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Process safety enhancement in maritime operations: A Bayesian network-based risk assessment framework for the RCEP region

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ABSTRACT

Implementing the Regional Comprehensive Economic Partnership (RCEP) has intensified maritime activities, highlighting the need for effective risk assessment methodologies to ensure process safety and environmental protection. This study presents a Bayesian Network model as an innovative approach to evaluating and mitigating maritime accident risks in the RCEP region. By analyzing 549 maritime accidents recorded in the Global Integrated Shipping Information System (GISIS) from 2016 to 2023, the research identifies and quantifies key factors influencing accident severity, such as accident category, ship flag, vessel type, and environmental conditions. The framework provides a systematic method for predicting accident severity and prioritizing safety interventions, enabling maritime authorities and stakeholders to enhance safety management processes and implement targeted risk reduction strategies. Key contributions include identifying critical risk factors unique to the RCEP maritime environment, developing and validating the Bayesian Network model, strategically ranking influencing factors, and exploring RCEP's regional maritime safety management implications. This study offers practical decision-making support for policymakers and ship operators, contributing to the maritime sector's broader discourse on process safety and environmental protection. The proposed framework is an adaptable tool for ongoing monitoring and improvement of maritime safety processes, aligning with global standards and regulatory requirements while addressing the unique challenges of the RCEP region to advance maritime process safety and support sustainable economic integration.

1. Introduction

Maritime transportation is characterized by large volumes and low prices, making it the mainstream mode of cargo transportation worldwide. At the same time, developing the maritime transportation industry is beneficial for improving the national industrial structure and international trade (Zhou et al., 2020). Therefore, maritime transportation plays a vital role in international trade and the development of economic globalization.

In order to promote regional economic and trade development, countries in the Asia-Pacific region have been committed to promoting multilateral trade cooperation for many years. The Regional Comprehensive Economic Partnership (RCEP) was initiated by the Association of Southeast Asian Nations (ASEAN) in 2012. It took eight years to be signed by 15 countries, including China, South Korea, Japan, Australia, New Zealand, and 10 ASEAN countries. The entry into force of the RCEP marks the official establishment of the free trade area with the largest population, the most significant trade scale, and the most remarkable development potential in the world. This fully reflects the confidence and determination of all parties to safeguard multilateralism and promote regional economic integration jointly. RCEP will contribute to global trade and investment growth, economic recovery, and prosperity in the East Asian region. China is a major maritime trading country; maritime transport accounts for more than 90 % of its international trade (Zhou et al., 2020). Additionally, China trades frequently with other RCEP member countries. According to China's customs statistics in 2022, China's imports and exports with other 14 RCEP member countries were valued at 12.95 trillion yuan (Ministry of Transport of People's Republic of China, 2023), representing an increase of 7.3 % over that seen in 2021 and accounting for approximately 30.8 % of China's

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total foreign trade value. China's trade with other RCEP member countries has the following characteristics: Firstly, the proportion of import and export trade within the first to fourth quarters of 2022 accounted for 30.4 %, 30.5 %, 30.7 %, and 31.4 %, respectively, demonstrating a consistent upward trend. Secondly, the promotion of RCEP effectively boosts trade between China and other member countries. In 2022, eight of China's imports and exports to other RCEP members grew by more than 10 percent, and those to Indonesia, Singapore, Myanmar, Cambodia, and Laos grew by more than 20 percent on average compared with 2021. Thirdly, RCEP promotes industrial cooperation. In 2022, China imported and exported 8.7 trillion yuan of intermediate products to other RCEP member countries, up 8.5 percent year-on-year, accounting for 67.2 percent of the total import and export value in the same period. (From the perspective of the types of commodities, China's exports of electromechanical products and labor-intensive products to other RCEP member countries have increased substantially; China's imports of electromechanical products, mineral raw materials, and energy products from other RCEP member countries have also seen substantial growth.) Fourthly, RCEP advancement promotes private enterprise development. In 2022, China's private enterprises imported and exported 6.56 trillion yuan to other RCEP member countries, up 17.4 % year-on-year, accounting for 50.6 % of China's private enterprises' total import and export value in the same period, a share that was 4.3 % higher than in 2021.

With RCEP being implemented on January 1st, 2022, the world's largest free trade area has officially set sail. RCEP will form an economic alliance regarding trade flows, cargo supply, commodity prices, investment, and finance. It promotes complementarity and a virtuous circle among the region's countries, raising the volume of seaborne trade and stimulating the demand for the port and shipping industry. In the bulk and oil transport sector, the entry into the force of RCEP will support maintaining the stability of the global commodity trade and supply chain, mainly in iron ore and steel (Jin, 2021). At the same time, port enterprises in the region are riding on the momentum of RCEP to usher in historic development opportunities. In addition to world-class trunk ports such as Shanghai, Ningbo, Qingdao, Tianjin, Busan, Tokyo, and Singapore, regional hub ports such as Klang, Laem Chabang, Tanjung Priok, and Jakarta are also stepping up their expansion and upgrading to share the dividends brought by RCEP.

There are safety concerns behind the booming shipping industry. The European Marine Safety Agency's statistics indicate 23,814 global marine traffic accidents between 2014 and 2022, with an average of 2646 incidents annually. Of these, 2510 maritime casualties were reported in 2022 (European Maritime Safety Agency, 2023). Once a maritime traffic accident occurs, most of them will produce the severe consequences such as casualties, property loss, and environmental pollution. Hence, the research on the causes and prevention of maritime accidents is a traditional and important issue in shipping. According to the International Maritime Organization (IMO), a total of 381 "very serious" shipping accidents occurred in the waters of RCEP countries and their vessels from 2016 to 2023, of which collision of ships and human errors were the most frequent causes of accidents (International Maritime Organization-Global Integrated Shipping Information System, 2024). Therefore, to ensure the safety of ship transportation, identifying and analyzing the risk of shipping accidents with RCEP region as the research object is of great significance.

The risk identification and analysis of shipping accidents are divided into forward and reverse paths. The forward path is to deduce the influencing factors based on the results of ship accidents. The reverse path is to predict ship accidents based on the influencing factors (as shown in Fig. 1). From a data modeling perspective, the two paths, forward and reverse, are the training construction and testing application process of the model, respectively. Currently, most studies on shipping accidents are either macro studies on a global scale (Hänninen et al., 2014; Galieriková, 2019; Li et al., 2023; Zhang et al., 2021) or micro (Zhang et al., 2016) studies on a particular single country/region.

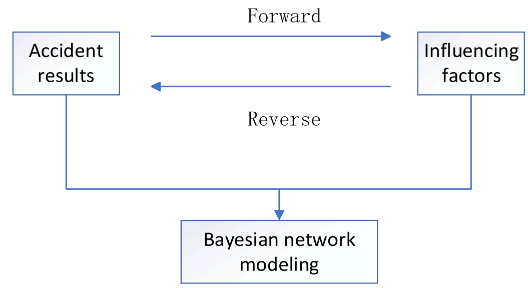

Fig. 1. Forward and reverse research paths on factors influencing shipping accidents.

At the same time, less work has been done on specific trade regions, such as the RCEP, as the object of study. Therefore, establishing an accurate identification model of risk factors for maritime ship accidents and providing more targeted recommendations for ship risk prevention in the RCEP are urgent issues in shipping. A large number of studies have shown that the severity of shipping accidents is affected by a variety of factors, including direct factors such as weather factors, geographic location, and type of accidents; indirect factors such as vessel type, flag, classification society, age, and vessel tonnage (Hänninen et al., 2014; Galieriková, 2019; Li et al., 2023; Zhang et al., 2016). Among them, different factors impact the severity of accidents differently. The data sources used in the studies have been updated as the times have evolved. In the 1960s, research on maritime accidents primarily relied on reports from Lloyd's Register and related research papers. In the 1970s, researchers generally utilized the government data published by locally owned coast guards, maritime commissions, and government agencies. In the 1980s, Norwegian vessel-owning companies began releasing reports on maritime accidents, and the UK also made accident-specific data from the Marine Accident Investigation Branch (MAIB) available as open data, which became the mainstream source of research information. In the 1990s, computer database technology began to develop, and numerous studies began to use Global Integrated Shipping Information System (GISIS) and Automatic Identification System (AIS) databases. After the turn of the century, the data sources of maritime accidents tend to be diversified, with GISIS data, Port State Control (PSC) data, AIS data, International Comprehensive Ocean Atmosphere Data Set (ICOADS), and the Clarkson Index have all become mainstream sources of data for marine accident studies. Besides, maritime accident reports released by China's State Maritime Administration (SMAC) have gradually become essential for researching maritime accidents.

A comprehensive international system has been established to prevent maritime risks. In December 1980, the French Minister of the Sea met with ministers from 13 European countries to discuss drafting the PSC memorandum. The gradual improvement of the PSC regulations has facilitated the establishment of eight regional PSC Memorandums of Understanding (MOU) around the world, namely the Paris MOU, Tokyo MOU, Regional agreements in Latin America, Caribbean MOU, Mediterranean MOU, Indian Ocean MOU, West and Central Africa MOU, and Black Sea region MOU. The United States does not belong to any MOUs; its Coast Guard (United States Coast Guard, USCG) performs independent port inspections. For PSC, all ships passing through the ports must be examined by the port authorities of their respective regions. When there are safety hazards on the ships, the ports will detain the ships in order to avoid accidents caused by high-risk ships going out to sea. All RCEP members, except Myanmar and Cambodia, are members of the Tokyo MOU. The inspection system of the Tokyo MOU is highly modeled on the inspection system implemented in the Paris MOU jurisdictions, which classifies ships into three categories according to their risk: low-risk, standard-risk, and high-risk, based on a computerized database that automatically evaluates and calculates the classification according to the indicators of the ships over the past 36 months. Indicators for ships include: type of the ship, age of the ship, status of the ship's recognized organization, status of the shipping company responsible for the ship's safety by the International Safety Management Code, number of hull defects, and number of times the ship has been detained.

According to previous studies, the standard methods for identifying and analyzing the risk of shipping accidents are divided into qualitative and quantitative methods. Qualitative methods include the Functional Resonance Analysis Method (FRAM) (Lee et al., 2020), Root Cause Analysis (RCA) (Li et al., 2023), Human Factors Analysis and Classification System (HFACS) (Li et al., 2023), and Accident Analyze Mapping (AcciMap) (Puisa et al., 2018). Quantitative methods include Evidential Reasoning (ER) (Li et al., 2023), Event Tree Analysis (ETA) (Li et al., 2023), Fault Tree Analysis (FTA) (Li et al., 2023), K-means clustering algorithm (Zhang et al., 2021), and Bayesian Network (BN) (Hänninen, 2014; Chen et al., 2022) models. Although qualitative analysis methods can provide an in-depth understanding and explanation of the problem and help to discover new research questions and perspectives, with the improvement of computational power, quantitative analysis methods have demonstrated significant advantages in terms of data processing capability, model complexity, and accuracy, and reproducibility and validation of results. Therefore, this paper adopts quantitative analysis methods to analyze the problem of analyzing the influencing factors of shipping accidents. Among them, there are six significant advantages of the BN model in the identification and analysis of shipping accident risks:

(1) BN can reduce the complexity of analyzing the problem by decomposing the joint probability distribution into relatively simple modules. BN requires fewer data and can even reason under incomplete information, which effectively couples with uncertainty factors.

(2) BN can synthesize prior knowledge, and real data mitigates the individual bias brought about by subjective factors and weakens the noise problem that arises from using data alone, making the results of BN's reasoning more convincing.

(3) BN combines a "static" presentation with a "dynamic" research process, effectively combining historical data with newly generated changes to make informed decisions about dynamic situations.

(4) BN can visually represent variable relationships through simple graphical models, achieving a high level of problem generalization and making reasoning easier to understand.

(5) BN has been extensively applied in various engineering fields, such as accident causation and land transportation accident analysis, and has already realized mature applications.

(6) BN can be analyzed in both forward and reverse directions in accident analysis studies, considering both factor analysis and accident prediction functions.

This paper constructs a BN model based on the GISIS dataset to analyze the maritime accidents of 15 members in the RCEP. Recognizing that reverse path research of ship accident prediction is heavily influenced by uncertain factors, modeling research in this area is deemed to have limited significance. Therefore, this paper mainly adopts the forward analysis path to derive the significant influencing factors leading to different severity levels of accidents by taking the severity level of maritime accidents as a benchmark. We also analyze the importance level of each influencing factor to provide a reasonable risk avoidance reference basis for the risk management decision of shipping organizations.

The structure of this paper is as follows: Section 2 reviews previous studies on maritime accident risk, shipping accident risk factors, and BN modeling in the field of risk factor identification; Section 3 describes the dataset and data processing methodology used in this paper; Section 4 introduces the modeling of the risk in the RCEP region based on the BN and the validation of the model's rationality; Section 5 presents the empirical analysis and results of the data in this paper; and finally, Section 6 delivers the main conclusions drawn from this study along with future outlooks.

2. Literature review

2.1. Maritime transportation accident risk study

Scholars have long used mathematical modeling to quantify potential risks with limited data, including Hazard Identification and Ranking (HIRA) (Khan and Abbasi, (1998), Quantitative Risk Assessment (QRA) Kalantarnia et al. (2009), Data Envelopment Analysis (DEA), and BN models. The typical research is summarized as follows: Schröder et al. (2013) analyzed the documents with simple experts reviewing and score method submitted to the Maritime Safety Committee (MSC) of the IMO in order to assess the priority level of the MSC's agenda on human factors in maritime accidents. The results confirmed that the IMO rarely considered human factors in accidents in the 1990s but gradually introduced them into maritime accident analysis after the 21st century. Hänninen (2014) systematically analyzed BN's research strengths and weaknesses in maritime traffic accidents. The advantages are concluded in the introduction section of this paper. The disadvantages are that selecting and determining prior knowledge is challenging, and model validation is complex (this paper employs the constant prior to including the information of data to the greatest extent and conducts a comprehensive model validation before application). Wu et al. (2015) analyzed the effectiveness of maritime safety control. They proposed an improved Data Envelopment Analysis (DEA) model based on grey relational analysis, particularly considering navigational environmental factors as inputs and shipping accident data as outputs. The results show that the improved model can effectively screen the key factors affecting maritime safety. Luo and Shin (2019) summarized the development history of maritime risk research, found that BN models are widely employed in maritime risk research, and explained that BN has an outstanding advantage in maritime risk research due to its excellent data reasoning ability. The above research has played a crucial foundation role in the field of maritime traffic accident risk factors. BN is the most commonly utilized one, but the prior choice and model validation need to be further studied in the application.

