (1) the rising number and volume of ships have created enormous pressure on port traffic; (2) the high-speed operation of ships has reduced the stay time of ships entering and leaving ports, thus increasing the difficulty of ship manoeuvring and port congestion; (3) the narrow channels and complex traffic environment in port areas also contribute to the risk of maritime accidents. This finding underlines the need for maritime authorities to strengthen port traffic management, improve channel facilities, and enhance the safety of ship operations in ports.

Analysing from the perspective of 'ship operations', the risk of maritime accidents significantly increases during 'at anchor' or 'manoeuvring'. Table 10 reveals that the probabilities of these two operational states increase by 11.82% and 3.8%, respectively. This finding highlights the challenges posed by the large dimensions and high speed of ships, which require longer berthing times and greater manoeuvring space during entry and exit from ports and anchorages. Such actions can create unfavourable navigation conditions for surrounding vessels, heightening the risk of accidents. Therefore, it is crucial for crew members to strictly adhere to operational procedures to ensure the precision of ship operations and minimise the likelihood of maritime accidents.

Table 10
Comparison of the states' probabilities of RIFs (↑ and ↓ indicate increase and decrease, respectively).

The state of RIFs	2012–2017	2017–2021	Trends
Gross tonnage (GT)			
<10,000	67.8%	54.7%	↓
>20,000	–	35.3%	↑
Length (meters)			
<100	65%	39.6%	↓
>100	29.6%	60.4% (36.6% + 23.8%)	↑
Ship speed (knots)			
Normal (6–12)	87.1%	30.6%	↓
Fast (>12)	12.9%	20.6%	↑
Weather condition			
Poor	40.3%	36.3%	↓
Sea condition			
Poor	53.2%	34.8%	↓
Voyage segment			
In port	7.53%	19.2%	↑
Ship operation			
At anchor	5.48%	17.3%	↑
Manoeuvring	10.8%	14.6%	↑

5.2.3. The states of newly added RIFs in constructed TAN

In addition to the common RIFs that show novel findings regarding state changes, the newly added RIFs in this study have also revealed valuable discoveries.

According to the analysis of 'hull construction', the likelihood of double-bottom ships is 17.4%, while single-hull ships have a probability of 43.7%. This implies that single-hull ships are more vulnerable to maritime accidents. The reason behind this is that double-bottom ships have two layers of the hull at the bottom, whereas single-hull ships have only one layer. In case of external impacts or grounding, single-hull ships are more prone to hull damage, which may result in leaks, fires, and other severe accidents. Consequently, maritime authorities should implement measures to gradually decrease the proportion of single-hull ships and enhance the safety of ships.

From the analysis of 'wind' and 'visibility', the probability of high wind is 32.8%, and the likelihood of low visibility is 22.1%. This analysis further confirms that with the advancement of meteorological forecasting technology and shipbuilding technology, maritime accidents caused by severe weather conditions such as strong winds and poor visibility are gradually decreasing. It highlights the importance of accurate weather forecasting and enhancing ship safety measures to minimise the likelihood of maritime accidents.

5.3. Comparative analysis of scenario simulation

Scenario simulation is crucial for maritime risk analysis as it enables the identification and evaluation of potential risks. In this study, various comparative scenario simulations are conducted based on the constructed TAN model to explore the new characteristics and trends of maritime accident risks in the latest five years, compared to previous research.

5.3.1. Scenario one: ship-related factors

Scenario one investigates the characteristics of maritime accident risks in the same ship condition in the two periods. Ship-related factors and their corresponding conditions are set as follows: 'ship age' > 20, 'ship type' is others, 'information' is good, 'ergonomic design' is bad, 'equipment device' is good, 'vessel condition' is good, and 'ship speed' is high. The BN network of this study after setting the corresponding states is shown in Fig. 9.

When the ship conditions mentioned above are the same, the previous study shows that the most probable accident type is 'collision' (82.2%). In contrast, this study reveals that the most likely accident type is 'capsize' (38.1%), and the probability of 'collision' is only 6.81%. This finding reveals that in the specified conditions, the likelihood of

