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An object-oriented Bayesian network model for the quantitative risk assessment of navigational accidents in ice-covered Arctic waters

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ABSTRACT

Merchant ship operations in the ice-covered Arctic waters may encounter traditional navigational accident risks (i.e., grounding, collision, etc.) and risks from sea ice, such as ship besetting in ice. However, describing, modeling, and quantifying the multiple risks in ice navigation are challenges from maritime risk assessment perspective. This paper proposes an object-oriented Bayesian network (OOBN) model for the quantitative risk assessment of multiple navigational accidents in ice-covered Arctic waters. The OOBN model makes use of the accident database from Lloyd's intelligence and maritime accident investigation reports. The proposed model decomposes navigational accidents into five levels based on accident causation theory: environment, unsafe condition, unsafe act, probability of navigational accident, and consequence of the navigational accident. Consequently, collision, grounding, ship besetting in ice, and ship–ice collision accidents are selected as the cases to interpret the quantitative risk assessment for navigational risk factors identification, risk analysis, and evaluation. The results demonstrate that (1) the risk is the highest in grounding accidents, followed by besetting in ice, collision, and ship–ice collision in ice-covered Arctic waters; (2) unsafe speed and unsafe condition are the critical mutual factors of these four accident scenarios; (3) and the critical risk influencing factors for the specific navigational accidents are identified to propose corresponding risk control options. The proposed OOBN model can be used for quantitative risk assessment of navigational accidents in ice-covered Arctic waters.

1. Introduction

In recent years, with global climate change and the melting of the Arctic sea ice, the volume of maritime traffic in Arctic waters has increased rapidly. The increase in ship activities has resulted in more navigational accidents in Arctic shipping. According to the 2021 Safety and Shipping Review issued by Allianz Global Corporate and Specialty [1], 520 maritime accidents occurred in Arctic Circle waters from 2011 to 2020. Grounding and collision accidents are still the typical navigational accidents corresponding to global maritime accident characteristics [2,3]. At the same time, ship operations in ice-covered waters may encounter risks from the harsh and rapidly changing sea ice environment. Ship besetting in ice and ship–ice collisions are common occurrences in Arctic shipping [4–6]. Therefore, describing, modeling, and quantifying the risks from multiple navigation accidents are essential for the safety management of Arctic shipping.

To date, the research on the risk analysis of navigational accidents in ice-covered waters has focused on (1) risk modeling for single navigational accident, (2) risk identifying and analyzing for typical accident scenarios in Arctic waters.

Regarding collision accidents in ice-covered waters, the major risk origin arises from collisions between the escorting and the icebreaking ship. As well as open sea causes, the human factor is a significant risk influencing factor (RIF) for collision accidents in ice navigation. Zhang et al. [7] incorporated a human factors analysis and classification system (HFACS) and a fault tree analysis (FTA) to explore the impacts of unsafe acts and conditions on collision accidents during escort operations in icebreaker assistance. Khan et al. [8] proposed a cellular automation model for predicting the probability of a collision between a ship and its assisting icebreaker during convoy operations. Regarding grounding accidents in Arctic waters, their root causes are not due to the sea ice; most of the studies have analyzed the risks of grounding accidents