With the enhancement of computer processing power in recent years, standard maritime traffic accident risk factor sharing models primarily rely on multi-dimension data analysis, such as FRAM, KDE, NLP, Lempel-Ziv, and Dynamic Bayesian Network (DBN). Lim et al. (2018) reviewed and summarized maritime risk analysis models and categorized the models into three main categories: statistical, simulation, and optimization. Puisa et al. (2018) attributed the causes of accidents at sea to three areas, namely inadequate control and feedback mechanisms between the ship management company and the ship, insufficient feedback from the crew on the results of skills, and dysfunctionality in the design and construction of ships. Kulkarni et al. (2020) took the Baltic Sea as the object of research, reviewed the research history of shipping accidents, and established risk prediction models to assess the safety and reliability of maritime transportation in waterway regions. The summary found that there are relatively few frameworks for applying risk modeling, analysis, and assessment in maritime waterway decision-making, and there is room for further research. Lee et al. (2020) analyzed the level of human collaboration based on FRAM analysis by classifying human collaborative relationships, including specified or unspecified relationships. The article analyzes the human collaborative relationships in two maritime accident cases and the system's technological, human, and organizational state. Zhang et al. (2021) employed the Kernel Density Estimation (KDE) and K-means algorithm methods to statistically classify the data of shipping accidents in GISIS from 2013 to 2018 to summarize that part of the sea area around the UK and Denmark, the sea area around Shanghai and Singapore are the highest frequency areas of maritime accidents within the data. Zhang et al. (2022) analyzed maritime traffic complexity from a micro perspective and concluded that it is due to its irregularity and unpredictability. They proposed a traffic safety management prediction method utilizing the Lempel-Ziv algorithm and similarity ranking preference technique for optimizing inland waterway traffic flow scenarios. Li et al. (2022a) proposed a risk performance inference strategy for LNG ships sailing in Arctic waters through a dynamic BN model and revealed that the main risks in Arctic summer waters were composed of difficult-to-detect obstacles in the passage, such as icebergs and coral reefs. Gan et al. (2023) used the Natural Language Processing (NLP) model to analyze a total of 241 accident reports issued by the SMAC from 2018 to 2022. They constructed a knowledge graph to discover the internal relationship between accidents. The related conclusions can be used to speed up the judicial process and simplify investigating maritime accidents. Huang et al. (2023) focused on the development of Maritime Transportation Risk Analysis (MTRA) from 2000 to 2021 and analyzed the related research methods. They found that maritime transportation risk assessment methods are developing in the direction of systematization and synthesis. They concluded that integration with artificial intelligence methods will be the leading research direction in the future. Eliopoulou et al. (2023) conducted a statistical analysis of maritime accidents of passenger ships operating worldwide and concluded that the accident fatality rate of cruise and (pure) passenger ships has increased in the last decade, while the accident fatality rate of Ro-Ro ships has decreased significantly. Passenger ships' safety level has remained the same. Liu et al. (2023a) addressed the safety issues of offshore platforms by integrating machine learning, deep learning, and natural language processing techniques to develop an automated risk identification method. A BN model is constructed for data-driven risk assessment using the identified risk factors. Taking the Bohai Oilfield as an example, the effectiveness of this method has been validated. The results indicate that this approach enhances risk factor identification and assessment automation.

As shown in Table 1, the current relevant research mainly studies the risk of marine accidents from three perspectives: industry management optimization, accident risk estimation, and accident influencing factor analysis. This paper focuses on the research from the accident influencing factor analysis perspective. Regarding the model choice, it has been noted that the FRAM, KDE, and advanced machine learning models have recently been very popular in identifying maritime accident risk factors. However, the BN model is still typical because of its fast construction and clear graphical interpretability in this "big data" era. Also, based on the results of this paper, the accuracy of risk factor identification of BN is not less than any other (95 % accuracy in the 20 sample tests in Section 4.3), with the most simple model structure.

2.2. Forward-path research of risk factors for maritime accidents

Maritime accident risk factor studies are categorized into forward and reverse. Forward research focuses on the derivation of influencing factors based on the occurrence of accidents, where influencing factor selection and mathematical model choice are the main aspects of the research. Balmat et al. (2011) proposed a fuzzy approach to evaluate the application of maritime risk assessment to maritime safety, especially pollution prevention on the high seas. The system defines risk factors for each vessel based on vessel characteristics and weather conditions. Montewka et al. (2014) collected vessel collision accident data and operated the BN model to identify variables in the Gulf of Finland waters that significantly impact vessel collision accidents. Zhang et al. (2016) studied predicting the consequences of accidents in Tianjin port based on years of accident statistics and expert knowledge to construct a BN model to predict the possible consequences. Galieriková (2019) included human factors in the accident investigation plan, and utilized human factors analysis to classify the factors affecting shipping accidents into 19 categories, and reclassified the factors for a comprehensive explanation. Wan et al. (2019) proposed a new risk classification framework to identify the main factors of significant safety issues from five perspectives: social, natural environment, management, infrastructure, and technical operations, and quantitatively assess the identified risk factors based on their likelihood of occurrence and severity of consequences. Li et al. (2023) categorized the influencing factors of shipping accidents into dynamic and fixed factors to construct a BN model. They found that the most influential factors of shipping accidents are not the same in different types of accidents and provided the ranking of the importance of each influencing factor. Cao et al. (2023) conducted a bibliometric analysis of maritime accident research and proposed that the crew's psychological state factor has a significant impact; for example, LNG and LPG vessels have higher operational standards and more severe consequences of accidents compared to other vessels, so the crew has more psychological pressure. It is more likely to cause human error. In summary, the prediction of consequences of vessel collision accidents, the analysis of factors affecting shipping accidents, and the safety of the maritime supply chain are the main research contents of the forward research on risk factors of shipping accidents, among which most scholars choose the BN model due to its reasonable reasoning ability. Ma et al. (2024) used 980 maritime incidents off the Liaoning coast between 2000 and 2023; the Tree Augmented Network (TAN) learning algorithm and Expectation Maximization (EM) algorithm are used to construct the data-driven BN model. A comprehensive BN analysis was conducted, including impact intensity assessment, sensitivity analysis, scenario simulation, and model validation. The results demonstrate that distinct types of maritime accidents exhibit varying sensitivities to seasonal variations and time of day. For example, fire and explosion accidents are more common in bulk carriers.

Table 1
A review of water transportation risk research methods.

Literature	Methodology	Objective	Perspective
Wu et al. (2015)	DEA	Yangzi River basin navigation environment	Risk estimation
Zhang et al. (2016)	BN	Predicting the consequences of the Tianjin Port accident	
Lee et al. (2020)	FRAM	Manufactured relationships with maritime accidents	Influencing factors
Zhang et al. (2021)	KDE	Characteristics of shipping accidents	
Liu et al. (2023a)	Machine Learning +BN	Bohai Oilfield risk factor identification	
Gan et al. (2023)	NLP	Report on the investigation of a shipping accident	Industry management optimization
Zhang et al. (2022)	Lempel-Ziv	Inland waterway traffic safety management	

2.3. Reverse-path research of risk factors for maritime accidents

In addition to analyzing the influencing factors of maritime accidents based on accident data, prediction of accidents based on known influencing factors is also gradually emerging. Pula et al. (2005) aimed at the problem of marine fire accidents and carried out risk analysis on various possible consequences to reasonably predict the losses caused by marine fire accidents. Trucco et al. (2008) established the Marine Information System (MIS) BN model to analyze the impact of changes in human factors on shipping risk by taking the human organizational factors in maritime accidents as the primary research object, in which the human factors are subdivided into the shipping company, the maritime department, the port management, and all kinds of rules and regulations. Hänninen et al. (2014) used the expert consultation method, a standard construction method for BN models, and applied PSC data to propose a maritime safety management model for predicting and evaluating the safety management of vessels navigating in Finnish waters. Sotiralis et al. (2016) focused on the impact of predicting the occurrence of shipping accidents due to human factors to apply to the Dover Sea area, incorporating it more into the quantitative analysis of operational risk based on BN model. The study categorized crew status into normal conditions, abnormal conditions, and critical operations. Baksh et al. (2018) propose a new risk model applicable to the Northern Sea Route (NSR) to investigate the possibility of marine accidents such as collision, foundering, and grounding. The model is developed using BN. The proposed risk model has considered different operational and environmental factors that affect shipping operations. The application of the model is demonstrated through a case study of an oil tanker navigating the NSR that has the highest collision, foundering, and grounding probabilities in the East Siberian Sea. Cai et al. (2021) proposed a residual useful life (RUL) re-prediction method based on the Wiener process, establishing a DBN model for system performance degradation. Using the Subsea Christmas Tree system as an example, the effectiveness of this method was validated. Khan et al. (2020) used a Dynamic BN model to analyze the risk of ship-ice collision in Arctic waters. A tanker sailing in the Barents Sea is taken as an example to explain the proposed model. Cai et al. (2019) utilized DBNs to propose a hybrid structural system RUL estimation method based on physical models and data-driven approaches. This method considers the influence of multiple factors and establishes an RUL estimation model, validated using subsea pipelines in offshore oil and gas production systems as an example. Yu et al. (2021) utilized the data from the new inspection system of the Paris MOU on PSC to construct a dynamic risk prediction model for vessels using both BN and ER models to collect the factors influencing shipping risk based on the vessel's inspection records. Li et al. (2022b) proposed a new method for risk management and emergency decision-making of offshore oil spill accidents based on BN and Influence Diagram (ID). This method combines pre-accident risk management with post-accident emergency response, which can balance risk and cost and make optimal decisions. The results show that this method can effectively support decision-making in risk management and emergency response to offshore oil spill accidents. Liu et al. (2023b) proposed a dynamic assessment method for oil spill risk under extreme wind conditions based on DBNs. They converted physical models such as advection, diffusion, evaporation, and dispersion into DBNs and established a vulnerability model based on coastline types and socio-economic resources. Using Laizhou Bay as an example, the effectiveness of this method was validated, and the risk probabilities of oil leaks at potential locations were calculated to facilitate proactive risk prevention efforts. Fan et al. (2023) used neuropsychological data to analyze the psychological factors of seafarers and designed a vessel-board piloting simulation experiment to obtain the conclusion that pre-service training for crew members, which has a significant advantage on mental health.

In summary, the prediction of shipping accident consequences is the mainstream research direction in the reverse research of accident risk factors, and the research on the prediction of accident consequences is also gradually coming into practical application. The Paris MOU has published an official shipping risk model in which vessel operators can get the risk level by inputting the vessel parameter information to prevent accidents. The main contents of shipping risk reverse research are the influence of human factors on risk and the analysis of risk levels based on PSC data. Table 2 summarizes the current research on maritime accidents from both forward and reverse perspectives.

2.4. Literature summary

Compared with other risk factor studies, the research of maritime accidents in terms of influencing factors started later. Ship risk research has formed a relatively structured system in recent years, and screening risk factors affecting the occurrence and development of accidents, modeling risk prediction using specific methods, and putting forward suggestions for improvement are its main contents. Numerous factors influence the risk of ship accidents, and each influence is complex, making it difficult to track and extract effectively. Based on the summary of various literature, this paper selects the BN model to analyze and research ship accident influencing factors. Although the BN model is a "classic" one compared with machine learning methods, it is still powerful enough for this work regarding identification accuracy. Also, BN has excellent interpretability and a straightforward model structure, suitable for management applications and further extension. The main flow of our research is shown in Fig. 2.

3. Data collection and processing

3.1. Data collection on maritime accidents

3.1.1. Data source

This study is based on the GISIS database, which contains a total of 754 records during the period from January 1, 2016, to December 31, 2023. Among them, the accident information includes the time, location, basic information of the vessel involved and accident casualties. Meanwhile, the accident reports contain detailed descriptions of the accident process, which can be used as supplementary information (e.g. whether it was affected by extreme weather). In addition, the maritime accident database is fused with other vessel information databases through the vessel's Maritime Mobile Service Identify (MMSI) number, which is used to supplement other information needed for the study in this paper (i.e., vessel age, size of the vessel, vessel company information) to ensure the completeness, accuracy and validity of the collected data.

3.1.2. Description of data

There were 379 and 375 records of accidents reported by RCEP member countries and accidents occurring globally on ships belonging to RCEP member countries, respectively, totaling 754 records. The data were screened, including removing duplicate and accident records with

Table 2
A review of forward and reverse maritime accidents research.

Forward research	Literature	Reverse research	Literature
Research on factors influencing pollution in the high seas	Balmat et al., 2011	Prediction of maritime fire losses	Pula et al., 2005
Research on accident prediction based on vessel collision records	Montewka et al., 2014 Zhang et al., 2016	Prediction of the impact of human factors on maritime accident consequences	Trucco et al., 2008 Sotiralis et al., 2016
Human factors on vessel risk	Galieriková, 2019	Prediction of ship safety inspection results	Hänninen et al., 2014
Research on maritime supply chain security guarantee based on maritime accident prediction	Wan et al., 2019	Prediction of arctic shipping routes risk	Baksh et al., 2018 Khan et al., 2020
Research on manufactured relationships with maritime accidents	Lee et al., 2020	Prediction of residual useful life of subsea christmas tree systems	Cai et al., 2021
Research on the analysis of influencing factors of vessel accidents and accident prediction	Li et al., 2023 Ma et al., 2024	Prediction of residual useful life of subsea pipelines	Cai et al., 2019
Research on factors affecting offshore platform safety	Liu et al., 2023a	Impact of vessel inspection records on vessel risk	Yu et al., 2021 Li et al., 2022b
Research on the impact of crew psychological factors on maritime accidents	Cao et al., 2023	Prediction of potential oil spill locations risk at sea	Liu et al., 2023b
		Influence of crew psychological factors on vessel risk	Fan et al., 2023

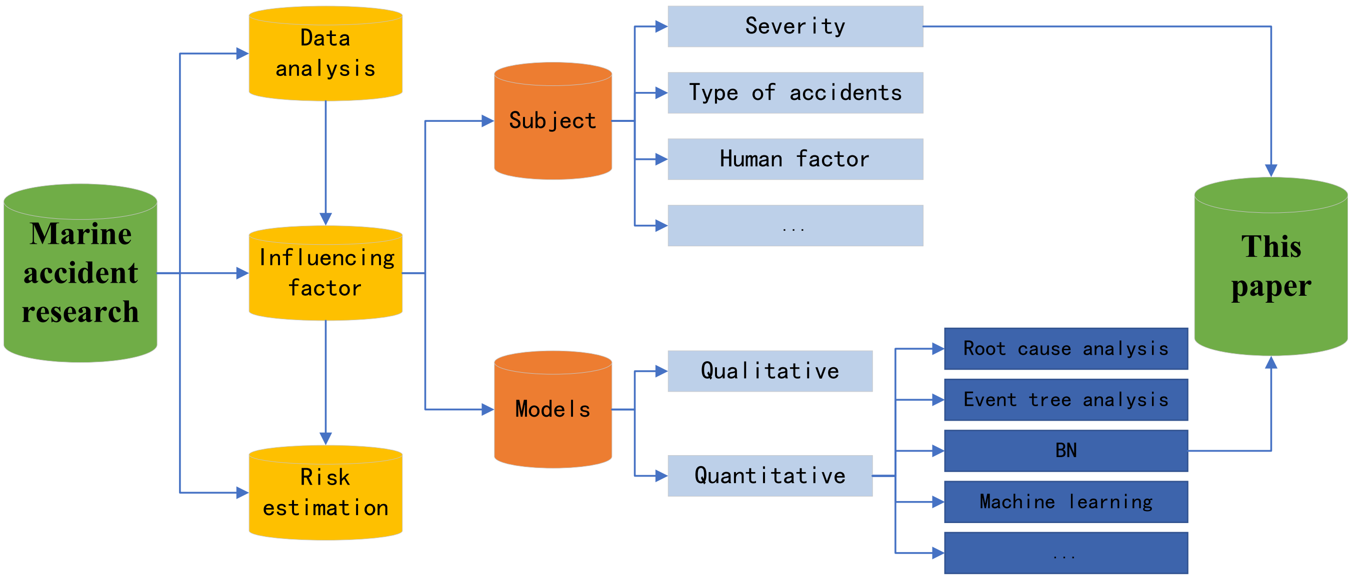

Fig. 2. Development network diagram of literature research.

significantly missing information. 549 accident records were retained after data cleaning.