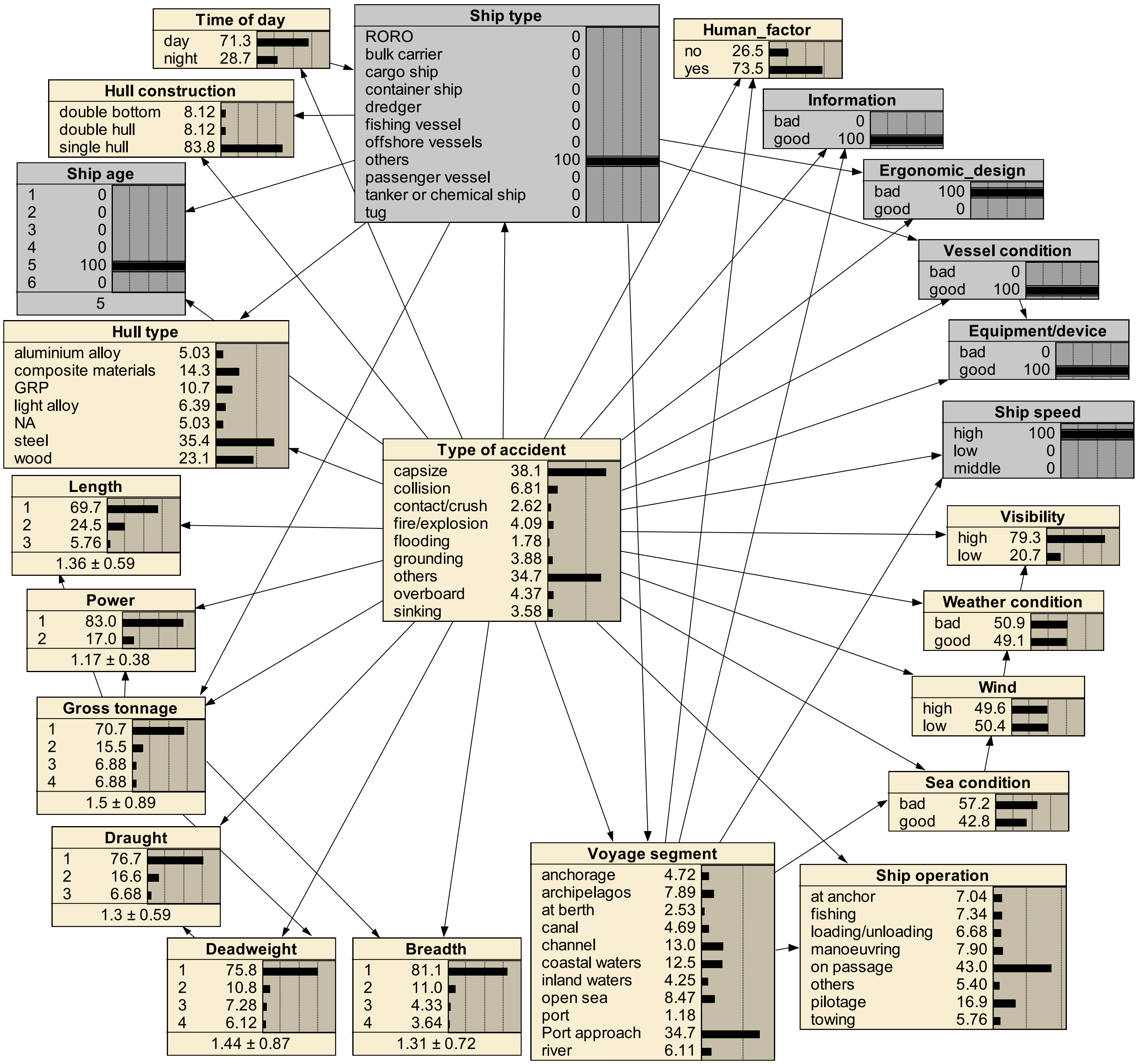

Fig. 9. The combined effects of ship-related factors in this study.

collision is significantly reduced in modern ships equipped with advanced navigation and communication devices. This allows the crew to precisely control navigation routes and monitor ship movements in real time to avoid collisions with other vessels. Nevertheless, factors such as older ship age and poor ergonomic design increase the risk of ‘capsize’ accidents, as ageing and fatigue of the ship’s structure can reduce its strength and stability over time. In addition, poor ergonomic design can lead to operational difficulties and elevate the risk of ‘capsize’ accidents. Therefore, relevant authorities should intensify inspections and maintenance for older ships, improve the ergonomic design of ships, and decrease the risk of ship capsizing.

5.3.2. *Scenario two: external environment-related factors*

Scenario two investigates the characteristics of maritime accident risks under the same external environment. The relevant factors of the external environment are set as follows: ‘ship operation’ is on passage, ‘voyage segment’ is port approach, ‘weather condition’ is bad, ‘sea condition’ is bad, and ‘time of day’ is night. The corresponding BN for this study is shown in Fig. 10.

It is observed that under the same external environmental conditions, the previous study shows that the most probable type of accident was ‘grounding’ (63.5%). In contrast, the current study indicates that the most probable accident type is ‘sinking’ (50.6%). This new finding suggests that in the latest five years, ships have been more susceptible to sinking accidents than grounding accidents during ‘port approach’, especially at night and under adverse weather conditions. As port traffic becomes more complex, ships encounter increased risks while entering ports compared to the previous six years. Furthermore, coupled with adverse external environmental conditions, even minor errors in ship operations could result in sinking accidents. Moreover, sinking accidents tend to have more severe consequences, such as environmental pollution and casualties, compared to grounding accidents. Therefore, maritime authorities should formulate effective strategies to prevent sinking accidents based on this new risk characteristic, such as improving port