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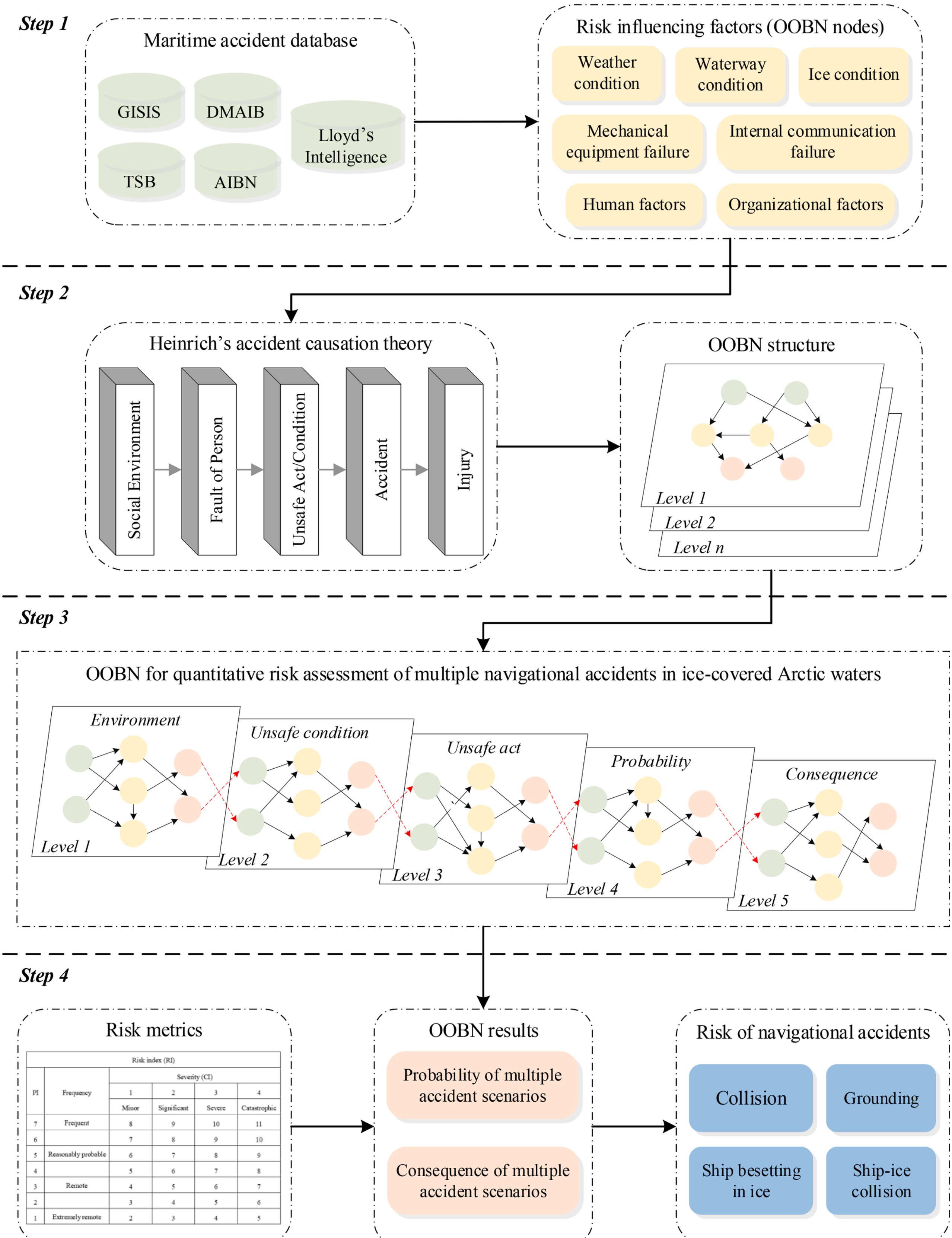

Fig. 1. Research framework for the risk analysis of Arctic shipping.

together with some other scenarios in Arctic shipping [3], and only a few studies have focused solely on grounding accidents. Fu et al. [9] proposed a framework for quantitative analysis of the causes of grounding accidents in Arctic shipping by developing an accident map–Bayesian network (BN) model. For independent voyages in ice-covered waters, ships may be beset in ice when the vessels' ice class cannot withstand the harsh sea ice [10]. How to accurately predict the probability of ship besetting in ice is a practical issue for the risk management of ice navigation in the Northern Sea Route. Fu et al. [6,11], Vanhatalo et al. [4], and Xu et al. [5] used dynamic ship voyage data to estimate the probability of ship besetting in ice. Regarding ship–ice collision accident analysis in Arctic waters, Afenyo et al. [12] and Khan et al. [13] used BN to assess the risk of ship–ice collision accidents. Obisesan and Sriramula [14] used an efficient surrogate model and FTA to estimate the probability of ship–iceberg collision accidents. Oil spills, the noteworthy secondary accident in Arctic waters, have also attracted research attention [15]. Currently, studies have focused on identifying causes, predicting the probability, or simulating the potential consequences of navigational accidents in ice-covered waters. However, less attention has been paid to a comprehensive quantitative risk assessment by aggregating the occurrence probability and severity of the accident scenarios.

Some studies have attempted to analyze the risks from multiple navigational accidents in Arctic waters. For example, Kum and Sahin [3] determined the root causes of collision and grounding accidents based on maritime accident investigation reports (MAIRs) from 1993 to 2011. Baksh et al. [16] proposed a BN to predict the probability of collision, foundering, and grounding accidents. Aziz et al. [17] established a bow-tie model to assess the risk of fire/explosion and machinery failure accidents under the influences of ship failure and human error. Zhang et al. [18] proposed a comprehensive risk assessment model for two main accident scenarios in ice-coved Arctic waters, i.e., ship besetting in ice and ship–ice collision. Fu et al. [19,20] summarized the critical RIFs that induced collision, grounding, ship besetting in ice, and ship–ice collision accidents in terms of environmental, technical (i.e., ice-class ships [21], mechanical equipment [12], internal communication failure [7]), human, and organizational aspects. Browne et al. [22] proposed a framework for rating the severity of the total consequences by considering the multiple consequences of accidents in ice-covered Arctic waters. Furthermore, Ma et al. [23], Qiao et al. [24], and Panahi et al. [25] discussed the safety of Arctic maritime transportation systems from a resilience perspective. These studies have discussed the effect mechanism of navigational accidents in Arctic waters and have focused on the coupling effects of complex sea ice environmental RIFs in ice operations. However, human and organizational factors (HOFs) as the primary RIFs that induce navigational accidents [26], the coupling effects of HOFs for voyaging ships, and navigational accidents should be given more attention and further discussed.