IMO divides maritime accidents into "very serious", "serious" and "less serious" according to the severity. "Very serious accident" refers to an accident caused by total damage, casualties, or severe pollution on the vessel; "serious" refers to an accident that does not belong to a "very serious accident" caused by the vessel due to fire, explosion, collision, stranding, contact, lousy weather damage, ice damage, hull rupture or suspected hull defects; "less serious" refers to other accidents that are not "very serious" and "serious". The number of accidents of various severity is shown in Fig. 3.

The number of data for which specific geographic coordinates were recorded was 436 out of 549, and the accidents' distribution is shown in Figs. 4 and 5. Among them, the red marking indicates the location of accidents occurring in the sea area of RCEP reported by each member country, and the blue indicates accidents involving ships from RCEP member countries worldwide.

The maritime accidents of RCEP member countries are mainly concentrated in the East and South seas of China, the Straits of Malacca, the waters of Japan and Korea, and the east coast of Australia. Except for the Asia-Pacific region, the accident locations of vessels of RCEP member countries are relatively scattered. Common accidents are also on the west coast of Europe, the Mediterranean region, and the east coast of the United States.

3.2. *Analysis of risk influencing factors (RIFs)*

3.2.1. *Selection of RIFs*

Define factors affecting maritime transportation safety as RIFs. Based on the RCEP maritime accident database established in the previous section, the following principles are combined to select the risk factors for shipping accidents.

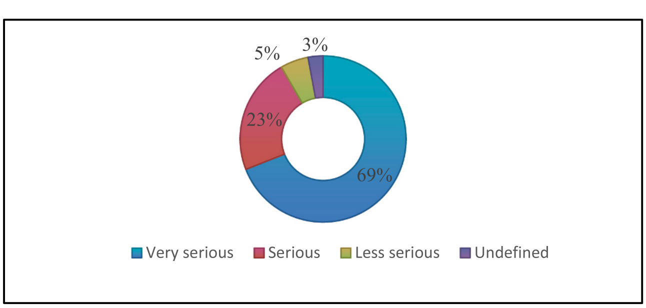

Fig. 3. Distribution of accident severity categories.

(1) Principle of independence: the selected RIFs should be independent of each other, and there is no cross or containment relation between different categories of RIFs.

(2) Principle of effectiveness: the collected accident data is the basis of the BN model; if the selected RIF has no data or an extreme amount, the RIF should not be set as a node. Therefore, when building the BN model, it should be combined with the data that have been collected for comprehensive consideration.

(3) Principle of timeliness: with the improvement of the scientific level, the factors affecting shipping accidents will also change to a certain extent, so the selected node should be in line with the background of the times so that the BN model can infer the present.

This paper finalized 19 RIFs:

(1) Flag: the flag is a symbol of the nationality of a vessel. Every year, on July 1, the Paris MOU releases the latest version of the white list, grey list, and black list to the public, evaluating the long-term performance of the work done by the flag state authorities. To a certain extent, the flag's ranking can be utilized as a straightforward way to identify advantages and disadvantages in a large amount of information. The white, grey, and black lists can show the results of all its flag state evaluations, derived based on the total number of PSC inspections and the total number of stays of flag states that have undergone at least 30 PSC inspections during a rolling three-year period. This paper categorizes flag states based on the rankings issued by the 2020 Paris MOU.

(2) SOLAS certification: the International Convention for Safety of Life at Sea (SOLAS) is an international safety agreement published by IMO. This parameter is classified according to whether the vessel holds SOLAS certification.

(3) Place of vessel construction: classification is based on whether the country where the vessel was built is developed.

(4) Vessel company: classification is based on vessel operating and management companies.

(5) Classification society: this influencing factor refers to whether the accident vessel belongs to the world's top ten classification societies (take 40.12 % in the dataset of this paper). The top ten classification societies are DNV GL Group (6.32 %), ABS (American classification society) (5.02 %), Class NK (Japan classification society) (9.85 %), Lloyd's Register (5.95 %), Rina (2.04 %), Bereau Veritas (5.02 %), China Classification Society (3.35 %), Russian Maritime Register of shipping (0 %),

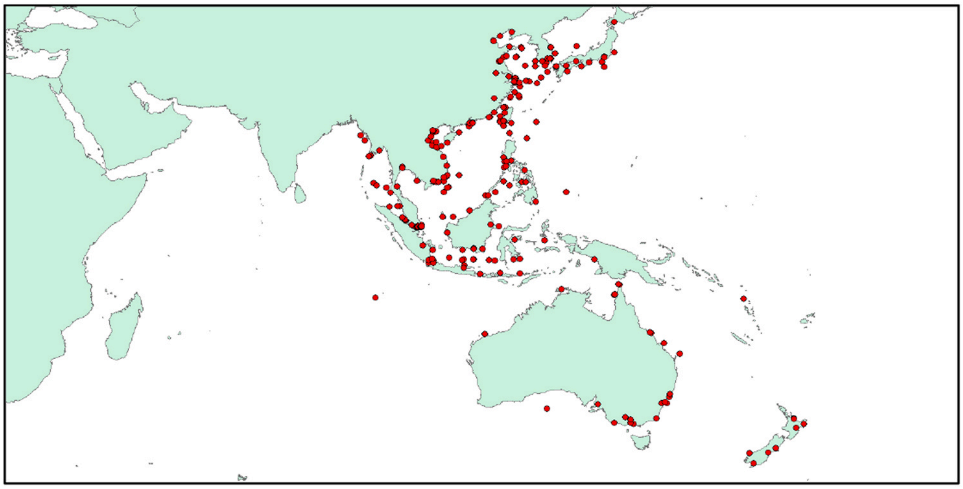

Fig. 4. Distribution of shipping accidents in the areas of RCEP.

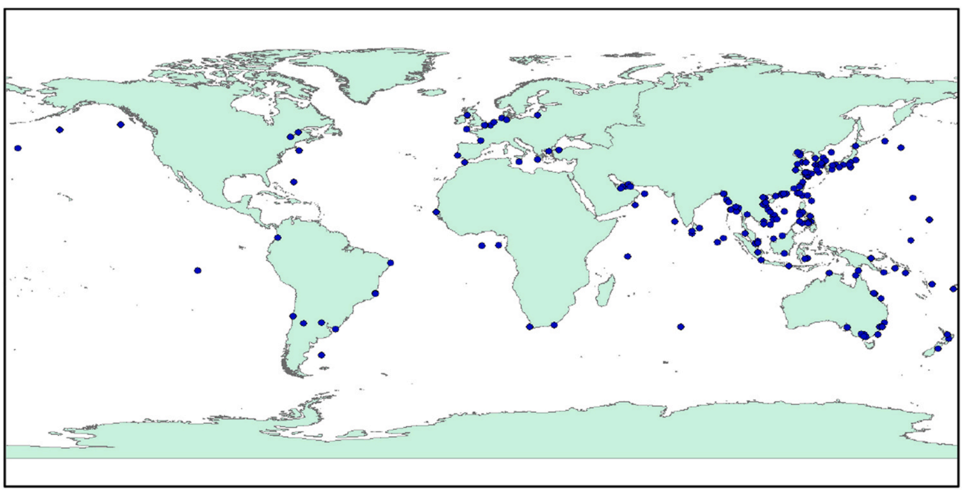

Fig. 5. Distribution of shipping accidents in the global area of RCEP member countries.

Korean Register of shipping (2.60 %), and Indian Register of shipping (0 %).

(6) Extreme weather: extreme weather includes high winds, high waves, and heavy fog. The accidents are categorized according to the presence or absence of extreme weather.

(7) Accident location: classification is based on the location of the accident in the accident report.

(8) Coastal administration: vessel accidents are reported and processed by the country where the accidental sea area belongs, and sometimes multiple countries report the same accident. In order to avoid duplication of data, it is chosen to report the accident report first for recording.

(9) Accident time: it categorizes the time of day into 0:00–7:59, 8:00–15:59, and 16:00–23:59.

(10) Accident season: classification based on the quarter when the accident occurred, of which the first quarter is from March to May, the second quarter is from June to August, the third quarter is from September to November, and the fourth quarter is from December to February next year.

(11) Accident month: categorized according to the accident's occurrence.

(12) Vessel type: the vessel type with the most accidents in the selected data was dry bulk carriers, accounting for 66 % of the total incidents.

(13) Number of persons on board: classified according to the number of persons on board at the time of the accident.

(14) Gross registered tonnage: it is a measurement of a ship's overall internal volume. It is calculated based on the total enclosed spaces within the ship, including cargo holds, crew quarters, and machinery spaces. Gross registered tonnage is expressed in "register tons," where one register ton equals 100 cubic feet of space. This metric is used primarily for regulatory and tax purposes, such as determining port fees, docking charges, and safety regulations. Gross registered tonnage provides a standardized way to assess the size of a vessel, although it does not directly indicate the ship's weight or cargo-carrying capacity.

(15) Vessel's main engine power: according to this parameter, it can reflect the vessel's carrying capacity.

(16) Vessel age: categorized according to the vessel's age, the most significant number of vessels involved in accidents in the selected data were between 6 and 10 years old.

(17, 18) Vessel length and width: classified according to the size of the vessel.

(19) Type of accident: categorized according to the accident type. According to statistics, the most frequent types of accidents are collisions, accounting for 27 %.

Finally, the labeling results of the RIFs used in this study are shown in Table A1.

3.2.2. Classification of RIFs

This section further categorizes the 19 RIFs for BN modeling, i.e., the secondary risk factor structure. These include four types: vessel information, vessel management information, vessel environment, and accident categories, as shown in Table 3.

Vessel management information refers to the information on vessel management and operation involved in the operation of a vessel. Whether a vessel can navigate safely on the water depends on whether the organization implements suitable management measures. Therefore, the management factor is usually regarded as the leading RIF that can cause marine traffic accidents and is thus included in the scope of research. Management consists of two main aspects: First, relevant international organizations and national maritime authorities externally supervise shipping enterprises and their vessels. The local maritime authorities, in particular, are more familiar with the local situation and can formulate scientific and practical regulations on shipping safety management according to local conditions. Second, the vessel companies with their supervision. They will regard their situation to establish a sound and standardized management system. Vessel management information and vessel information constitute the static factors of vessel accident RIFs together, and the static factors are determined when the vessel is in port, so the static factors are often used as the measure of vessel risk during port inspection.

Vessel information is defined as the various factors inherent to the vessel itself. Vessel factors are important causal factors of maritime transportation accidents. Vessel factors are numerous, such as the maneuvering equipment, life-saving and fire-fighting equipment, the materials used in the construction of the hull and its quality, the structural design of the hull, the sealing and compartmentalization of the hull, as well as the vessel's buoyancy, the dry side, and the swaying properties of the vessel, which can be reflected in the age of the vessel, the performance of the equipment, and other factors. This paper mainly categorizes vessel factors into vessel size, loading condition, vessel age, vessel type, and power.

Vessel environmental factors are usually the main factors that induce marine traffic accidents, including meteorological and hydrographic conditions. Natural environmental factors include visibility, sea currents, wind, and waves. For example, when there is rain, fog, and other particular weather, the driver's lookout will be interfered with, and the field of vision will not be precise, leading to the vessel in the process of driving accidents. Wind and waves will destroy the vessel's stability, greatly enhancing the possibility of vessel accidents. Meanwhile, this will cause great difficulty in the subsequent rescue work. Vessel environmental factors are dynamic factors, which refer to the factors that change dynamically during the vessel's traveling process, such as weather, time, season, and location.

Table 3
Classification of factors influencing vessel accidents.

Classification of risk influencing factors	RIFs	Classification of risk influencing factors	RIFs
Vessel management information	Flag	Vessel information	Vessel type
	SOLAS certification		Number of persons on board
	Place of vessel construction		Gross registered tonnage
	Vessel company		Vessel's main engine power
	Classification society		Vessel age
	Extreme weather		Vessel width
	Accident location		Vessel length
Vessel environment	Coastal administration	Accident category	Type of accident
	Accident time		
	Accident season		
	Accident month		

The accident category is the most critical in RIFs, and different accident categories may lead to different consequences. This paper combines the existing data to categorize the accident categories into six cases: grounding, collision, fire and explosion, vessel wreck and capsize, vessel damage and cargo damage, and other accidents. Among them, grounding, collision, and fire/explosion incidents refer to accidents due to crew operational errors or equipment failures, resulting in direct damage to the vessel or delays in scheduled arrangements, leading to losses. Shipwrecks, capsizing, and cargo and vessel damage refer to losses caused to the cargo on board or the vessel due to weather or other factors. Other incidents refer to accidents that do not fall into any of the above categories but still result in casualties or property damage, such as a crew member falling from the lookout tower due to inadequate training and dying.