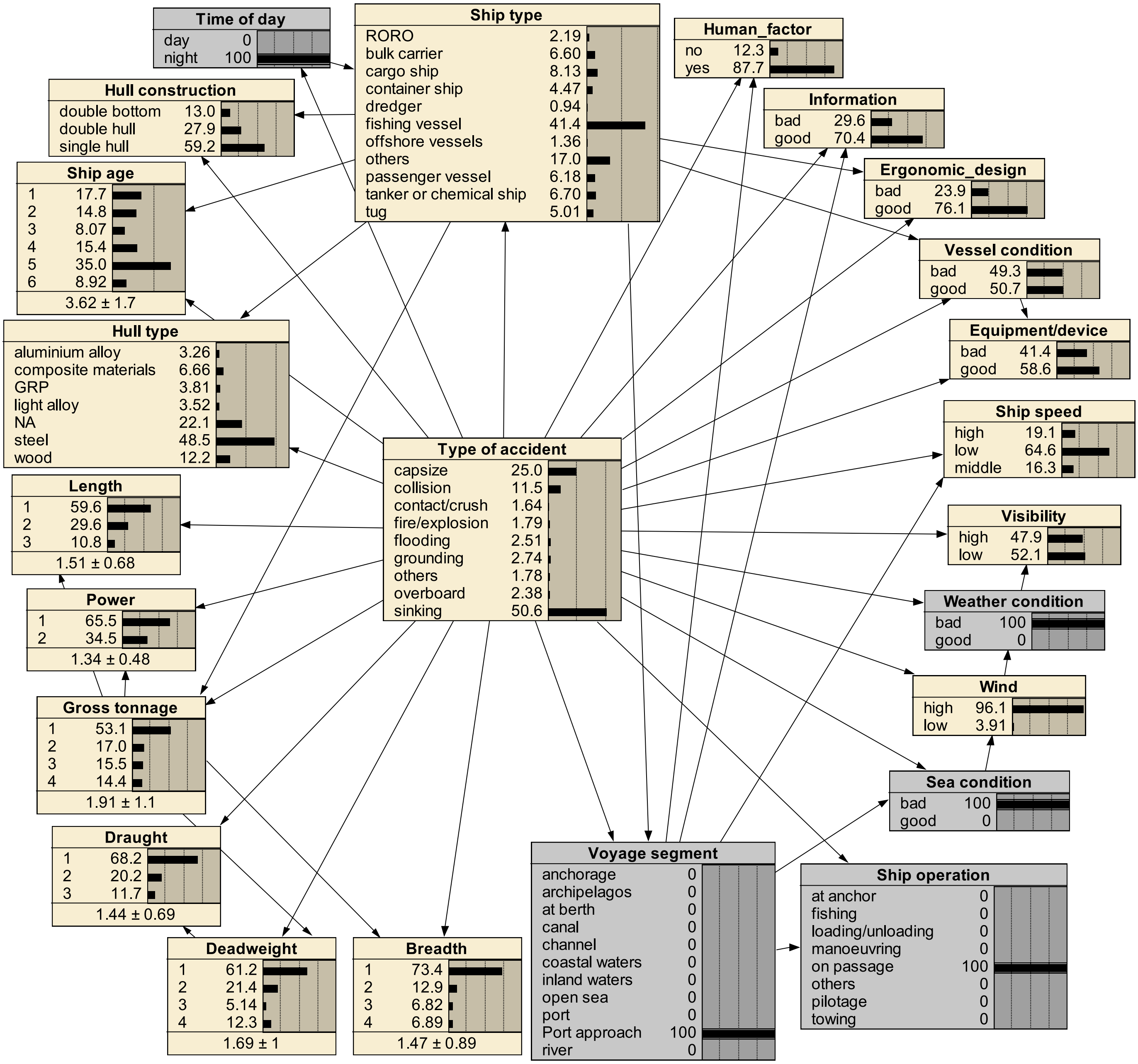

Fig. 10. The combined effects of environment-related factors in this study.

facilities and rescue organisations and enhancing ship communication during adverse weather conditions.

5.3.3. Scenario three: the most likely scenario for specific accident types

To exploit the reverse diagnostic analysis capability of BN, Scenario three fixes the accident type node to a particular state to compare and analyse the corresponding performance of RIFs in the two periods. The aim is to uncover the most probable scenarios associated with specific accident types.

In both BNs, the accident type node is set to 100% for 'overboard'. It was found that in the previous study, the most probable type of ship to encounter overboard accidents is 'fishing vessels' (41.4%), with the ship operation being 'fishing' (37%). In the current study (i.e., Fig. 11), 'fishing vessels' also have the highest likelihood of experiencing overboard accidents (27.8%), but the most likely vessel operation is 'at anchor' (39%).

This change observed in the current study indicates that advancements in fishing techniques and equipment have significantly reduced the likelihood of overboard accidents occurring during fishing operations. On the contrary, crew members must perform more complex vessel operations (such as operating winches and anchors) when a fishing vessel is at anchor, making overboard accidents more probable. In addition, the state of the newly added RIF 'human factor' reveals a new finding. The probability of the 'yes' in the 'human factor' is 88.4%, indicating that most overboard accidents on fishing vessels are related to human factors. Specifically, these factors include (1) negligence, (2) operational errors, (3) fatigue and work pressure, (4) improper behaviours such as alcohol consumption, and (5) inadequate safety training. Therefore, based on this latest finding, shipping companies should heighten safety awareness among fishing vessel crew members, provide necessary operational skills training, and address human factors to minimise overboard accidents.