Accident causation theory acts as the foundation of safety science analysis and has assisted researchers and practitioners in comprehending and analyzing why accidents occur and how to prevent them [27]. Since 1919, many accident causation theories have been put forward. Greenwood and Woods [28] proposed the accident-prone tendency, which claims that accidents frequently happen to individuals that are more accident-prone. Heinrich [29] suggested that the occurrence of a casualty accident was not an isolated event but a process similar to collapsing dominoes. Namely, accidents result from a series of causal events occurring in succession. According to Heinrich's domino theory, accidents are directly caused by unsafe human acts and unsafe object conditions caused by the social environment and ancestry [30]. Like Heinrich's domino theory, Reason [31] proposed the Swiss cheese model, which establishes a relationship between unsafe acts, unsafe conditions, and organizational factors. In general, accident causation theory focuses more on the human factor in accidents and suggests that the direct cause of accidents is unsafe object conditions and unsafe acts. However, using accident causation theory to quantify the risk of navigational accidents is complicated.

The object-oriented Bayesian network (OOBN) is an extension of the BN. Compared to a standard BN, the OOBN is simple to construct, flexible to modify and provides a modular approach, all of which effectively reflect the complexity among factors in accident evolution [32]. This method has been applied to numerous fields, including the aviation [33], oil spills [34,35], and system risk assessment [36,37]. For example, Obeng et al. [38] used an OOBN to identify the RIFs for small fishing trawler capsizing accidents. In addition, Khan et al. [39] proposed an OOBN model to dynamically predict the probability of oil tanker–ice collision accidents in ice-covered Arctic waters.

This study aims to develop a quantitative risk assessment model to analyze the risk of multiple navigational accidents in ice-covered Arctic waters by utilizing an OOBN and risk metrics. The proposed model is based on the accident causation theory and decomposes four typical navigational accidents in Arctic shipping into five levels, including environment, unsafe condition, unsafe act, probability of navigational accident, and consequence of navigational accident. To quantitatively analyze the model, the related literature and historical accident data are utilized. Moreover, a risk metrics analysis is employed to determine the risk levels of multiple navigational accidents. The proposed risk assessment model is entirely driven by objective data, which effectively avoids the subjectivity of expert judgment and accurately reflects the risk level of ship navigational accidents in ice-covered Arctic waters.

The proposed OOBN has several advantages that contribute to the accuracy of the risk assessment. By using a data-driven approach, the model can capture important factors that may not have been identified using traditional expert-driven approaches, improving the accuracy of the risk assessment and reducing the potential for subjective biases or oversights. The OOBN model can also reflect the relationship between RIFs in the same and different classifications and integrates RIFs and accident scenarios in ice-covered Arctic waters. Additionally, the model can integrate various data sources, including historical accident data, environmental conditions, and vessel characteristics, capturing the relationships between these factors, and quantifying their impact on the risk of navigational accidents in ice-covered Arctic waters. By utilizing risk metrics, the proposed model can provide quantitative estimates of the probability and consequences of different types of accidents. The model's structured and objective approach allows for informed decision-making in risk management, providing a probabilistic estimate of the probability and consequences of different scenarios. Overall, the proposed OOBN provides a comprehensive and structured approach to modeling complex risk factors and improves the accuracy and reliability of quantitative risk assessments in ice-covered Arctic waters.

The rest of this paper is organized as follows. Section 2 introduces the framework and associated methods for the quantitative risk assessment of multiple navigational accidents. Section 3 interprets the risk-modeling process using the OOBN. Section 4 validates the OOBN model in terms of data and model and describes the results of the risk metrics. Finally, Section 0 summarizes this study and proposes relevant conclusions.

2. Methods

This section first introduces the framework for the risk assessment of navigational accidents in ice-covered Arctic waters (Section 2.1). Then, the methods are introduced that were used to construct the model (Section 2.2) and calculate the results of the risk aggregation (Section 2.3).

2.1. Quantitative risk assessment framework

Fig. 1.

The framework for the quantitative risk assessment of multiple navigational accidents in ice-covered waters can be decomposed into four steps with respect to the risk management regulation [40], through