4. Maritime risk model by BN

4.1. BN model introduction

BN is also known as a confidence network and is one of the most compelling theoretical models in uncertainty and reasoning. It is a model for handling the uncertainty of causal relationships in simulating human reasoning. In BN, variables are represented by nodes, and the relationship between variables is represented by directed arcs, with the cause node pointing to the result node. In summary, BN is a set of (DAG and a collection of related parameters. Among them, the DAG represents the model structure attributes, that is, the network structure; the relevant parameters represent each variable's Conditional Probability Table (CPT), representing the dependencies between variables. In a BN, the random variables involved in a particular research system are represented in a directed graph based on their conditional independence, thus forming the BN. It is primarily used to describe the conditional dependencies between random variables, with circles representing random variables and arrows indicating conditional dependencies. For example, if node E directly influences node H, represented as E→H, a directed arc (E, H) is established from E to H, and the weight (i.e., connection strength) is represented by the conditional probability P(H|E), as shown in Fig. 6 below:

Denote each node by x_i, v_i denotes the set of parent nodes corresponding to x_i, $i = 1,2...n$. $\boldsymbol{X}$ denotes the set of n nodes, n denotes the total number of nodes.The joint probability $p(\boldsymbol{X})$ of the set of n node variables in the model is denoted as:

$$p(\boldsymbol{X}) = \prod_{i=1}^{n} p(x_i|v_i) \tag{1}$$

$p(\boldsymbol{X})$ is considered the strength between x_i and v_i. Prior probability refers to the probability derived from experience and analysis, such as in the total probability theorem. It often appears as the probability of the 'cause' in the 'cause and effect' problem. Marginal probability refers to the probability of an event occurring among all possible scenarios involving a summation or integration process. It reflects the likelihood of an event occurring and is one of the fundamental concepts in probability statistics. Marginal probability is obtained by merging the unnecessary events in the joint probability into the total probability of those events, a step known as marginalization. Specifically, a marginal probability f_k can be derived from the joint probability of $x_1, x_2, ..., x_n$, with the following formula:

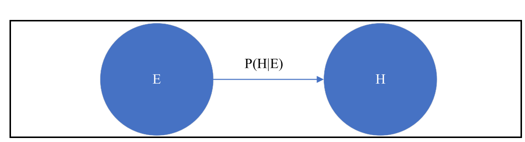

Fig. 6. Example of causal relationship.

$$\bar{f}_k(x_k) = \sum_{\substack{x_1,\dots,x_n \\ except\ x_k}} f(x_1,\dots,x_n) \tag{2}$$

Posterior probability refers to the probability of an event occurring after obtaining some observational information. The posterior probability of an event is commonly calculated using Bayes' theorem, which is as follows:

$$P(A|B) = \frac{P(B|A)\cdot P(A)}{P(B)} \tag{3}$$

4.2. BN structure determination

There are two main methods to determine the structure of BN. The first is using prior knowledge to construct the network structure; this approach is based on expert experience and knowledge or similar structure of the previous literature for model construction, subject to the influence of prior knowledge, under the premise of insufficient data commonly used in this method. The second is to obtain the network structure through structural learning by analyzing data, such as using the scoring search method to train the data, and obtain the network structure. This method needs a tremendous amount of data. Based on data analysis, the causal relationship between various nodes is obtained, and the execution of this method is complex. At the same time, increasing nodes will lead to an exponential increase in data relationship analysis, seriously affecting learning efficiency. This paper chooses the first method after referring to a large amount of literature. The main reason is that specific results have been achieved in identifying and analyzing RIFs, which can be reliably referenced in classifying influencing factors. The second method will limit the number of nodes studied. Based on the existing data, a BN model is constructed, and the detailed construction process is shown in Fig. 7.

The BN model structure is shown in Fig. 8.

19 RIFs are divided into primary factors and secondary factors. Among them are 8 primary factors (green mark) and 11 secondary factors (blue mark). The primary factors are the direct factors leading to the accident's severity, and the secondary factors are the sub-factor of the primary factors, which are the indirect factors leading to the severity of the shipping accidents. The primary factors cover all four types of factors in Table 3. Among them, the vessel environment provides five primary factors, and each of the other three categories provides one primary factor. That is, the direct impact of the vessel environment on the severity of vessel accidents is the most remarkable.

4.3. Model rationality validation

The rationality of our proposed model is verified by forward inference, that is, whether the relationship between nodes in the established BN model is reasonable with reality to prove the rationality of the model.

This paper utilized 20 samples of maritime accident cases outside the training sample to verify the rationality of the proposed model and selected the identified influencing factors, that is, the set of risk sub-factor nodes that have an impact on the accident, which are input as evidence into the established BN model for forward reasoning in order to validate the reasonableness of the shipping accident simulation model, and the following is the validation process.

The collision between Greek-registered bulk carrier Spartan and Australian rock lobster fishing vessel Hannah Lee

At 05:35 on April 17th, 2005, 17 nautical miles off Bouvard, off the southwest coast of Western Australia, the Greek-registered bulk carrier Sparta collided with the Australian rock lobster fishing vessel Hannah Lee at 32°43′8″S, 115°16′9″E. The Sparta was on its way to the port of Banbury to load alumina. Hannah Lee left the small port of Mandurah at 03:45 and went to work in the rock lobster pools located approximately 37 nautical miles southwest of the port.

The following risk sub-factors were extracted from the accident description: vessel type, coastal administration, accident season, accident month, accident time, flag, extreme weather, and accident location. They were entered into the BN model as evidence and forward reasoning to obtain the following results, as shown in Figs. 9 and 10. The results of the forward reasoning are shown in Table 4.

Substituting the RIFs extracted from the accident case descriptions into the simulation model reveals that the probability of the severity level being "serious" is significantly higher. In contrast, the results for other types of accidents are significantly lower, and the accident's severity level in the accident record is also "serious", which is in line with the facts.

Hong Kong cargo vessel "Huilong" sinks

On May 18th, 2005, the general cargo vessel "Huilong", registered in Hong Kong, sailed from Indonesia to India. This vessel carried 11,245 tons of mixed general cargo, including 5185 tons of fluorite minerals in

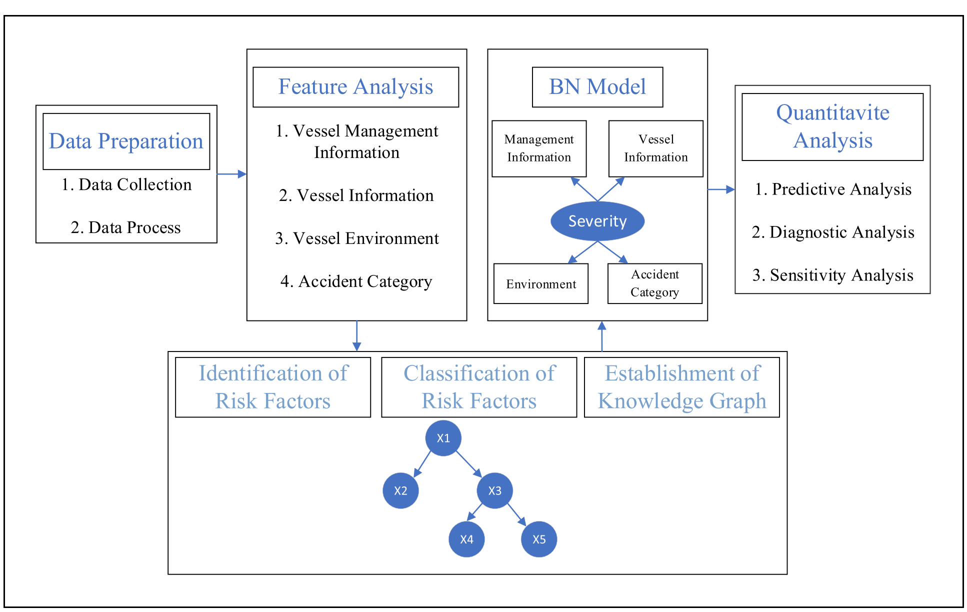

Fig. 7. Process of BN model constructions.

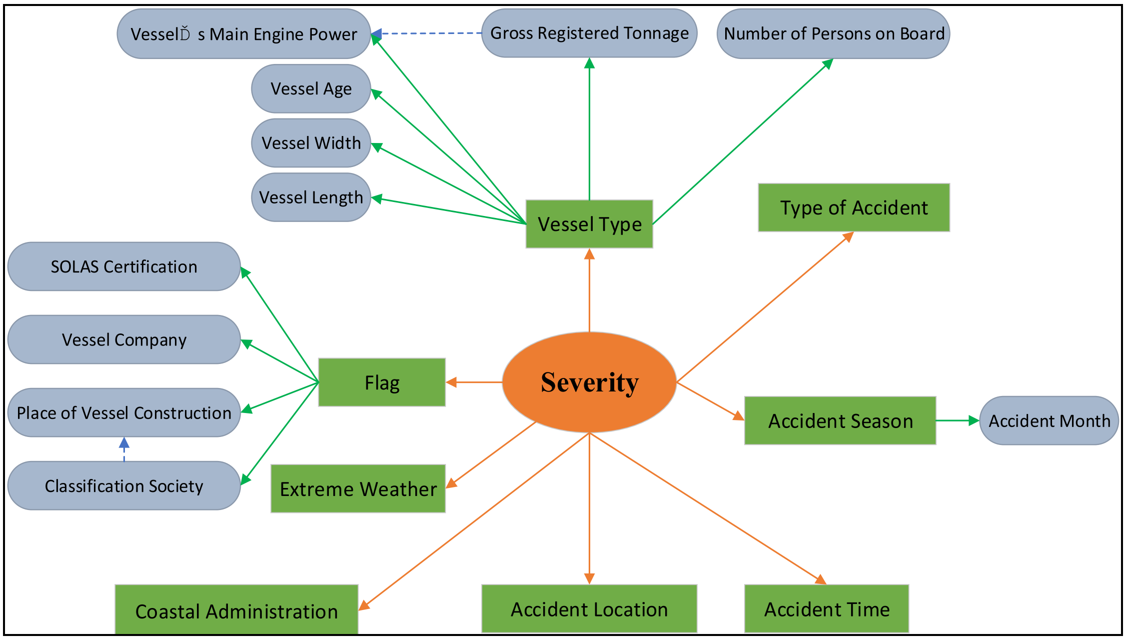

Fig. 8. BN model constructions.

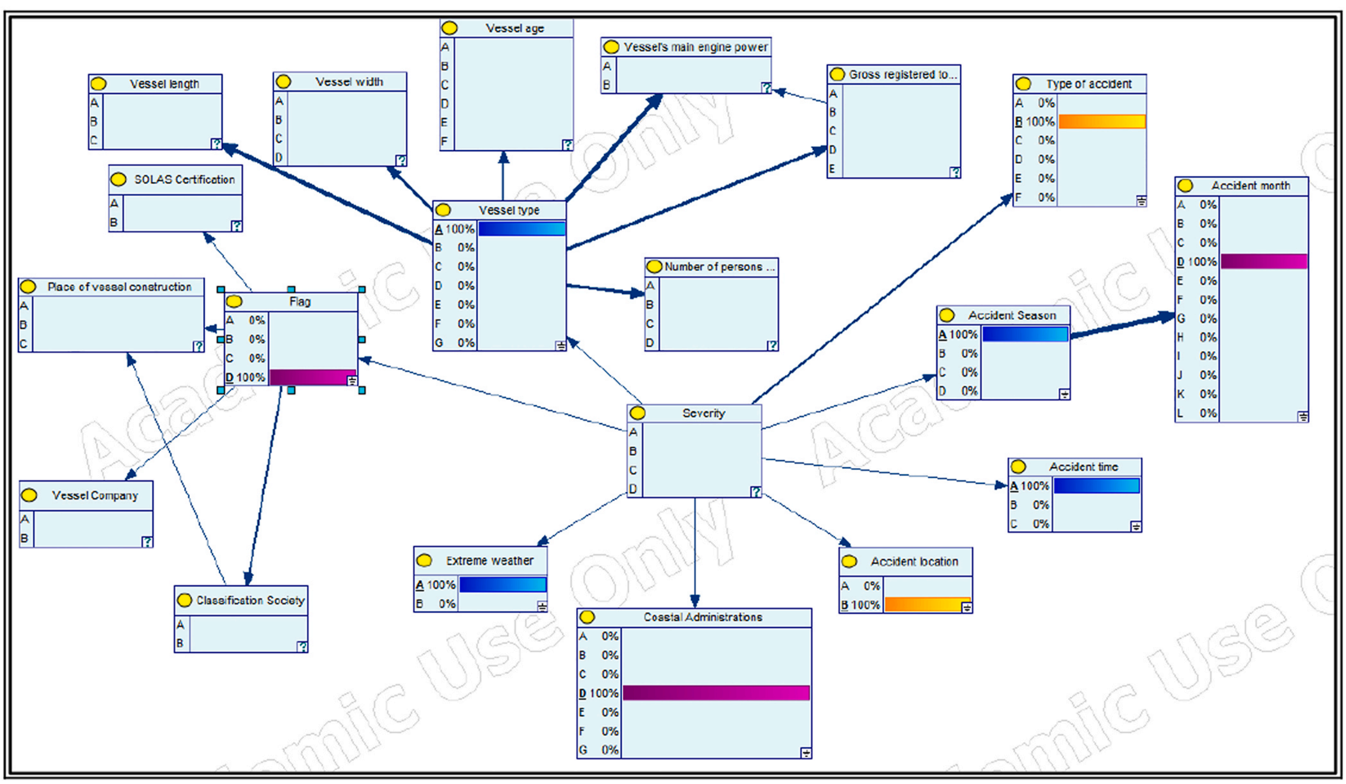

Fig. 9. Setting the node state (Case 1).

bulk. At 15:35 local time (UTC+5), the vessel was 173 nautical miles from Shangri Lanka, located at 5°55′30″N, 84°20′42″E; the vessel suddenly tilted 15 degrees to the port side. The situation continued to deteriorate, and the captain abandoned the vessel at 16:02 after the port deck was submerged in 40-degree water, and all 23 crew members were rescued by the passing container freighter Nedlloyd Asia. The next day, a salvage tug was called in an unsuccessful attempt to rescue the vessel, which sank on May 20th, 2005.

The exact reason for the sinking of "Huilong" could not be determined. After investigating the possible causes of the accident, it was concluded that the liquefaction of the bottle stone in cargo holds No. 1 and No. 3 was the cause of the accident. The flow state of bottled stone goods may cause the vessel to sink.