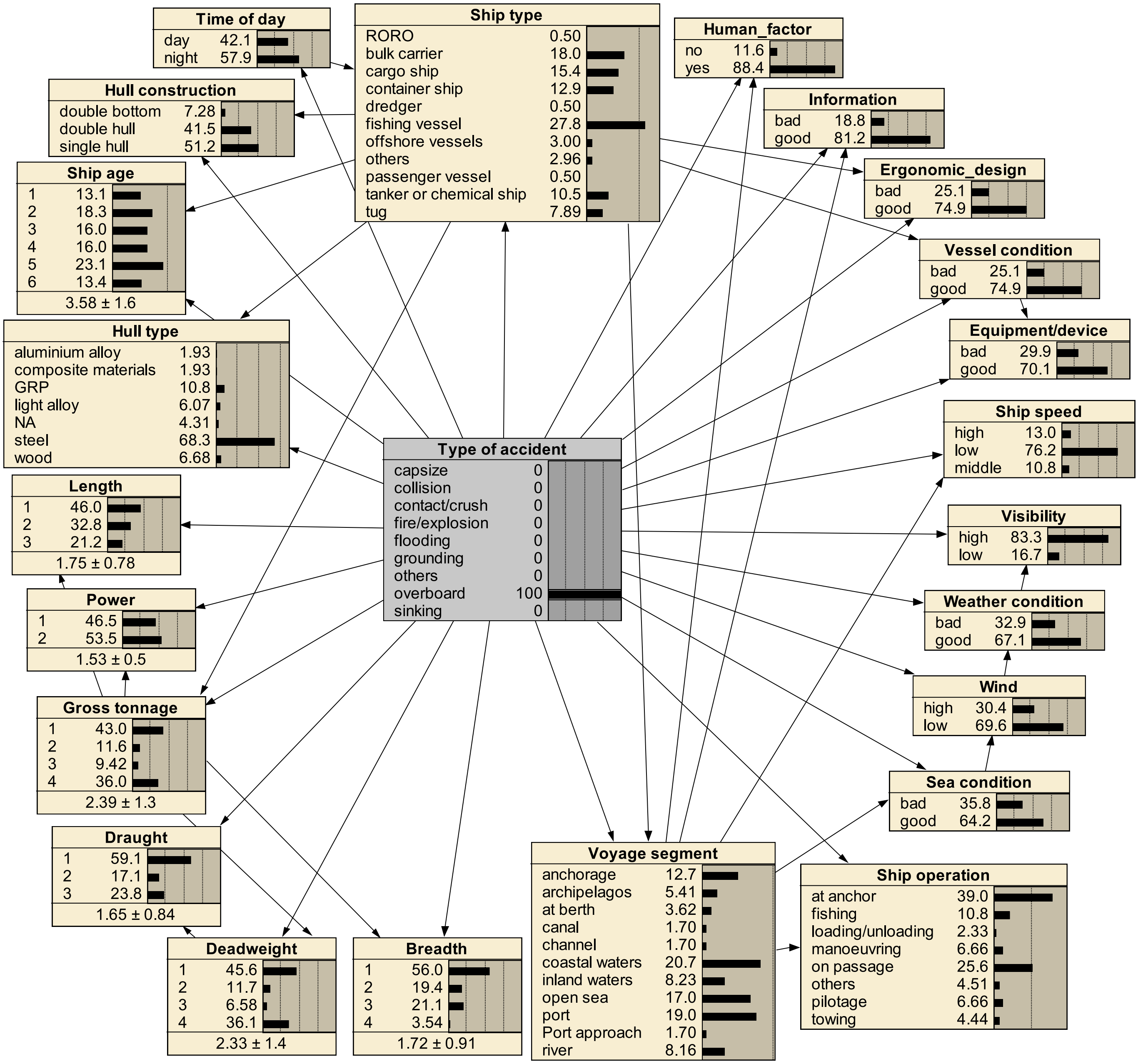

Fig. 11. The most probable scenario for overboard in this study.

Then, the probability of 'fire/explosion' state is set to 100% in the accident-type nodes of the two BNs. It can be observed that in the previous study, the most likely ship type to experience fire/explosion is 'fishing vessels' (23.8%), with 'equipment/device' in 'good' (69.2%) and 'vessel condition' in 'good' (53.8%). However, in this study (i.e., Fig. 12), the most likely ship type to encounter 'fire/explosion' is 'tanker or chemical ship' (19.3%), with 'equipment/device' in 'bad' (75.9%) and vessel condition in 'bad' (65.9%).

This change in ship type reveals new characteristics of maritime risks. Historically, fishing vessels frequently used various electrical equipment and had potential ignition sources during operations. Their older age and subpar maintenance further heightened the likelihood of fire/explosion accidents. However, with the recent surge in global trade and a rise in the transportation volume of hazardous goods like liquefied gas and petroleum, tanker or chemical ships have become the type most prone to 'fire/explosion' accidents. Furthermore, the change in 'equipment/device' and 'vessel condition' states indicates that the maintenance condition of ships is gradually becoming an important factor influencing the occurrence of 'fire/explosion' accidents. As maritime transportation continues to evolve, the risk of 'fire/explosion' is greatly heightened by the damage to ship equipment and the degradation of vessel conditions. Hence, it is imperative for relevant authorities to reinforce the safe supervision of tanker or chemical ships, provide sufficient safety skill training for crew members, and conduct regular inspections of ship equipment and vessel conditions to ensure compliance with international safety standards.

5.4. Comparison analysis of annual models from 2017 to 2021

The dynamic evolution characteristics of annual models from 2017 to 2021 are constructed by TAN and investigated to extract useful information and reveal valuable insights. Table 11 is structured to show data over several years, from 2017 to 2021, and compares the overall accuracy of data sets with different types of accidents (labelled from T1