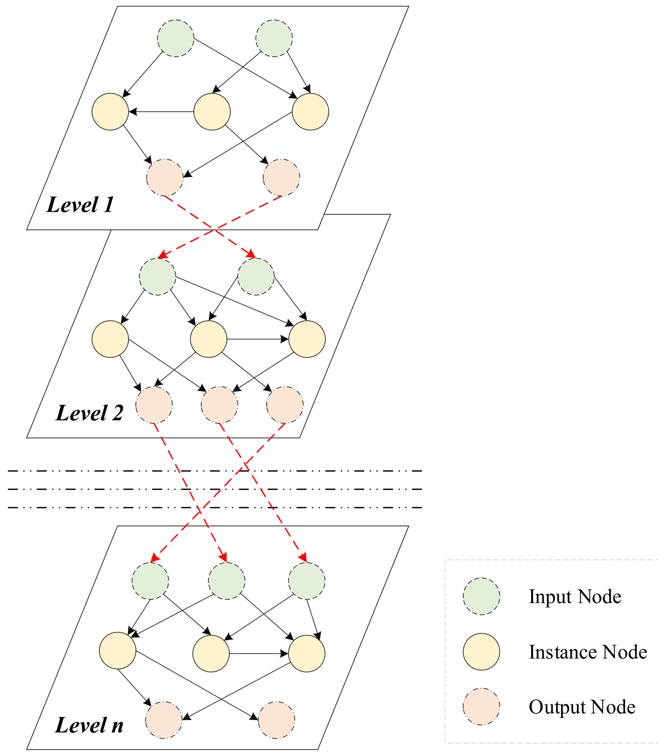

Fig. 2. Conceptual graph of the OOBN model.

a combination of Heinrich's accident causation theory, an OOBN, and risk metrics.

Step 1: Risk identification - identify the OOBN model nodes. The potential RIFs are identified by an in-depth analysis of the collected MAIRs and the literature from environmental, technical (ship-related), human, and organizational aspects. Then, the critical RIFs are selected by a statistical analysis of the frequency of the potential RIFs involved in the MAIRs and the related literature. The critical RIFs are then reclassified according to Heinrich's accident causation theory [29].

Step 2: Qualitative risk analysis - construct the OOBN model structure. Under the Step 1, based on the identified critical RIFs in ice-covered Arctic waters, an OOBN model is established with five subnetwork levels. The model describes the complex relationship between the different RIFs and navigational accidents. The relevant literature also informs these RIF relationships. The subnetwork levels are environment (Level 1), unsafe condition (Level 2), unsafe act (Level 3), probability of navigational accident (Level 4), and consequence of navigational accident (Level 5).

Step 3: Quantitative risk analysis - calculate the conditional probability tables (CPTs). This step uses the literature and historical accident reports to calculate the CPTs in the OOBN model proposed under Step 2. The maritime accident data include the accident database from Lloyd's intelligence and the MAIRs from the Global Integrated Shipping Information System, Transportation Safety Board of Canada, Danish Maritime Accident Investigation Board, and Accident Investigation Board Norway. The probability and consequence of multiple navigational accidents are evaluated by OOBN inference.

Step 4: Navigational risk evaluation in ice-covered waters. Based on the International Maritime Organization's formal safety assessment (FSA) guidelines [41], each accident's occurrence probability and consequence severity identified under the Step 3 are rated and their logarithmic indices are calculated. The combination of these indices is represented in the form of risk index, which are then compared with the risk acceptance criteria to make decisions.

2.2. OOBNs

BNs have been widely used as uncertainty modeling methods by transforming complex problems into probabilistic graphical models [42, 43]. As the network structure expands, BNs become inefficient at managing the variables in a single network simultaneously with respect to the occurrence probability and consequences of navigational accidents [32]. Therefore, the complex network must be decomposed into smaller subnetworks or submodels, which comprise the OOBN. Similar to a normal BN, OOBN modeling consists of three parts: nodes analysis, structural analysis, and the CPTs estimation, which are described in Section 2.2.3.

2.2.1. Nodes analysis

The basic element in an OOBN is the class, which is a fragment of a BN with three nodes: input, output, and internal [32]. The input and output nodes are visible and act as class interfaces. The internal nodes are hidden inside the class and cannot be observed from the outside. OOBNs have the characteristics of object-oriented modeling, such as abstraction, modularity, interface, and encapsulation. The instance node in an OOBN is a single-unit abstraction of a network fragment, which can transmit all the properties of the network fragment (encapsulation). Thus, OOBNs can be considered hierarchical problem descriptions.

2.2.2. Structural analysis

OOBNs are complex models consisting of many subnetworks. Fig. 2 depicts a simple illustration of an OOBN. As shown in Fig. 2, the subnetworks are interconnected by the input and output nodes, and each subnetwork class can be viewed as a classical BN. Similar to a BN, each subnetwork represents the dependent and independent relationships between different variables through a directed acyclic graph consisting of directed arcs and nodes. The node can represent a variable involved in the event's consequence, indicating the event's state. The variable can be a Boolean, an integer, or a continuous value. The directed arcs which point from the parent node(s) to the child node(s), can express the dependent relationships between the nodes by connecting them. The input node cannot have parent nodes in each class and can be connected only to an output node of the other class. Moreover, loops are not allowed, either in a class or between classes, so the OOBN can only propagate forward.

2.2.3. CPTs estimation

In determining the OOBN structure, each input node is assigned a marginal probability table, and the other nodes are assigned CPTs. CPTs can reflect the node relationship strength. CPTs contain all known information about the variable states from the available data and expert options. On the basis of the Bayes rule, the Eq. (1) of conditional probability distributions P is as follows:

$$P(V) = \prod_{X \in V} P(X|parents(X)), \tag{1}$$

where V means a set of variables (RIFs), $V = \{x_1, x_2, \ldots, x_n\}$, P is a set of conditional probability distributions of V, and $parents(X)$ represents all the variables that point directly to X.