The following risk sub-factors were extracted from the accident introduction: type of accident, vessel type, accident season, accident time, accident month, accident location, extreme weather, flag and

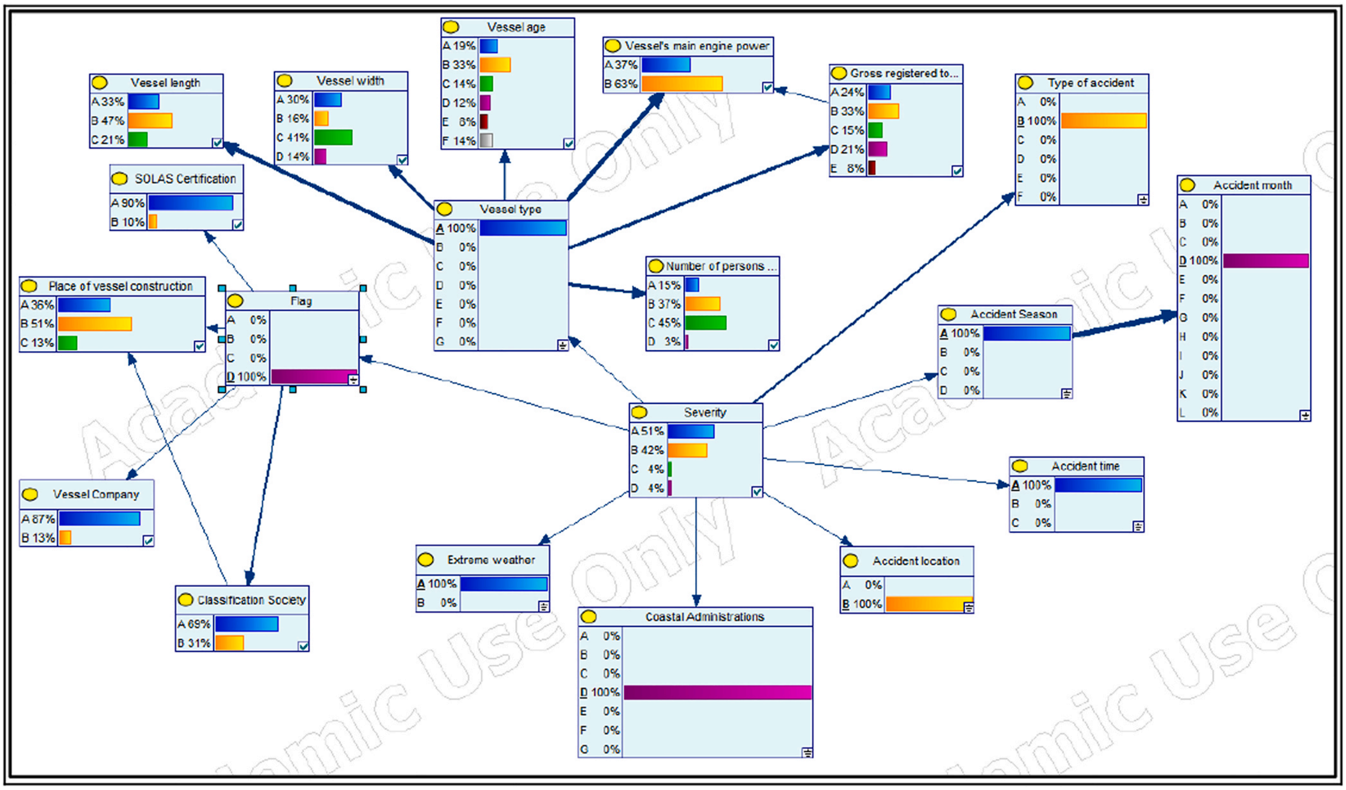

Fig. 10. Forward reasoning results (Case 1).

Table 4
Accident simulation forward reasoning results (Case 1).

Severity	Before entering evidence (%)	After entering evidence (%)	Probability variation (%)
Very serious	69	51	−26.09
Serious	23	42	82.61
Less serious	6	4	−33.33
Undefined	3	4	\

classification society. They are entered into the BN model as evidence, and forward inference is performed to obtain the following results, as shown in Figs. 11 and 12. The results of the forward reasoning are shown in Table 5.

Analysis of forward reasoning results: The RIFs extracted from the accident case descriptions were substituted into the simulation model. It was found that the probability of the severity level of "very serious" is significantly higher, while the results of the other severity are not significant. The severity level of this accident in the accident record is "very serious", which is in line with the facts. Twenty samples were tested according to this process, and the results are shown in Table A2 and Table A3.

We followed strict standards and processes when selecting 20 data points to validate the mathematical model. The sample data comes from maritime incidents in the RCEP region from 2011 to 2016 (out of the analysis data range in Section 3.1.2), and the selection of sample data adhered to three principles: randomness, representativeness, and non-overlapping. First, the sample dataset was grouped by year, and then it was further grouped by the severity of the incidents. A stratified sampling method was employed to obtain 10 groups from each category. In determining the sample size, this study initially tried groups of 10, 20, and 30 data points. After 100 repeated sampling analyses, it was found that when the sample data consisted of 20 groups, the test results could achieve the desired outcomes more quickly while ensuring stability. Therefore, 20 data points were chosen as the sample test set, and ultimately, one group was selected through simple random sampling as the test group for validating the effectiveness of the model presented in this paper. When determining the adequacy of a model's predictive results by assessing whether the "posterior probability change of the target type corresponding to the tested cases" is highest and if the model aligns with actual real-world situations, it has been verified that the overall qualification rate of 20 cases is 95 %. This certification confirms that the validated result of this model is reasonable.

5. Empirical results

5.1. Identification of key risk factors

To accurately identify the influence of each sub-factor in ship accidents and put forward targeted suggestions on the prevention of shipping accidents, this section uses the proposed model for reverse reasoning and empirical research. When analyzing accidents of a certain severity, the posterior probability of each risk subfactor can be deduced by adjusting the state probability of the "severity" node in the BN. Generally, the subfactor with a higher posterior probability is considered the critical subfactor at that severity.

(1) Identify critical sub-factors based on 549 RCEP regional maritime accident data, taking "very serious" as an example.

(1.1)Record the posterior probability of each risk factor in the initial state, as shown in Fig. 13;

(1.2)Set the probability of "very serious" to 100 %, as shown in Fig. 14;

(1.3)Inference is performed to obtain the posterior probability under the set state, as shown in Fig. 15.

Based on the severity of "very serious", it can be observed that among the eight primary factors, "type of accident (D: vessel wreck and overturning)" and "type of accident (F: other accidents)" emerge as

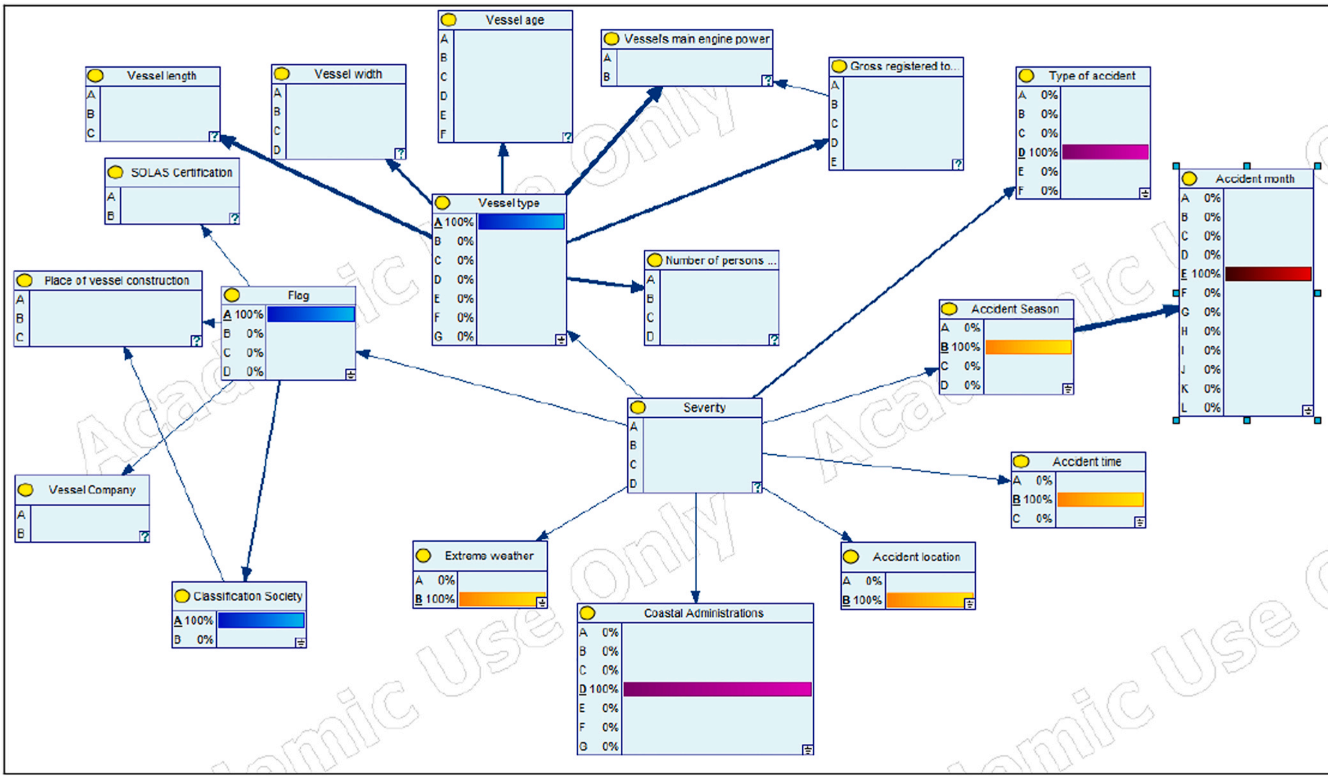

Fig. 11. Setting the node state (Case 2).

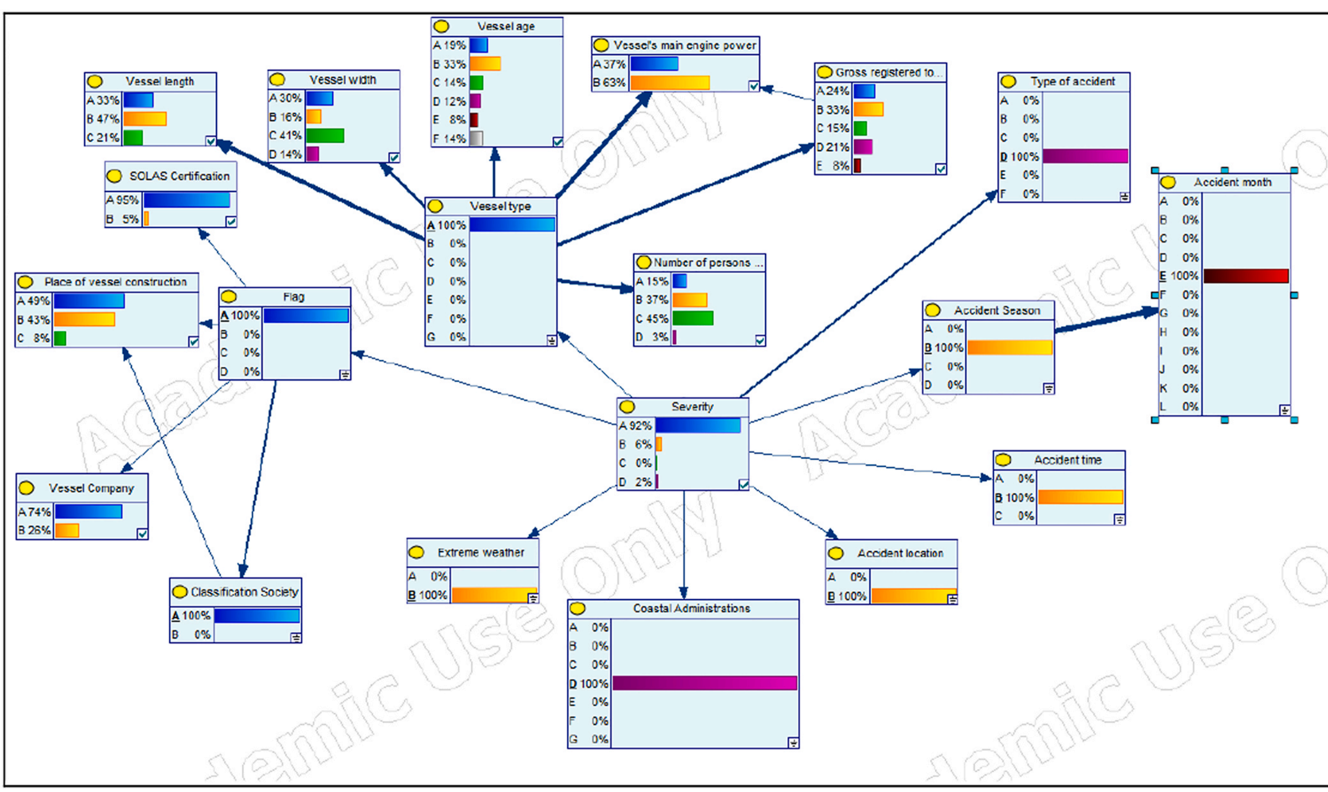

Fig. 12. Forward reasoning results (Case 2).

significant ones. According to the findings, when the accident is classified as "very serious", there is a decrease in the posterior probability of occurrence for "flag (A: white)", while there is an increase in posterior probability for both "flag (B: grey)" and "flag (C: black)". This aligns with common sense that ships displaying flags indicating more satisfactory performance have lower risk levels. Regarding "extreme weather"

Table 5
Accident simulation forward reasoning results (Case 2).

Severity	Before entering evidence (%)	After entering evidence (%)	Probability variation (%)
Very serious	69	92	33.33
Serious	23	6	−73.91
Less serious	6	0	\
Undefined	3	1	\

impact, there has been a decline in the posterior probability of occurrences categorized as "extreme weather (A: not affected by extreme weather)", whereas occurrences classified as "extreme weather (B: affected by extreme weather)" posterior probability have shown an increase. These results suggest that ship accidents are more likely to be labeled "very serious" under extreme weather conditions. The remaining primary factors have exhibited minimal changes.

Among the secondary factors, "SOLAS certification (B: no SOLAS certification)", "classification society (A: not part of the top ten classification societies)", "vessel length (A: 0–100 m)" and "vessel age (F: more than 25 years)" posterior probability all increased, indicating that in the RCEP area, ships with the above factors are more likely to have "very serious" accidents.

Repeat the same analyzing approach for the remaining two severity levels.

(2) Fig. 16 shows the result of a "serious" accident. Based on the severity of "serious", it can be seen that among the eight primary factors, "type of accident (A: grounding)", "type of accident (B: collision)", "type of accident (C: fire)" and "type of accident (E: damage to vessel and cargo)" posterior probability are significantly increased. Accident time is more concentrated in the "accident time (A: 0:00–7:59)" period; The "flag (A: white)" posterior probabilities has risen, while the "flag (B: grey)" and "flag (C: black)" posterior probability have fallen. The "vessel type (A: dry bulk carrier)" posterior probability has decreased, while the "vessel type (B: container vessel)" posterior probability has increased. In the secondary factors, the probability of "classification society (B: belongs to the top ten classification societies)", "vessel's main engine power (B: more than 3000 kW)", and "SOLAS certification (A: possesses SOLAS certification)" posterior probability increased, while "vessel age", "gross registered tonnage", "vessel length" and "vessel width" posterior probability all have the trend of improvement.

(3) Fig. 17 shows the results of "less serious" accidents. Based on the severity of "less serious", it can be seen that among the eight primary factors, the posterior probability of "flag (A: white)" increases significantly; "type of accident (A: grounding)", "type of accident (B: collision)", and "type of accident (E: damage to vessel and cargo)" posterior probability all increased significantly. "extreme weather (A: not affected by extreme weather)" and "accident location (B: sea area)" posterior probability have increased. In terms of vessel type, the posterior probability of "vessel type (A: dry bulk carrier)" has increased, while "vessel type(G: others)" posterior probability has decreased significantly. In terms of coastal administration, the posterior probabilities of "coastal administration (A: China)" and "coastal administration (G: non-RCEP countries)" have decreased. Among the secondary factors, "vessel length", "vessel width", "vessel's main engine power" and "registered gross tonnage" posterior probability have all increased. These show that with the expansion of ship size, safety measures will be more ideal and less likely to occur "very serious" ship accidents. In addition, the posterior probability of "classification society (B: belongs to the top ten classification societies)" is increased.