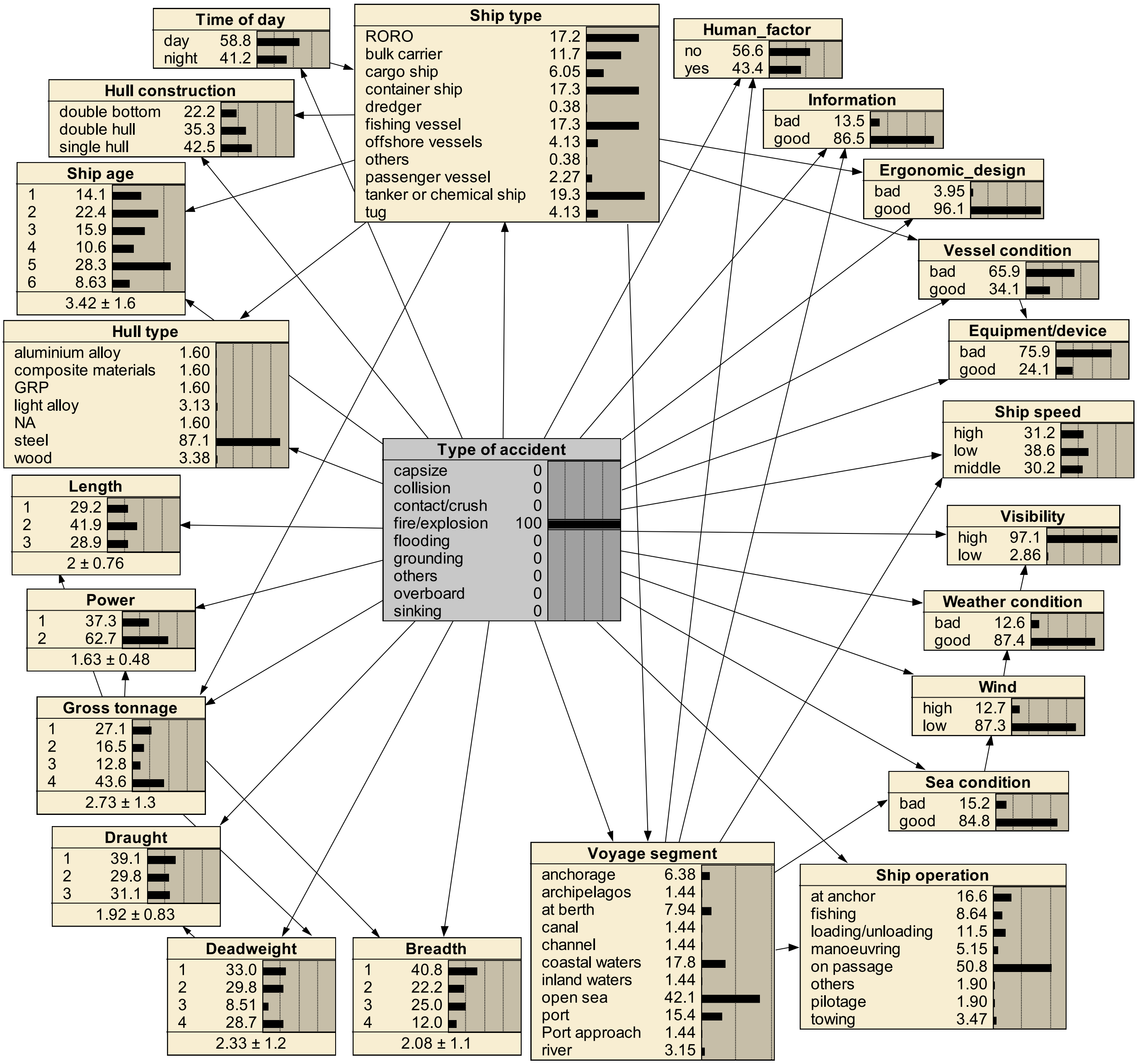

Fig. 12. The most probable scenario for fire/explosion in this study.

Table 11
Comparative analysis of five annual models (unit: %).

Datasets	Overall accuracy	Type of accident								
		T1 (capsize)	T2 (collision)	T3 (contact/ crush)	T4 (fire/ explosion)	T5 (flooding)	T6 (grounding)	T7 (others)	T8 (overboard)	T9 (sinking)
2017	95.83	8.89	22.5	10.5	14.5	2.48	27.3	–	4.89	8.89
2018	100	6.72	27.6	8.92	21	–	12.2	3.41	17.7	2.31
2019	100	10.2	26.3	4.22	12.2	–	22.3	6.22	14.3	4.22
2020	100	4.69	18.1	11.4	15.8	–	18.1	11.4	18.1	2.46
2021	100	–	48.6	–	10.5	–	10.5	–	10.5	20

to T9).

In 2017, the overall accuracy was 95.8%, with the highest percentage of accidents being 'grounding' (T6) at 27.3%, followed by 'collision' (T2) at 22.5%. The lowest was 'flooding' (T5) and 'sinking' (T9) both at 2.48%.

In 2018, the accuracy was perfect at 100%. 'Grounding' (T6) again had a significant percentage at 12.2%, but 'collision' (T2) had the highest at 27.6%. There was no data for 'flooding' (T5).

For 2019, accuracy remained at 100%. ‘Collision’ (T2) was still the most frequent at 26.3%, and ‘overboard’ (T8) accidents increased to 14.3%. No data was recorded for ‘contact/crush’ (T3).

In 2020, the trend of 100% accuracy continued. ‘Collision’ (T2) accidents decreased to 18.1%, with ‘overboard’ (T8) accidents also decreasing to 11.4%. No data was presented for ‘flooding’ (T5).

The 2021 data also shows a 100% accuracy. There was a marked increase in ‘contact/crush’ (T3) accidents at 48.6%. No information was provided for ‘capsize’ (T1), and ‘sinking’ (T9) accidents increased to 20%.

The comparative results indicate a positive trend in prediction accuracy, highlight specific recurring risks, show shifts in accident patterns over time, and underscore the importance of continuous monitoring and analysis for effective safety and risk management.

These findings indicate that certain types of accidents, like ‘collision’ and ‘grounding’, are more common than others. This information could be crucial for focusing on safety measures and prevention strategies. There are also some years with missing data for specific accident types. The variation in the prevalence of different accident types over the years (e.g., the increase in ‘contact/crush’ (T3) accidents in 2021) indicates changing patterns or conditions. This could be due to various factors like changes in operational practices, environmental factors, or evolving risks in the field. For policymakers and safety officers, understanding which types of accidents are most frequent and how their occurrences change over time is essential for effective risk management. This data can inform safety regulations, training programs, and emergency response planning.