BNs can update the conditional probability of each node based on the obtained information. CPTs can describe the node states under different conditions and can be calculated by observational data, expert knowledge, or a combination of both. The Eqs. (2) and (3) for the conditional posterior probability distribution and joint probability distribution are as follows:

$$P(X_i = x_i | X_j = x_i) = \frac{P(X_i = x_i) P(X_j = x_j | X_i = x_i)}{p(X_j = x_i)} \tag{2}$$

$$P(X_i = x_i, X_j = x_j) = P(X_i = x_i) P(X_j = x_j | X_i = x_i) \tag{3}$$

Table 1
The logarithmic probability/frequency index (PI), adapted from the FSA [41].

Scale	Frequency	Definition	Frequency (per ship year)
1	Extremely remote	Likely to occur once in the lifetime (20 years) of a world fleet of 5,000 ships	10^{-5}
3	Remote	Likely to occur once per year in a fleet of 1,000 ships	10^{-3}
5	Reasonably probable	Likely to occur once per year in a fleet of 10 ships	0.1
7	Frequent	Likely to occur once per month on one ship	10

Table 2
The logarithmic severity index of the consequences (*CI*), adapted from the FSA [41].

Scale	Severity	Effects on human safety	Effects on ship	S (Equivalent fatalities)
1	Minor	Single or minor injuries	Local equipment damage	0.01
2	Significant	Multiple or severe injuries	Non-severe ship damage	0.1
3	Severe	Single fatality or multiple severe injuries	Severe damage	1
4	Catastrophic	Multiple fatalities	Total loss	10

Eqs. (2) and (3) can be used to calculate and infer the CPTs for predicting the occurrence probabilities and consequences for multiple navigational accidents in ice-covered waters.

2.3. Risk metrics

Many measures can be used to quantify risk. Traditionally, the probability and severity of adverse effects [44], the combination of the probability and magnitude of the consequences [45], or the magnitude/severity of the consequences [46] are all necessary measures of risk. Thus, the risk can be expressed as [41]:

$$Risk = probability * consequence. \tag{4}$$

Operatively, risk can be seen as a combination of various risk scenarios s_i, $i = 1, 2, \dots, n$. Risk contribution r_i, from scenario s_i, can be described by three elements: s_i, c_i and p_i. Among them, s_i is the *i*th scenario, p_i is the probability (frequency/likelihood) of the *i*th scenario, and c_i is the consequence of the *i*th scenario. Thus, the risk contribution r_i, from scenario s_i can be expressed as:

$$Risk = r_i = p_i * c_i. \tag{5}$$

For a quantitative analysis of the risk scenarios, a risk index ($\log r$) *RI* can be introduced, the Eq. (6) for calculating on a logarithmic scale which follows:

$$RI_i = \log r_i = \log(p_i * c_i) = \log p_i + \log c_i, \tag{6}$$

where r_i represents the risk of scenario s_i, p_i represents the probability/frequency of s_i, c_i represents the consequences of s_i, $\log p_i$ means the logarithmic probability/frequency index, and $\log c_i$ means the logarithmic severity index of consequences.

Based on the FSA [41], the logarithmic probability/frequency ($\log p$) and the logarithmic severity of accident consequences ($\log c$) can be defined as *PI* and *CI*. The scale criteria for *PI* and *CI* are given in Tables 1 and 2. The values of *PI* and *CI* can be integers or decimals when qualitative or quantitative approaches are used, respectively.

Since the accident probability is continuous value, while the value in Table 1 is discrete, the equation for calculating *PI* needs to be derived. According to Table 1, when the frequency/probability equals to value 10^{-5}, the logarithmic probability equals to -5. In order to make the *PI* equal to value 1, a constant 6 needs to be added to the logarithmic probability. Therefore, the equation for calculating the *PI* can be derived as shown:

$$PI_i = 6 + \log_{10} p_i, PI_i \in [1, 7], \tag{7}$$

where PI_i is the logarithmic probability index of the s_i, and p_i is the probability of occurrence of the s_i. $\log_{10} p_i$ plus 6 causes the distribution of PI_i to belong to $[1, 7]$.

Table 2 shows that the consequences are divided into four categories, corresponding to the four scales. In this paper, the consequence severity includes the latter three categories—catastrophic, severe, and significant—corresponding to Scales 4, 3, and 2 in Table 2, since the records for minor accidents are often underreporting [47]. Moreover, an accident scenario can be calculated by aggregating the occurrence probability of accident consequences and its corresponding scale. Thus, the *RI* can be calculated in the aggregate. Eq. (8) for calculating the *RI* follows:

$$RI_i = PI_i + CI_i = 6 + \log_{10} p_i + \sum q_{ij} c_j, RI_i \in [2, 11] \tag{8}$$

where RI_i is the logarithmic risk index under s_i, q_{ij} is the probability of the consequence with scale c_j under the s_i and c_j is the value represented by the severity of the *j*th consequence.