To sum up, among the eight primary factors, in terms of accident type, two sub-factors, "type of accident (D: vessel wreck and overturning)" and "type of accident (F: other accidents)", significantly lead to "very serious" accidents; "type of accident (A: grounding)", "type of accident (B: collision)", and "type of accident (E: collision)" tend to make the accident severity "serious" or "less serious". The posterior probability of "type of accident (C: fire)" increases significantly only when the

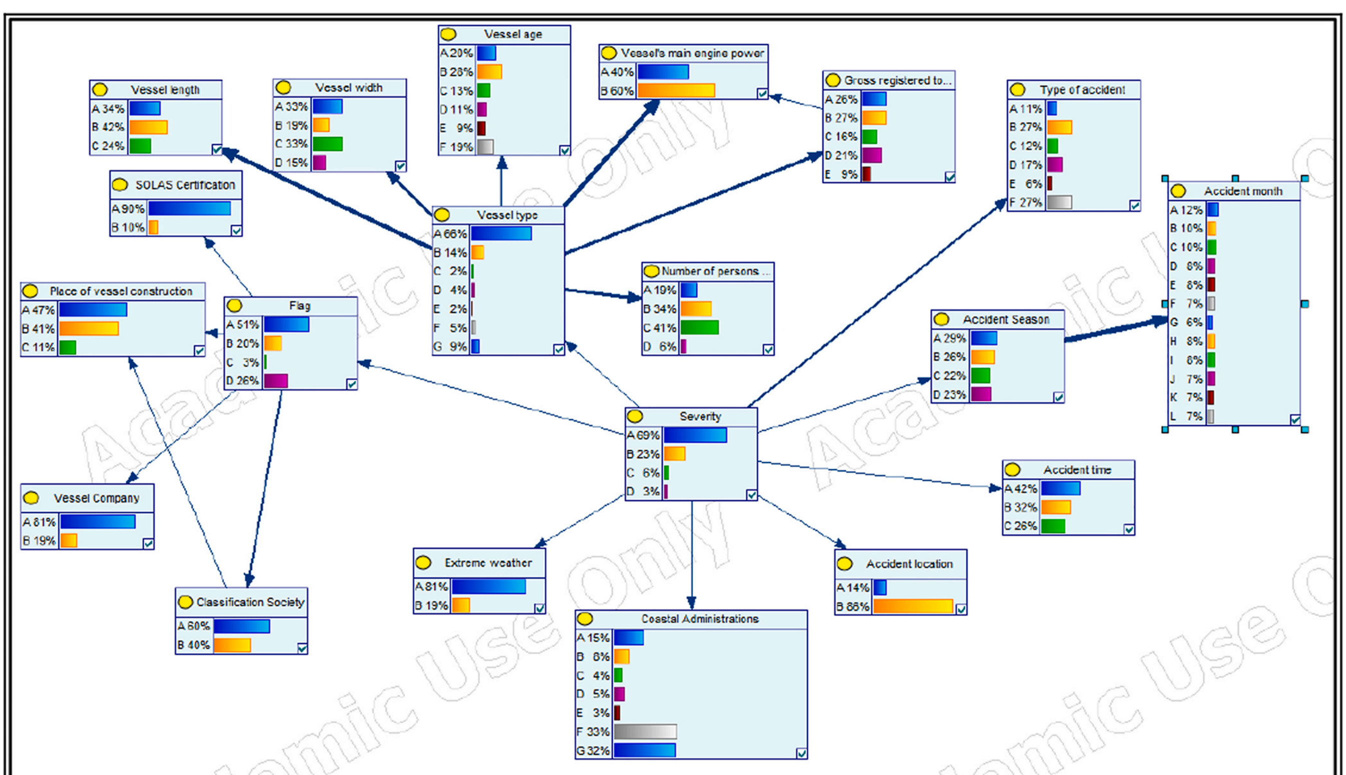

Fig. 13. Initial posterior probability.

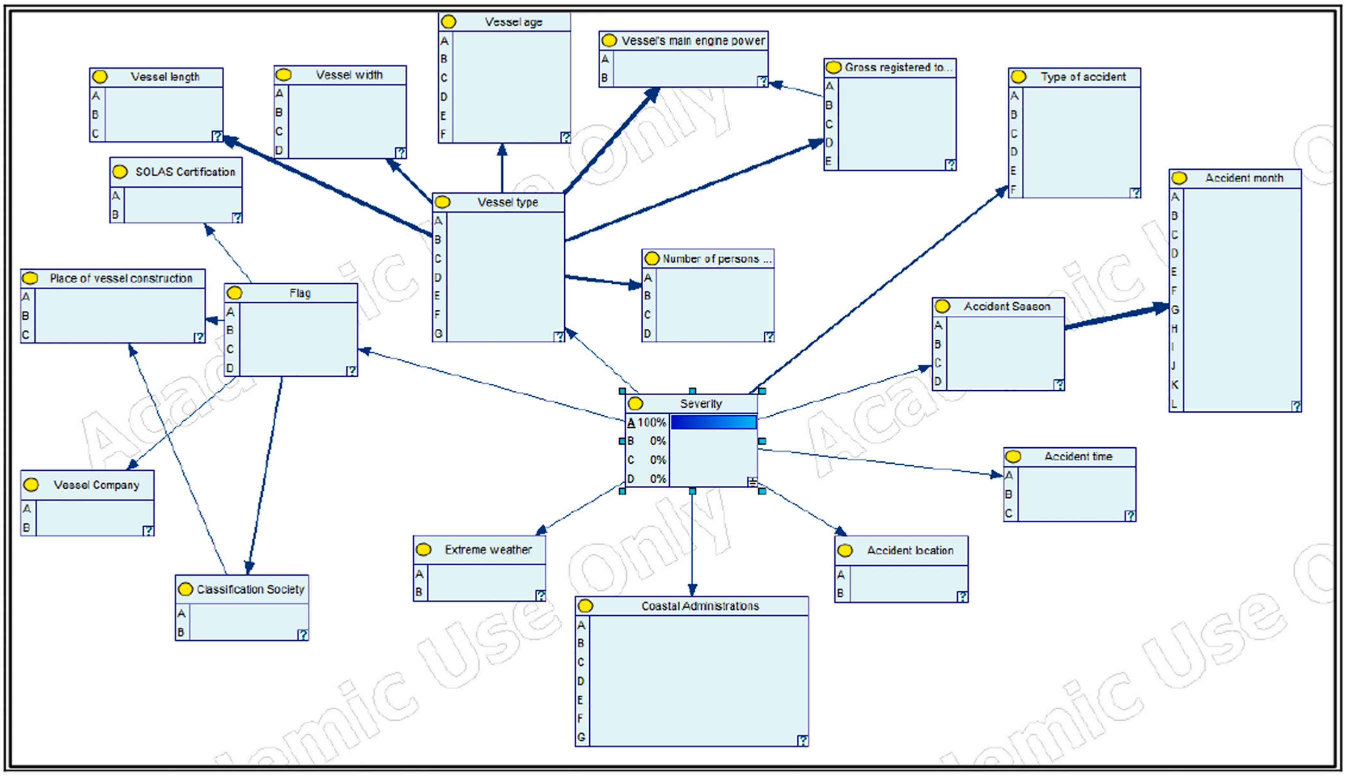

Fig. 14. Setting the node status (very serious).

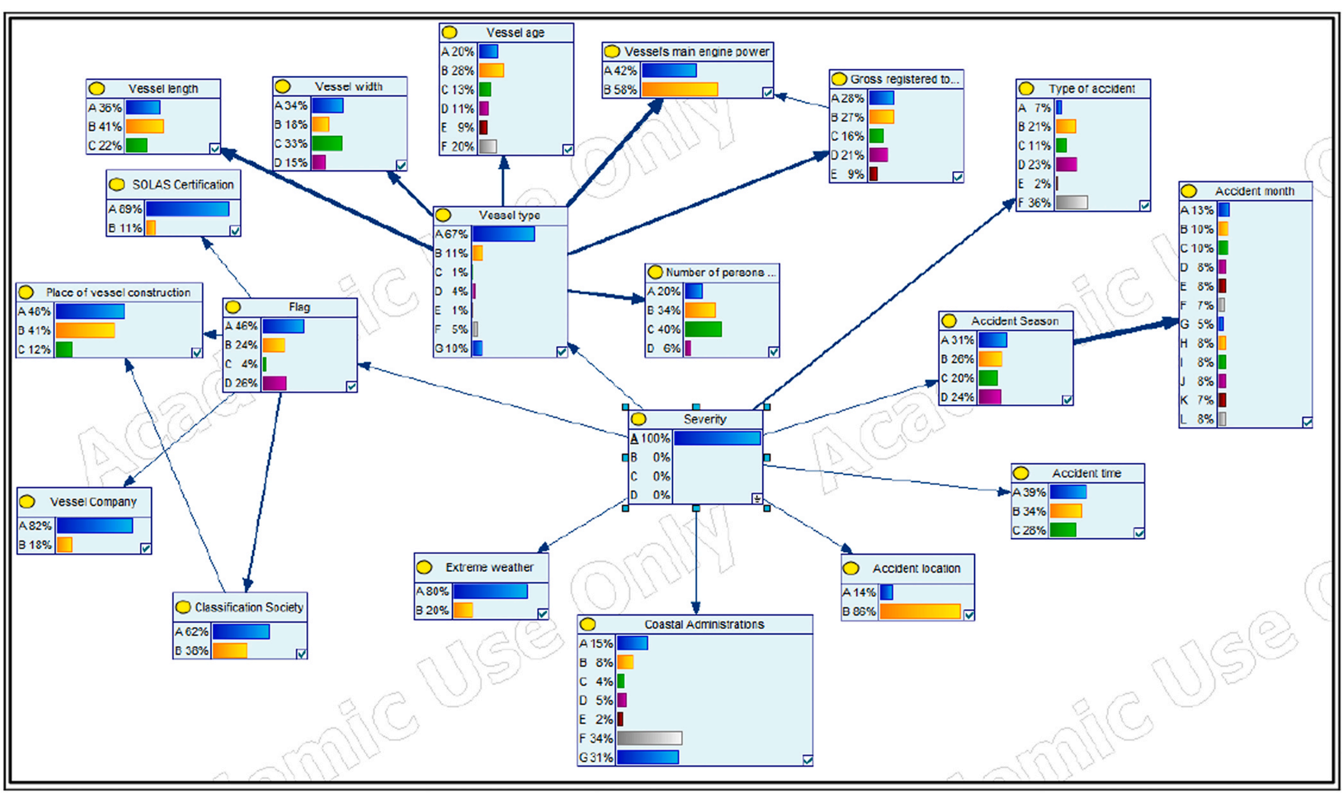

Fig. 15. Posterior probability of each risk subfactor (very serious).

severity is "serious". In terms of the flag, ships characterized by a "white" flag were more likely to have "serious" and "less serious" accidents than ships characterized by a "grey" flag and a "black" flag. In terms of extreme weather, "extreme weather (B: affected by extreme weather)" can lead to more severe accidents. In the secondary factors, "vessel length", "vessel width", "vessel's main engine power", "gross registered

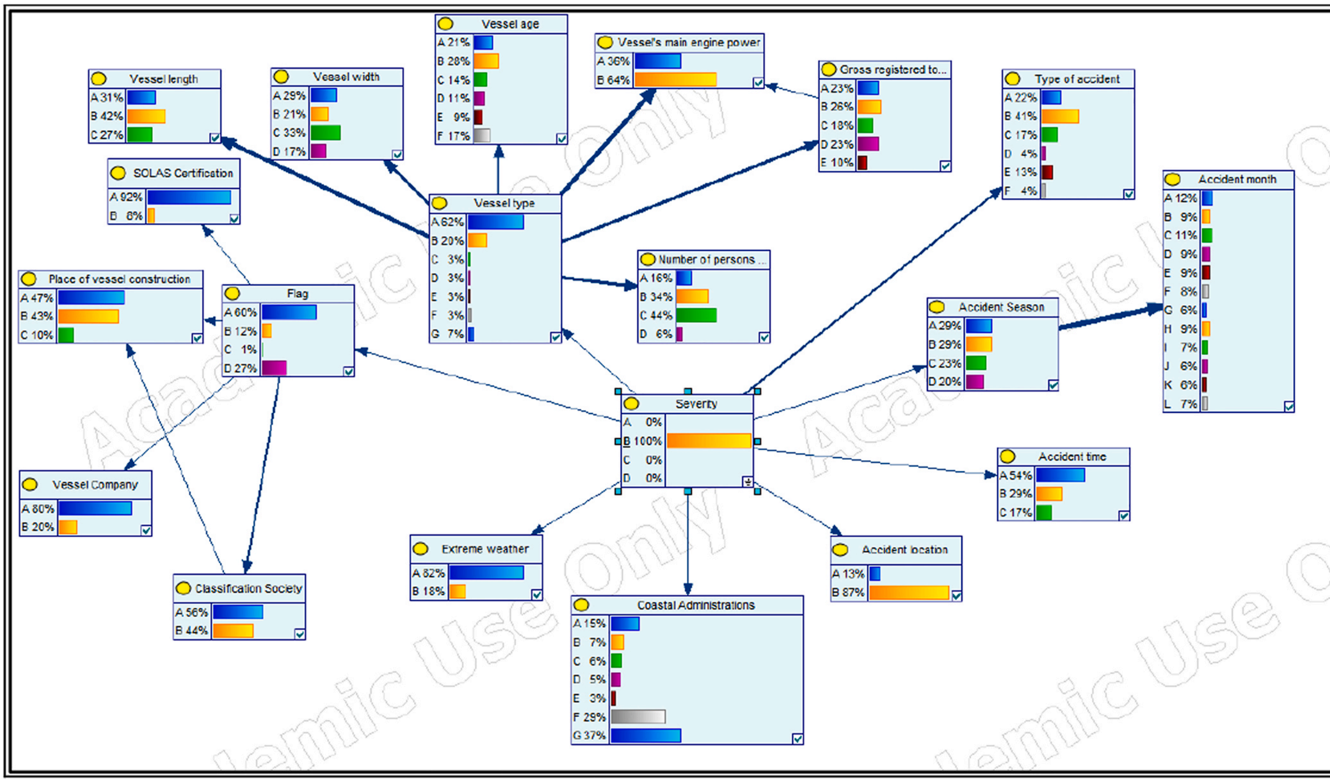

Fig. 16. Posterior probability of each risk subfactor (serious).