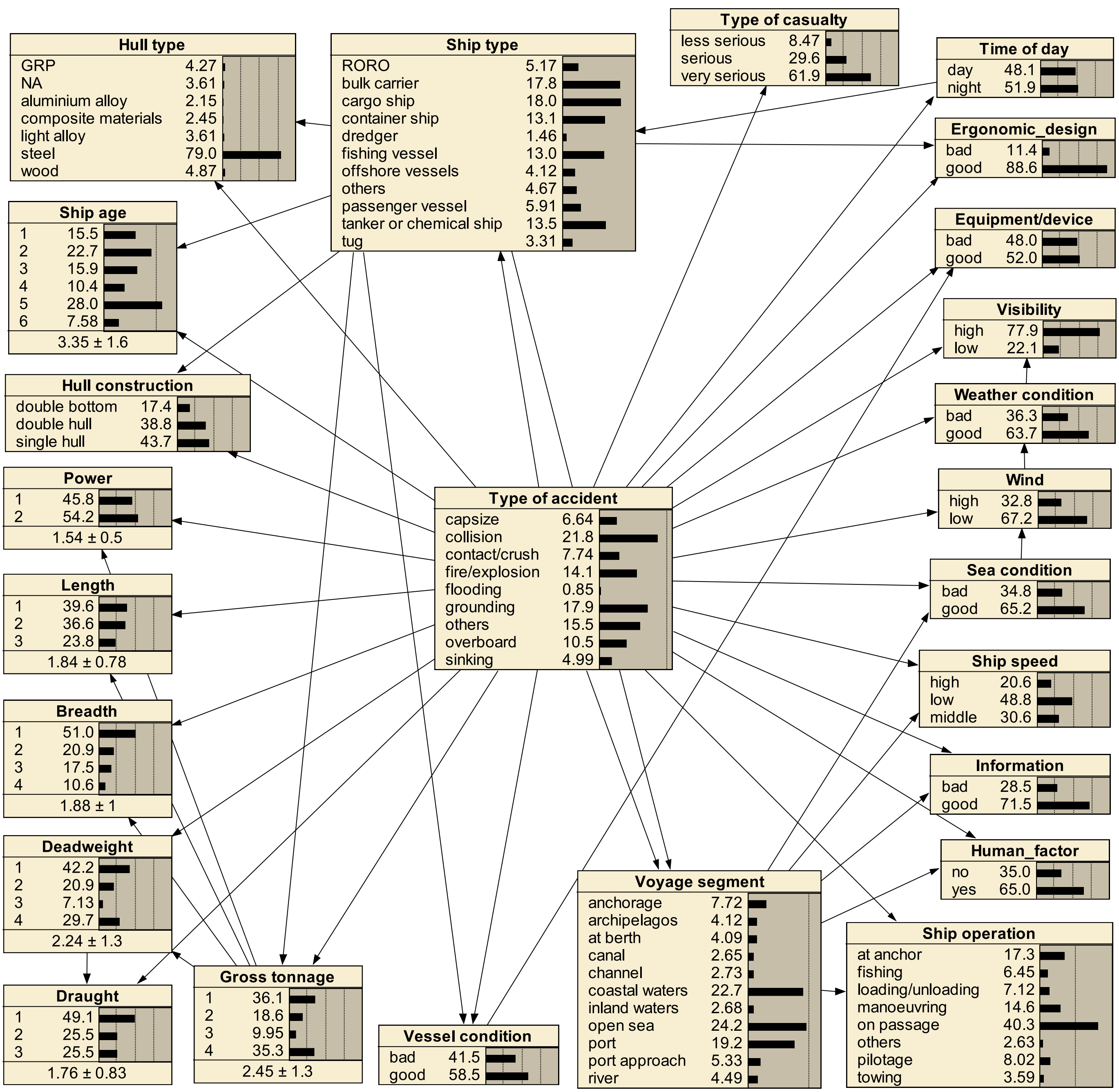

Fig. 13. A new layered BN with the ‘type of casualty’ node.

5.5. Comparison of different network structures on accident severity study

The connection between risk analysis and the severity of maritime accidents is significant. This study uses the same maritime accident dataset and adds accident severity descriptions (i.e., less serious, serious, and very serious). Layered BN and TAN are developed to investigate the impact of RIFs on the severity of maritime accidents under distinct network structures. It is noteworthy that the descriptions of accident severity used in this study are obtained from the IMO GISIS and maritime accident reports, ensuring rigour and accuracy.

To build a layered BN for maritime risk analysis, the process involves (1) adding a new node labelled 'Type of casualty' to the existing BN; (2) defining the states of the target node as 'less serious', 'serious', and 'very serious'; (3) establishing connections from the 'Type of accident' node to the 'Type of casualty' node; (4) updating the network with a new dataset to acquire the layered BN. The network results are illustrated in Fig. 13. Additionally, using the same dataset, the TAN structure is trained with accident severity serving as the parent node. The results are presented in Fig. 14.

The two constructed networks mentioned above are compared based on the performance of accident severity when ship-related and environment-related RIFs are set in the same states. The network results show that under the influence of environment-related RIFs, the probability of 'very serious' in the layered BN is 89.2%, which is 9.5% lower than that in TAN (98.7%). Furthermore, under the influence of ship-related RIFs, the probability of 'very serious' in the layered BN is 74.7%, which is 24.7% lower than that in TAN (99.4%). To compare the prediction accuracy of the two network structures, the accident data