3. Risk modeling

3.1. Step 1: Model nodes analysis

The data used for the quantitative risk assessment were acquired from the global MAIRs in Arctic waters and the related literature. The selected MAIRs conform to two criteria:

- The location of the maritime accident was in Arctic waters (above 66°34' N);
- The MAIRs were written in English.

Based on the collected MAIRs and the literature, the potential RIFs were identified by an in-depth analysis of these documents from environmental, technical (ship-related), human, and organizational aspects. Then, the critical RIFs were selected by a statistical analysis of the frequency of the potential RIFs involved in the MAIRs and the related literature. By an in-depth analysis of the selected 28 MAIRs (the detailed information of 28 MAIRs is listed in Appendix A) and the related literature, 32 potential RIFs were identified, as shown in Table 3. According to Heinrich's accident causation theory, these RIFs correspond to the environmental, unsafe condition, and unsafe act levels. Each RIF in Table 3 is represented as a single node in the OOBN model, and the node states are listed in the Appendix B.

3.2. Step 2: Model structural analysis for the qualitative risk analysis

The RIFs in Table 3 constitute the subnetworks in the OOBN: (Level 1) *environment*, (Level 2) *unsafe condition*, and (Level 3) *unsafe act*. These subnetworks are combined to form the models (Level 4) *probability of navigational accidents* and (Level 5) *consequence of navigational accidents*. The relationship among the nodes in each subnetwork is structured based on the MAIRs and literature. The directed arcs between the nodes in the subnetworks are shown in the following subsections, and the structure of the whole OOBN is shown in Fig. 3.

3.2.1. Level 1: Environment

Waterway, ice, and weather conditions are the main factors affecting navigational safety in ice-coved Arctic waters [51]. Thus, a subnetwork

Table 3
RIFs collected from the MAIRs and related literature.

Level	Category	RIFs	Scenarios**	MAIR	Literature
Environment	Weather condition	Fog	A4	√	[13,14,39]
		Rain	A1, A4	√	[7,12,13,39]
		Strong wind	A1, A2, A3, A4	√	[6,12,14,16, 39]
		Visibility	A1, A3, A4	√	[6,7,12-14,39]
		Air temperature	A3, A4	N/A	[6,13]
	Waterway condition	Sea current	A4	√	[14]
		Sea temperature	A3	N/A	[6]
		Channel depth	A1, A2, A3	N/A	[3,20]
		Environmental obstacles	A1, A2, A3	√	[16,20]
	Ice condition	Drift ice	A1, A2, A3, A4	N/A	[13,14,16,20, 39]
		Ice thickness	A3, A4	N/A	[6,39]
		Ice concentration	A3, A4	N/A	[6,12,13]
		Ice type	A1, A3, A4	N/A	[5,7,39]
		Ice strength	A2, A4	√	[13,39]
Unsafe condition	Mechanical equipment failure	Steering failure	A1, A2	√	[3]
		Propeller failure	A1, A2	√	[16]
		Power failure	A1, A2, A4	√	[3,7,12,16,17]
		Radar failure	A1, A2	N/A	[16]
		Navigator failure	A1, A2	N/A	[16]
	Internal communication failure	Communication equipment failure	A1, A2, A3, A4	N/A	[3,7,12,16,20, 39]
		Navigational aid failure	A1, A2, A4	√	[3,12,14,16, 39]
	Others	Unsafe speed	A1, A2, A3, A4	√	[6,7,12-14,39]
		Gross tonnage	A1, A2, A3, A4	N/A	[48,49]
		Ship type	A1, A2, A3, A4	N/A	[48,50,51]
Unsafe act	Human factors	Fatigue	A4	√	[39]
		Negligence	A1, A4	√	[7,12]
		Lack of situational awareness	A1, A2	√	[3,7]
		Inadequate knowledge	A1, A2, A4	√	[12,39]
		Judgment/decision failure	A1, A2, A4	√	[7,39]
	Organizational factors	Charts and publications not being updated	A1, A2	√	[16]
		Lack of communication/ miscommunication	A1, A4	√	[3,7,12,39]
		Lack of safety measures and preventive action	A1, A2, A4	√	[7,39]

Note: **A1: collision, A2: grounding, A3: ship besetting in ice, A4: ship–ice collision.

is established, retaining waterway, ice, and weather conditions as the output nodes to represent the environmental conditions in ice-coved Arctic waters. Moreover, the input nodes in this model are fog, rain, air temperature, strong wind, sea current, sea temperature, ice types, channel depth, and environment obstacles. The other nodes in this level are internal and act as child nodes influenced by their associated parent nodes in the subnetwork, as shown in Table 4.