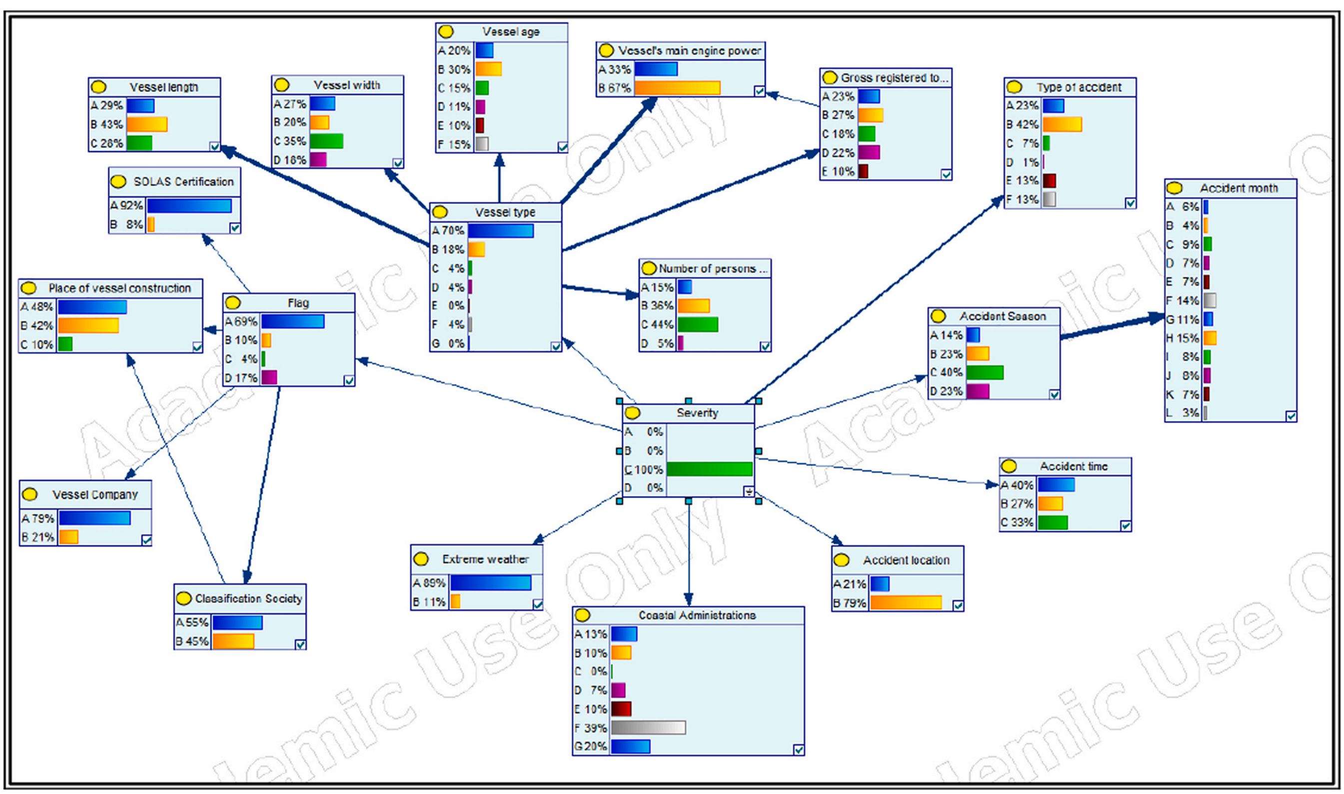

Fig. 17. Posterior probability of each risk subfactor (less serious).

tonnage", "number of persons on board", and other factors that express ship size reflect that smaller ships are more likely to have "very serious" accidents, which may be since small ships still have insufficient safety precautions and lack of safety awareness. In terms of maritime safety certification, ships with "SOLAS certification (A: having SOLAS certification)" characteristics are less likely to have "very serious" accidents.

The two sub-factors of "vessel company" and "place of vessel construction" have little influence on the severity of vessel accidents.

5.2. Ranking by RIFs

When different risk sub-factors are selected, the corresponding probability of the severity of ship accidents will change. The statistical change amplitude can reflect the influence of each factor on the severity of accidents; that is, the ranking of the importance of influencing factors can be obtained.

(1) Record the initial probabilities of each class severity when the probability of no impact is set, as shown in Fig. 18.

(2) Set the probability of "A" in "vessel length" to 100 % and record the probability of each class severity, as shown in Fig. 19.

(3) Repeat the above steps to complete the probability setting of all RIFs and record the probability of various class severity in each state.

Based on the above analysis of the results of "very serious", "serious", and "less serious", the top ten factors that have the most significant impact on the severity of each level are shown in Tables 6, 7, and 8.

As can be seen from Table 6, "type of accident: D (vessel wreck and overturning)" and "type of accident: F (other accidents)" are two primary factors that significantly cause the accident severity level to be "very serious". Two secondary factors, "flag: C (black)" and "flag: D (grey)", will lead to a greater probability of the accident grade changing to "very serious." Thus, it can be seen that the black, white, and grey of the flag state has a practical effect on the prediction of maritime risks to a certain extent. "Vessel type: G (others)", "vessel type: D (tug)", and "vessel type: F (ro-ro passenger vessel)" also increase the risk of ship accidents. In addition to the above factors, the vessel's SOLAS certification and accident time factors will also lead to an increase in the severity level, which requires the attention of the ship management personnel.

In Table 7, when the "type of accident: E (damage to vessel and cargo)", "type of accident: A (grounding)", "type of accident: B (collision)", and "type of accident: C (fire)" occur, the high probability of ship accident is a "serious" accident, and the common feature of this kind of accident is that it causes damage to the ship but does not have the impact of ship scrapping and casualties. "Vessel type: E (engineering vessel)" and "vessel type: C (liquefaction vessel)" are more likely to have "serious" class accidents in the event of an accident. In addition, coastal administration, accident time, and flag will also increase the number of "serious" ship accidents.

Table 8 shows that "coastal administration: E (New Zealand)" and "coastal administration: D (Australia)" in maritime accidents are more inclined to the "less serious" class. The probability of a ship accident being "less serious" is increased for the "type of accident: E (damage to vessel and cargo)", "type of accident: A (grounding)", and "type of accident: B (collision)". "Flag: A (white)" also tends to be the "less serious" type of accident. In addition to the above factors, "flag: A (white)" and the "accident location: A (coastwise)" also increase the posterior probability of the ship's accident severity being "less serious".

In summary, in the category of marine accidents, "capsizing" and "other accidents" are more likely to occur in "very serious" accidents, while "damage to vessel and cargo", "grounding", and "collision" make the severity of accidents more skewed towards the "serious" and "less serious" levels. In the ranking of the importance of influencing factors, it can be seen that the key influencing factors of "serious" and "less serious" accidents have a significant overlap degree, and some factors have similar impacts on the two severity levels, which may be due to the unclear classification criteria of "serious" and "less serious" in the severity of accidents, confusing the classification of accidents and room for improvement. In addition, the result proves that the classification of flag grades, that is, the classification of white, black, and grey flags, has a particular significance, which can reflect the risk of the ship to a certain extent. According to the SOLAS certification of the accident ship, it can also be found that the ship without relevant certification is more likely to have a "very serious" accident. From the perspective of vessel type, "tug", "ro-ro passenger vessel", and "others" are more likely to have "very serious" accidents. In contrast "engineering vessel", "liquefaction vessel",

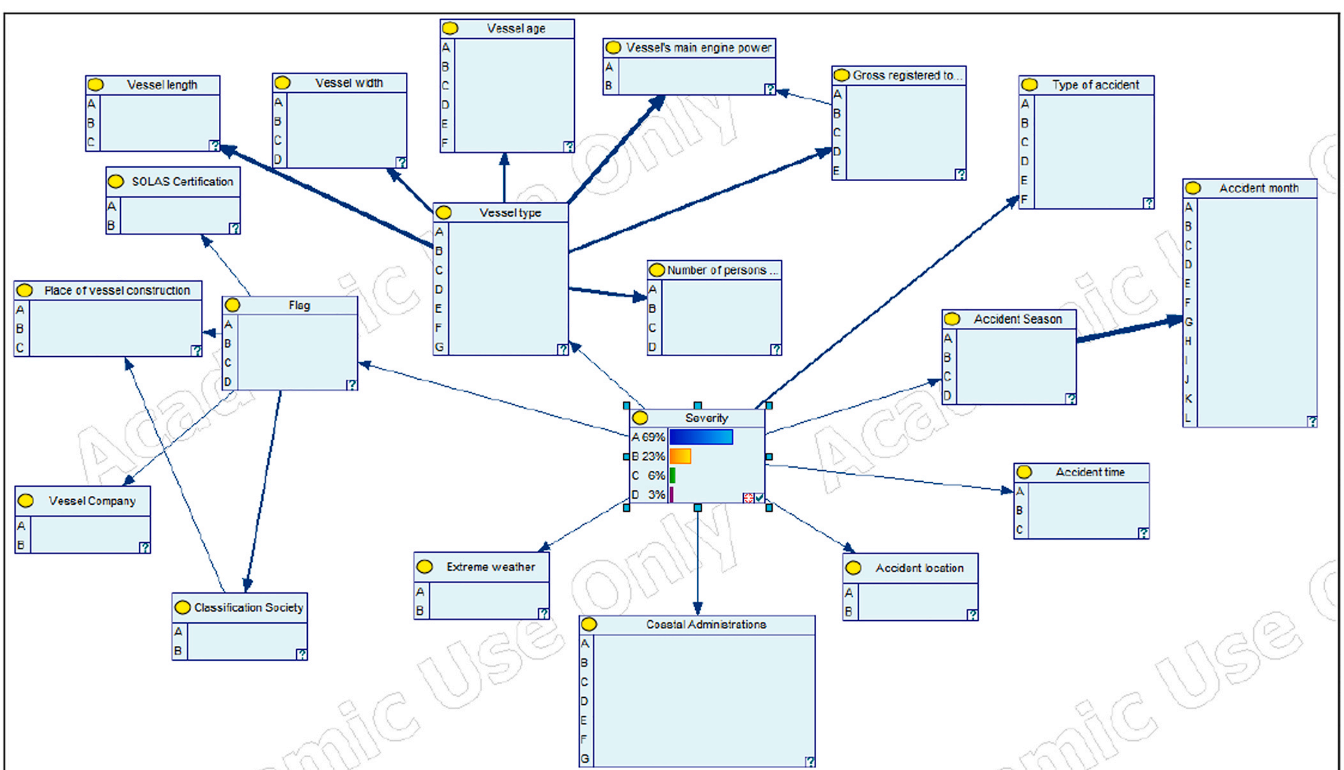

Fig. 18. Initial probability of each severity.

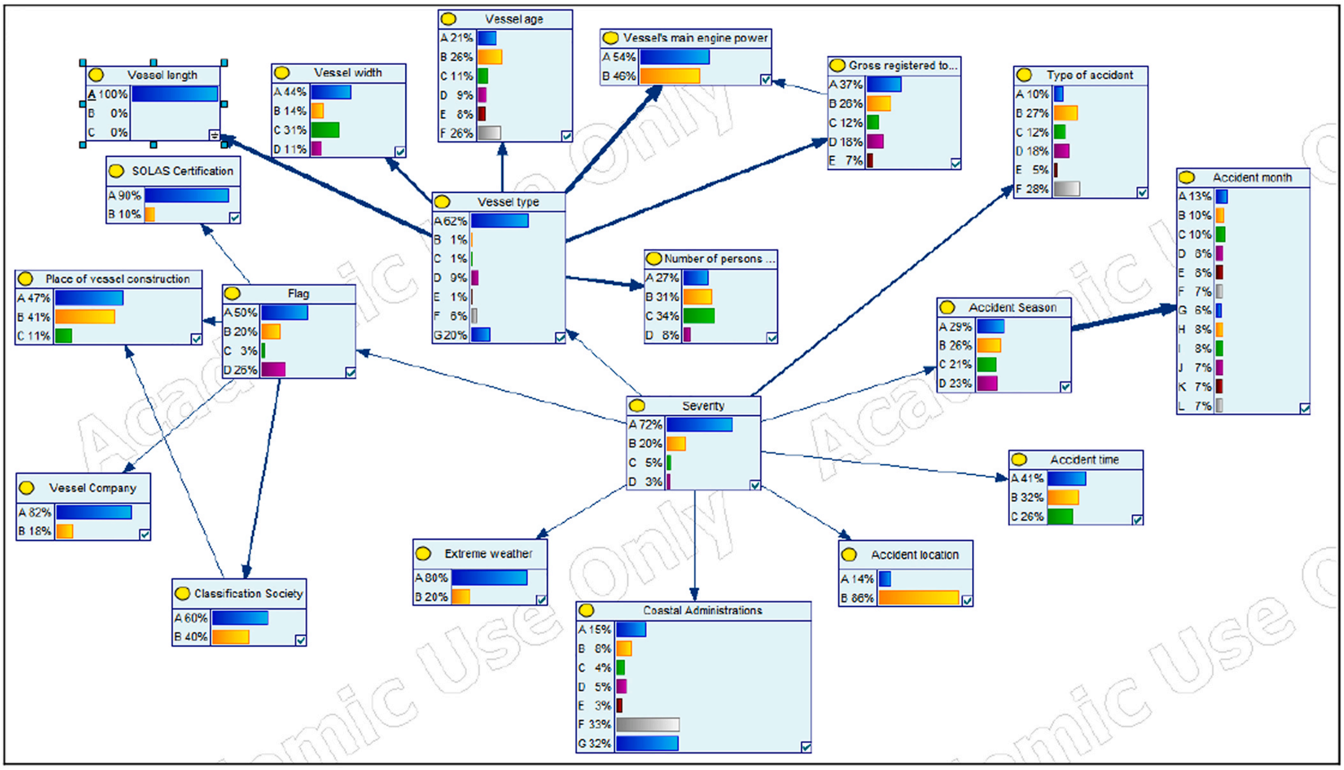

Fig. 19. Severity probability in the probability setting of "vessel length".

Table 6
Top 10 factors in the "very serious" category.

Ranking	Influencing factor code	Influencing factor	Probability change/%
1	Type of accident: D	Vessel wreck and overturning	35.41
2	Type of accident: F	Other accidents	32.47
3	Flag: C	Black	23.92
4	Flag: B	Grey	20.34
5	Vessel type: G	Others	13.33
6	Vessel type: D	Tug	12.17
7	Vessel type: F	Ro-ro passenger vessel	9.97
8	SOLAS certification: B	No SOLAS certification	7.32
9	Accident time: C	16:00–23:59	6.78
10	Number of persons on board: A	0–10	5.93

Table 7
Top 10 factors in the "serious" category.

Ranking	Influencing factor code	Influencing factor	Probability change/%
1	Type of accident: E	Damage to vessel and cargo	127.34
2	Type of accident: A	Grounding	97.52
3	Vessel type: E	Engineering vessel	60.69
4	Type of accident: B	Collision	49.56
5	Vessel type: B	Container vessel	45.59
6	Coastal administration: C	South Korea	45.12
7	Vessel type: C	Liquefaction vessel	42.56
8	Type of accident: C	Fire	33.84
9	Accident time: A	0:00–7:59	29.20
10	Flag:A	White	19.40

Table 8
Top 10 factors in the "less serious" category.