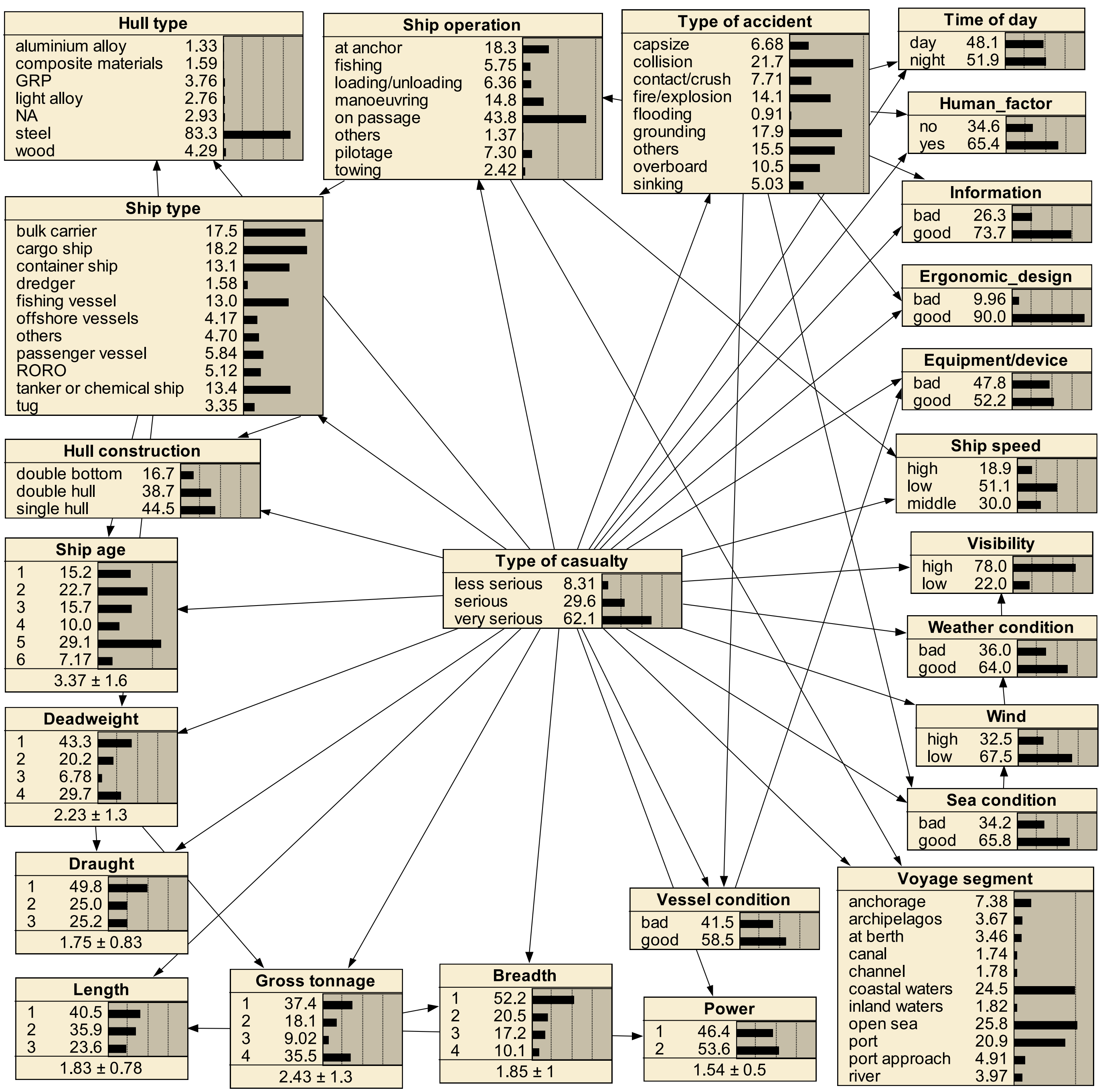

Fig. 14. A novel TAN with the 'type of casualty' as a parent node.

with the same states of the two types of RIFs are selected from the original data, and the severity of accidents in the original data is used as the baseline for verification. The results show that there are 1 and 2 data points with the same states of ship-related and environment-related RIFs, respectively. Moreover, the severity of all three accidents in these data points is 'very serious'.

Compared to the layered BN, the TAN structure is more sensitive and accurate in predicting maritime accident severity. Furthermore, the results better reflect the fact that accident severity is determined by the combined influence of multiple RIFs, and that considering accident types alone cannot objectively reflect reality. Finally, the excellent predictive ability of TAN for the target node state confirms its correctness for analysing the risk of maritime accidents in this study, ensuring the reliability of the research findings.

6. Implications

Table 12 presents a comparison of the data from 2012 to 2017 and 2017–2021, as summarised in the findings above. By examining the results and using three same scenario analysis settings for both periods, several key insights can be derived.

(1) This study incorporates eight new RIFs related to ship characteristics, weather conditions, and human factors. Specifically, 'deadweight' and 'power' have been identified as important RIFs. This recognition validates their inclusion and underscores their significant influence on maritime accident risk. Such insights highlight the need for stakeholders to emphasise these factors during ship selection, design, and maintenance to mitigate accident risks.

(2) A comparison of the state probabilities of common RIFs across the two periods reveals contemporary maritime risk attributes:

(i) The frequency of accidents involving large, high-speed vessels has seen a notable rise. This trend is also observed in accidents taking place near port approaches and during 'at anchor' or 'manoeuvring' stage.

(ii) There is a decline in the proportion of accidents happening in adverse weather and sea conditions. This suggests that advancements in modern shipbuilding technologies have bolstered ships' capacities to handle challenging weather conditions. However, the inherent characteristics of large high-speed vessels can amplify accident risks. Such insights indicate that maritime authorities should prioritise the navigation safety of these vessels, enhancing safety measures at port approaches and ensuring crews operate ships correctly.

(3) In Scenario one, when setting the ship-related RIFs to the same state in both studies, it is observed that the most likely accident has shifted from collision (82.2%) to capsize (38.1%). This shift indicates that advanced modern ships are effective in avoiding potential collision accidents. However, it also emphasises the need for ship owners and pertinent authorities to frequently inspect older vessels and enhance ergonomic designs to decrease the chances of capsizing.

(4) In Scenario two, when environment-related RIFs are consistent across both studies, the most likely accident transitions from grounding (63.5%) to sinking (50.6%). This shift underscores the importance for crews to remain highly vigilant and rigorously adhere to operating procedures, especially during night-time and challenging weather conditions in port approaches, to reduce the risk of ship sinking accidents.

(5) In Scenario three, a reverse analysis focusing on the accident types 'overboard' and 'fire/explosion' provides the following comparative insights:

(i) 'Overboard' accidents are most likely to occur during anchor operations of fishing vessels, with a strong correlation to human performance deficiencies. This highlights the need for fishing vessel crews to emphasise safety procedures during anchoring to reduce human errors and prevent such accidents.

(ii) 'Fire/explosion' accidents are predominantly associated with tanker or chemical ships where both equipment/device states and vessel conditions are suboptimal. This underscores the importance of rigorous adherence to safety standards in these ships to ensure the well-being of equipment and vessel conditions, thereby mitigating the risks of 'fire/explosion' accidents.

Table 12
Summary of comparison between the two periods.