3.2.2. Level 2: Unsafe condition

Mechanical equipment failure and unsafe speed are the main output nodes of the unsafe condition level [5]. Among them, communication equipment failure, as one of the parent nodes of mechanical equipment failure, is marked as an output node due to its relevance to the RIFs at the next level. Ship type and gross tonnage are connected to the input nodes of the consequence of navigational accidents level as the output nodes. The arc directions are presented in Table 5.

3.2.3. Level 3: Unsafe act

Unsafe act, as an output node, is mainly influenced by human error (e.g., negligence and judgment/decision failure) and organizational factors (e.g., lack of safety measures and prevention action and charts and publications not updated) [54]. The internal node judgment/decision failure is dependent on inadequate knowledge, lack of situational awareness, and lack of communication/ miscommunication. Research and surveys have shown that fatigue is a main factor in navigational accidents [55]. Fatigue can reduce the seafarer's concentration and cause them to be poorly aware of risks and situations. The arc directions are presented in Table 6.

3.2.4. Level 4: Probability of navigational accidents

In the probability of navigational accidents level, P_collision, P_grounding, P_besetting in ice, and P_ship–ice collision are the output nodes that represent the probability of different navigational accidents. According to Heinrich's accident causation theory, the direct causes of accidents are unsafe acts and unsafe conditions. The special weather condition in Arctic waters is also one of the main causes of navigational accidents. Thus, these three nodes are connected to each output node. Among them, unsafe condition is dependent on mechanical equipment failure and unsafe speed. Waterway condition is related only to grounding accidents, while ice condition is related to the other three accidents. The arc directions are presented in Table 7.

3.2.5. Level 5: Consequences of navigational accidents

The severity of accident consequences is mainly influenced by ship type and gross tonnage. Therefore, in this model, ship type and gross tonnage are directly connected to the accident consequences as input

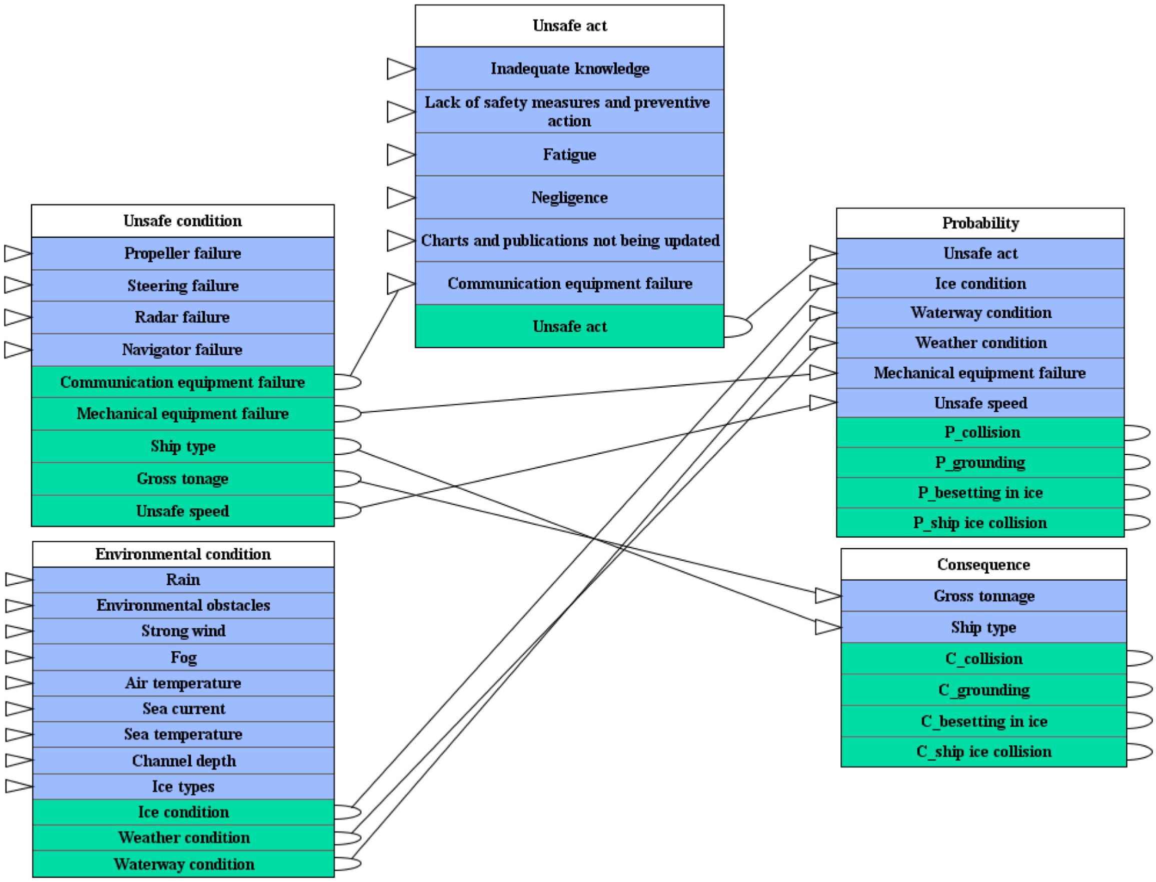

Fig. 3. Complete top-level view of the OOBN.