Ranking	Influencing factor code	Influencing factor	Probability change/%
1	Coastal administration: E	New Zealand	252.34
2	Type of accident: E	Damage to vessel and cargo	143.78
3	Vessel type: C	Liquefaction vessel	115.20
4	Type of accident: A	Grounding	111.15
5	Accident season: C	Third quarter	82.48
6	Type of accident: B	Collision	56.33
7	Accident location: A	Coastwise	50.97
8	Flag: A	White	35.59
9	Coastal administration: D	Australia	35.50
10	Accident time: C	16:00–23:59	28.35

and "container vessel" tend to have "serious" and "less serious" accidents, which may be due to the lack of adequate safety measures and standard safety precautions for ships such as "tug", more likely to occur crew casualties and ship damage.

5.3. Model evaluation

The BN model has undergone substantial development in influencing factor analysis. The motivation of this work to choose the BN model as the analysis method is because it can provide probability values for potential risks as a reference and offer graphical models that make the results more intuitive.

The BN model has significant advantages compared to other popular influencing factor analysis models. Probability Risk Assessment (PRA) models rely on historical data and fault tree analysis, often neglecting uncertainty and dynamic updates, while BNs can update risk assessments in real time and handle uncertainty. Multi-criteria decision-making (MCDM) models, such as the Analytic Hierarchy Process (AHP), mainly depend on expert judgment, which may introduce subjective bias. In contrast, BNs quantify uncertainty, providing data-driven decision support that reduces the impact of subjective factors. System Dynamics models focus more on the dynamic changes within systems but usually require complex model structures and numerous parameters. BNs, on the other hand, have a simple structure that is easy to construct and understand, making them more adaptable to different contexts, with minimal differences in final results. Machine learning models, such as random forests and neural networks, are often black-box models that are difficult to interpret regarding causal relationships. BNs provide transparent causal relationships and influence pathways, facilitating understanding and communication. BN models demonstrate more robust advantages over traditional models in handling uncertainty relationships, dynamic updating capabilities, integrating diverse information, and displaying causal relationships. BN is the most suitable model choice for this work, considering its accuracy (the accuracy is 95 % in the 20 samples test), efficiency (easy understanding of the model structure and fast construction with the software), and interpretability (clear graphic illustration). The comparison of BN and other typical models is listed in Table 9.

6. Conclusions and outlook

6.1. Conclusions

Under the background of the formal implementation of RCEP, this paper makes an in-depth discussion of the maritime risk assessment of RCEP member states. By constructing a simulation model based on BN, the key factors affecting the severity of ship incidents are successfully identified and quantified. It was found that factors such as accident category, ship nationality, ship flag, and extreme weather significantly impact predicting and inferring the severity of ship accidents. In addition, through specific case analysis, this paper verifies the effectiveness and practicability of the proposed model, provides valuable risk management suggestions for ship administration departments, and supports improved maritime safety in the RCEP region.

(1) Summary of influencing factors based on accident severity (forward analysis summary)

The categories of influencing factors that appear among the top 10 influencing factors with the most significant impact under each severity level of maritime incidents are defined as the key influencing factors for that severity level. The factors affecting the severity of accidents in Section 5 are sorted out, and the results are shown in Table 10. The primary factors impacting the severity of ship accidents are type of accident, flag, vessel type, and extreme weather. Among the secondary factors, vessel length, vessel age, vessel's main engine power, and SOLAS certification significantly affect the severity of ship accidents. In summary, two primary factors, type of accident and flag, and two secondary factors, vessel length and classification society, especially influence the severity of the three kinds of accidents (bold in Table 10). Therefore, shipowners and ship administration departments can prioritize the management and optimization of the above four factors to ensure ship safety.

Table 9
Modle comparasion with the 20 samples.

Model	Accuracy rate
BN	**95 %**
MCDM	90 %
FRAM	85 %
KDE	90 %
Lempel-Ziv	80 %
Decision tree	**95 %**
Convolutional Neural Network	**95 %**

Table 10
Influencing factors summary of forward analysis.

Severity	Primary factors	Secondary factors
Very serious	**Type of accident**、**Flag**、Extreme weather	**Classification society**、**Vessel length**、Vessel age、SOLAS certification
Serious	**Type of accident**、**Flag**、Vessel type	**Classification society**、Vessel's main engine power、SOLAS certification、**Vessel length**、Vessel width
Less serious	**Type of accident**、**Flag**、Extreme weather、Accident location、Coastal administration、Vessel type	**Vessel length**、Vessel width、Vessel's main engine power、Gross registered tonnage、**Classification society**

(2) Summary of accident severity based on influencing factors (reverse analysis summary)

The conclusions of accident severity caused by the ten factors with the most significant impact in Section 5 are concluded, and the results are shown in Tables 11 and 12, where "✔" indicates that the factor has a significant impact on accident severity. The influence of primary factors on the severity of ship accidents is significantly more influential than that of secondary factors, and the influence factors of "very serious" and "serious" are almost the same (except for the "coastal administration" factor). In contrast, the factors that influence "less serious" accidents are almost every primary factor (except the "extreme weather" factor).

To sum up, vessel type, type of accident, and flag are more likely to affect the severity of ship accidents. At the same time, the ship owners should also pay attention to updating the ship's SOLAS safety certification in time to meet the relevant requirements, significantly reducing the risk of ship accidents. Through an in-depth analysis of maritime ship incidents in the RCEP area, this paper not only improves the understanding of maritime traffic safety but also provides a scientific basis for further optimizing ship management and improving the quality of maritime safety research. The BN model in this study provides an effective analytical tool for future research, which enables more accurate assessment and prediction of the risk of ship accidents.

The usability of this study is multifaceted and significant for various stakeholders in the maritime industry within the RCEP region. The identified key risk factors for policymakers and regulatory bodies provide a data-driven basis for developing targeted safety regulations and inspection protocols. Shipping companies can use these findings to enhance their risk management strategies, prioritizing resources for the most impactful safety measures. Maritime insurance providers may find the risk factor rankings valuable for refining risk assessment models and pricing policies. Additionally, the BN model developed in this study

Table 11
Reverse analysis of primary RIFs.

Primary factors	Very serious	Serious	Less serious
Vessel type	✔	✔	✔
Type of accident	✔	✔	✔
Accident season			✔
Accident time	✔	✔	✔
Accident location			✔
Coastal administration		✔	✔
Extreme weather			
Flag	✔	✔	✔

Table 12
Reverse analysis of secondary RIFs.

Secondary factors	Very serious	Serious	Less serious
Vessel length			
Vessel width			
Vessel age			
Vessel's main engine power			
Gross registered tonnage			
Number of persons on board	✔		
SOLAS certification	✔		
Place of vessel construction			
Vessel company			
Classification society			
Accident month			

offers a practical tool for real-time risk assessment, which can be integrated into vessel management systems to support decision-making during operations. The methodology presented here is also adaptable, allowing for its application in other geographical regions or specific maritime sectors, thus extending its usability beyond the RCEP context. Overall, this study bridges the gap between academic research and practical application in maritime safety, offering actionable insights for improving process safety in the shipping industry.

6.2. Outlook

There is still room for further deepening and expansion of this research in the future:

(1) Build a dynamic BN model to achieve real-time data tracking and updating

The data employed in this paper is historical data, which is preprocessed and imported into the model for analysis, where naïve BN is most suitable regarding the model efficiency and simplicity. In the follow-up study, the data can be tracked in real-time. With the continuous growth of economic and trade activities in the RCEP region, maritime ship activities will also become more frequent. Therefore, continuous tracking and analysis of new data and real-time updating of risk assessment models will be a critical direction of future research. With the continuous influx of new data, the model can dynamically adjust internal parameters to optimize its decision-making process so that the model can continuously optimize its performance over the long run.

(2) Integration of large language model, directly put forward management suggestions

The large language model of continuous development can also be integrated into the future research of this paper. The data in this paper are based on accident information directly available in marine accident investigation results. After integrating the large language model, more abundant data support can be obtained through multiple channels such as marine accident investigation reports, articles, magazines, and Internet forums. The model has a robust self-updating ability and high data information coverage. In addition, the intelligence of the large language model can couple the professional knowledge information of shipping management and update it automatically. The model can directly give corresponding management suggestions while analyzing the factors of marine accidents.

(3) Increase the number of risk factors, enhance international cooperation and standardization

In terms of data, future studies can consider incorporating more types of risk factors into the model, such as crew quality and route channel conditions, to further improve the accuracy and applicability of the model. The results of this paper provide technical reference for ship administration departments in the RCEP region, and relevant divisions can focus on preventing high-risk factors in ship accidents according to the operation results of the proposed model to ensure the safety and stability of RCEP maritime trade. Therefore, according to the results of this paper, strengthening cooperation among RCEP member states and promoting the formulation of uniform maritime safety standards can jointly improve maritime traffic safety in the region.

CRediT authorship contribution statement

Wenyang Wang: Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization, Writing – review & editing. **Junrui Zhao:** Writing – original draft, Visualization, Software, Formal analysis, Data curation, Writing – review & editing. **Yulihe Chen:** Writing – original draft, Visualization, Software, Formal analysis, Data curation, Writing – review & editing. **Peng Shao:** Writing – original draft, Supervision, Software, Methodology. **Peng Jia:** Writing – original draft, Supervision.

Declaration of Competing Interest

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

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Appendix I. : RIFs and Accident Severity

Table A1
Vessel accident influencing factors and labeling

RIFs	Label	RIFs	Label
Flag	White—A Grey—B Black—C Unlogged—D	Accident month	From January to December—A to L
SOLAS certification	Possesses SOLAS certification—A No SOLAS certification—B	Vessel type	Dry bulk carrier—A Container vessel—B Liquefaction vessel—C Tug—D Engineering vessel—E Ro-ro passenger vessel—F Others—G
Place of vessel construction	Developed country—A Developing country—B Indeterminacy—C	Number of persons on board	0–10—A 11–20—B 21–30—C More than 30—D
Vessel company	Vessel operating companies and vessel management companies are the same—A Vessel operating companies and vessel management companies are different—B	Gross registered tonnage	(0, 1000]—A (1000, 3000]—B (3000, 5000]—C (5000, 10000]—D (10001, 20000]—E (20000, ∞)—F
Classification society	Not part of the top ten classification societies—A Belongs to the top ten classification societies—B	Vessel's main engine power	Less than or equal to 3000 kW—A More than 3000 kW—B
Extreme weather	Not affected by extreme weather—A Affected by extreme weather—B	Vessel age	(0, 6) years—A [6, 11) years—B [11, 16)years—C [16, 21) years—D [21, 26) years—E [26,∞) years—F
Accident location	Coastwise—A Sea area—B	Vessel width	(0, 20] meters—A (20, 30] meters—B (30, 40] meters—C (40, ∞) meters—D
Coastal administration	China—A Japan—B South Korea—C Australia—D New Zealand—E Other RCEP countries—F Non-RCEP countries—G	Vessel length	(0, 100] meters—A (100, 200] meters—B (200, ∞) meters—C
Accident time	0:00–7:59—A 8:00–15:59—B 16:00–23:59—C	Type of accident	Grounding—A Collision—B Fire—C Vessel wreck and overturning—D Damage to vessel and cargo—E Other accidents—F
Accident season	First quarter—A Second quarter—B Third quarter—C Fourth quarter—D	Severity	Very serious—A Serious—B Less serious—C Unspecified—D

Table A2
Summary of accident characteristics

Case serial number	Accident characteristics	Severity
1	Flag A, Accident time A, Accident location B, Accident season D, Accident month K, Vessel type A, Registered total tonnage C, Type of accident D, Coastal administration A	Very serious
2	Type of accident D, Accident time B, Accident location B, Flag B, Number of persons on board D, Coastal administration C	Very serious
3	Vessel type A, Flag A, Accident location B, Accident time B, Type of accident C	Serious
4	Vessel type A, Flag A, Classification society A, Extreme weather B, Coastal administration D, Accident location B, Accident time B, Type of accident D	Very serious
5	Type of accident F, Accident time B, Coastal administration B, Vessel type A, Extreme weather A, Accident location B, Accident month I, Flag A	Very serious
6	Vessel type A, Flag D, Extreme weather A, Coastal administration D, Accident location B, Accident time A, Accident month D, Type of accident B, Accident month E	Serious
7	Vessel type A, Flag B, Extreme weather A, Coastal administration C, Accident location A, Accident time A, Accident month B, Type of accident A	Serious

(continued on next page)

Table A2 (*continued*)

Case serial number	Accident characteristics	Severity
8	Flag B, Extreme weather A, Coastal administration E, Accident location B, Accident time A, Accident month L, Type of accident D, Vessel type G	Very serious
9	Vessel type A, Flag B, Extreme weather A, Coastal administration C, Accident location A, Accident time B, Accident month A, Type of accident A	Serious
10	Accident month F, Flag A, Accident location A, Accident season B, Vessel type B, Type of accident F, Coastal administration A	Very serious
11	Flag B, Extreme weather A, Coastal administration C, Accident location B, Accident time B, Accident month I, Type of accident D, Vessel type C	Very serious
12	Flag A,Extreme weather A, Coastal administration A, Accident location B, Accident time C, Accident month L, Type of accident D, Vessel type A	Very serious
13	Vessel type B, Extreme weather A, Accident time B, Accident month L, Type of accident C	Serious
14	Flag A, Vessel type B, Extreme weather A, Accident location A, Accident time C, Accident month L, Type of accident F	Very serious
15	Flag B, Extreme weather B, Coastal administration C, Accident location B, Accident time B, Accident month I, Type of accident B, Vessel type D	Very serious
16	Flag A, Extreme weather A, Coastal administration A, Accident location B, Accident time C, Accident month L, Type of accident D, Vessel type C	Very serious
17	Flag B, Extreme weather A, Coastal administration C, Accident location B, Accident time B, Accident month I, Type of accident D, Vessel type D	Very serious
18	Flag A, Vessel type D, Accident location B, Accident month B, Type of accident B, Extreme weather A	Very serious
19	Accident month K, Flag A, Accident location A, Accident season D, Vessel type F, Type of accident B, Number of persons on board D, Coastal administration F	Serious
20	Type of accident B, Accident time B, Vessel type B, Accident month G, Extreme weather A, Accident location A	Less serious

Table A3
Reasonability verification of proposed model

Case serial number	Type of accident	Posterior probability of target type /%	Posterior probability change of target type /%	Whether the target type has the greatest posterior probability change
1	Very serious	91	31.88	Yes
2	Very serious	96	39.13	Yes
3	Serious	31	34.78	Yes
4	Very serious	92	33.33	Yes
5	Very serious	89	28.99	Yes
6	Serious	42	82.61	Yes
7	Serious	47	104.35	Yes
8	Very serious	97	40.58	Yes
9	Serious	35	52.17	Yes
10	Very serious	84	21.74	Yes
11	Very serious	94	36.23	Yes
12	Very serious	94	36.23	Yes
13	Serious	39	69.57	Yes
14	Very serious	86	24.64	Yes
15	Very serious	83	20.29	Yes
16	Very serious	90	30.43	Yes
17	Very serious	98	42.03	Yes
18	Very serious	95	37.68	Yes
19	Serious	20	−15.00	No
20	Less serious	29	383.33	Yes

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