	2012–2017	2017–2021
RIFs	16 RIFs in total, of which 6 are important RIFs	23 RIFs in total, of which 7 are important RIFs
Network structure and dataset	NBN, 161 maritime accidents	TAN, 362 maritime accidents
The state change of common RIFs	(1) Gross tonnage <10,000 (67.8%); (2) Length (meters) < 100 (65%), >100 (29.6%); (3) Ship speed (knots) in (6, 12] (87.1%), >12 (12.9%); (4) Weather conditions in 'poor' (40.3%); (5) Sea condition is 'poor' (53.2%); (6) Voyage segment in 'port' (7.53%); (7) Ship operation in 'at anchor' (5.48%), in 'manoeuvring' (10.8%);	(1) Gross tonnage <10,000 (54.7%); (2) Length (meters) < 100 (39.6%), >100 (60.4%); (3) Ship speed (knots) in (6, 12] (30.6%), >12 (20.6%); (4) Weather conditions in 'poor' (36.3%); (5) Sea condition is 'poor' (34.8%); (6) Voyage segment in 'port' (19.2%); (7) Ship operation in 'at anchor' (17.3%), in 'manoeuvring' (14.6%);
Scenario one	The most probable accident type is 'collision' (82.2%)	the most likely accident type is 'capsize' (38.1%), and the probability of 'collision' is only 6.81%
Scenario two	The most probable type of accident is 'grounding' (63.5%)	The most likely type of accident is 'sinking' (50.6%)
Scenario three	(1) When the accident type node is set to 100% for 'overboard', the most probable type of ship is 'fishing vessels' (41.4%), with the ship operation being 'fishing' (37%); (2) When the accident type node is set to 100% for 'fire/explosion, the most likely ship type to experience fire/explosion is 'fishing vessels' (23.8%), with 'equipment/device' in 'good' (69.2%) and 'vessel condition' in 'good' (53.8%).	(1) When the accident type node is set to 100% for 'overboard', the most probable type of ship is 'fishing vessels' (27.8%), with the ship operation being 'at anchor' (39%); (2) When the accident type node is set to 100% for 'fire/explosion, the most likely ship type to experience fire/explosion is 'tanker or chemical ship' (19.3%), with 'equipment/ device' in 'bad' (75.9%) and vessel condition in 'bad' (65.9%).

7. Conclusion

To explore the latest characteristics in maritime risks in this study, a data-driven BN risk analysis model is built and founded on global maritime accident data from 2017 to 2021, consisting of 362 accidents. A comparative study of the findings on maritime accident analysis in two periods, 2012–2017 and 2017–2022, is conducted. To ensure the accuracy of the dataset, original data collection and review are conducted from the LRF and IMO GISIS databases, and key data is supplemented with maritime accident reports. In addition, 23 RIFs are identified for this study based on IMO standards and RIFs used in the previous literature in this field, serving as the baseline to guarantee the efficacy of the risk analysis in this study. Furthermore, the superior predictive performance of the model is demonstrated using multiple verification methods, reflecting the reliability of the results. Finally, multidimensional comparative analysis with the previous study reveals valuable findings. The results of this study indicate.

(1) By calculating MI values, the top 7 important RIFs in maritime accident risk are identified as 'ship type', 'ship operation', 'voyage segment', 'deadweight', 'gross tonnage', 'length', and 'power'. Among them, 'deadweight' and 'power' are newly added RIFs compared to the previous study, indicating their significant influence on maritime risk.
(2) From the perspective of RIFs in the two periods, the risks of maritime accidents involving large high-speed vessels, port areas, and anchoring or manoeuvring operations have significantly increased. In addition, the proportion of maritime accidents occurring in adverse external environmental conditions is gradually decreasing.
(3) Through the influence of RIFs in scenario one, the most likely accident type has shifted from 'collision', as found in the previous study, to 'capsize'. It indicates that modern vessels have excellent collision avoidance capabilities during navigation, but older vessels with poor ergonomic design are still vulnerable to the risks of capsize accidents. Furthermore, according to the results in scenario two, RIFs have led to a shift in the most probable accident types from 'grounding' to 'sinking'. This suggests that adverse weather conditions and the increasingly complex port traffic environment are more likely to cause serious sinking accidents.
(4) By comparing the results of reverse diagnosis analysis of BN in the two periods, it is discovered that inadequate human operations, such as at-anchor operations, on fishing vessels are significantly correlated with 'overboard' accidents, while tankers or chemical ships with subpar equipment and vessel conditions are more likely to cause 'fire/explosion' accidents.
(5) The comparative analysis of five annual models reveals a trend of high prediction accuracy over the years, with certain types of accidents, like 'collision' and 'grounding', being more common than others.
(6) The TAN structure has exhibited higher sensitivity and accuracy in predicting accident severity compared to the layered BN structure. This highlights that a single factor does not determine accident severity and maritime accident risk but is comprehensively influenced by multiple RIFs.

This risk model, based on data from 2017 to 2021, offers a more accurate depiction of recent maritime accident trends, improving prediction and diagnosis compared to earlier models. A thorough comparative analysis between the last five years and the previous six years uncovers new characteristics of maritime accident risks, providing valuable insights into their evolving nature. By developing risk models for each year from 2017 to 2021 and evaluating their predictive abilities, stakeholders in the maritime industry can gain valuable insights. The study pioneers the investigation of layered BN and TAN models in predicting the severity of maritime accidents, deepening our understanding of accident outcomes. While the findings provide pioneering implications for maritime authorities and future research, limitations include a lack of consideration of various human factors and limited detailed dataset coverage from 2012 to 2016.

Future research could explore integrating human factors and safety culture with the selected RIFs through two approaches. First, a long-term solution is to establish new databases by adding factors such as human and safety culture to the accident reports. BN can then be trained to model their impact on overall maritime safety. Secondly, we suggest adopting a multi-disciplinary approach that can combine the findings from the BN model in this study with the insights drawn from other risk analysis methodologies capable of dealing with safety culture and human fatigue. This approach would involve collecting data on safety culture indicators, such as leadership commitment, communication practices, and safety training effectiveness, as well as implementing fatigue monitoring systems and conducting crew fatigue assessments. Additionally, qualitative methods such as interviews, surveys, and focus groups could be employed to gather subjective insights into human factors and their impact on maritime safety. By integrating these elements into the analysis, future research can provide a more holistic understanding of maritime accident causation and inform targeted interventions to improve safety outcomes.

CRediT authorship contribution statement

Huanhuan Li: Writing – original draft, Visualization, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Writing – review & editing. **Kaiwen Zhou:** Data curation, Formal analysis, Investigation, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Chao Zhang:** Writing – original draft, Visualization, Formal analysis, Investigation, Validation. **Musa Bashir:** Writing – review & editing, Validation, Resources, Investigation, Formal analysis. **Zaili Yang:** Writing – review & editing, Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Zaili Yang reports financial support was provided by European Research Council.

Data availability

Data will be made available on request.

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