Table 4
Arc directions used at the environment level.

Child node	Parent node(s)	Reference
Waterway condition	Channel depth, environment obstacles	[24]
Ice condition	Ice strength, ice concentration, drift ice	[5,39]
Weather condition	Strong wind, air temperature, visibility	[24]
Ice strength	Ice thickness, ice type	[39]
Ice thickness	Sea temperature	[6]
Ice concentration	Sea temperature	[6]
Drift ice	Sea current, strong wind	[14]
Visibility	Rain, fog	[39]

Table 5
Arc directions used in the unsafe condition level.

Child node	Parent node (s)	Reference
Mechanical equipment failure	Aid navigation failure, communication equipment failure, power failure	[7]
Unsafe speed	Power failure	[6]
Aid navigation failure	Radar failure, navigator failure	[52]
Power failure	Steering failure, propeller failure	[9,53]

nodes. Furthermore, the C_collision, C_grounding, C_besetting in ice, and C_ship–ice collision, which represents the severity of navigational accident consequences, are the output nodes of this level and one of the output results of the whole OOBN model.

The structure of the whole OOBN model is shown in Fig. 3. The five subnetworks are linked and embedded in the higher-level model. This model encapsulates the internal nodes to display the input and output nodes for each subnetwork. The model can be updated by adding or

Table 6
Arc directions used in the unsafe act level.

Child node	Parent node(s)	Reference
Unsafe act	Negligence, judgment/decision failure, lack of safety measures and prevention action, charts and publications not being updated	[7]
Judgment/decision failure	Inadequate knowledge, lack of situational awareness, lack of communication/ miscommunication	[39,56]
Lack of situational awareness	Fatigue	[57]
Lack of communication/ miscommunication	Communication equipment failure	[5]

Table 7
Arc directions used in the probability of navigational accidents level.

Child node	Parent node(s)	Reference
Unsafe condition	Mechanical equipment failure, unsafe speed	[5]
P_collision	Unsafe condition, unsafe act, weather condition, ice condition	[19,48,50]
P_grounding	Unsafe condition, unsafe act, weather condition, waterway condition	[3,9,58,59]
P_besetting in ice	Unsafe condition, unsafe act, weather condition, ice condition	[4,5]
P_ship–ice collision	Unsafe condition, unsafe act, weather condition, ice condition	[39,52]

Table 8
CPTs for waterway condition in the OOBN model.

	Channel depth	Inadequate		Adequate	
	Environmental obstacles	No	Yes	No	Yes
Waterway condition	Poor	0.90	1.00	0.00	0.70
	Good	0.10	0.00	1.00	0.30

subtracting any input and output nodes.

3.3. Steps 3-4: CPTs estimation and navigational risk evaluation

The CPTs of each node in the OOBN model were calculated according to the 28 MAIRs and literature, see more in Table 3. The detailed CPTs for the BN model are listed in Appendix. According to the results of the ISOPE proceeding paper [60], the frequency of RIFs appearing in the MAIRs is approximated as the edge distribution probability of the input nodes in this paper. In addition, because of the lack of MAIRs, related literature was used as a reference to supplement the missing data in the CPTs of some nodes. For the output nodes in the environment, unsafe conditions, and unsafe act levels for each subnetwork, the available data cannot be sufficient to populate the CPTs for all the nodes. Therefore, the CPTs of some nodes in the OOBN model were calculated by hypothetical data. For example, this paper defined that when there are no environmental obstacles in the channel and the channel depth is adequate, the state of the waterway condition is 'Good'; when there are environmental obstacles in the channel and the channel depth is inadequate, the state of waterway condition is 'Poor'. Thus, the probability of poor waterway condition was assumed to be 1 when the channel depth is inadequate, and the state of environmental obstacles is yes; the probability of good waterway condition was assumed to be 1 when the channel depth is adequate, and the state of environmental obstacles is no, and the probabilities for the other condition are shown in Table 8.

In addition, due to the small number of MAIRs, to ensure the accuracy of the results, Lloyd's maritime accident data and the literature were used to calculate the probability of navigational accidents and the severity of the consequences. The accident probability was defined as 0 when all the parent nodes connected directly to the accident nodes were positive. Compared with other ship types, a general cargo ship is more likely to experience a total loss, while icebreaker and passenger ships rarely experience total losses in ice-covered Arctic waters.

For Level 1, Fig. 4 presents the resulting probabilities of environment nodes in the OOBN model. The resulting negative probabilities of the output nodes of waterway condition, ice condition, and weather condition are 5.289%, 14.143%, and 18.294%, respectively.

For Level 2, Fig. 5 presents the resulting probabilities of unsafe condition nodes in the OOBN model. The resulting negative probabilities

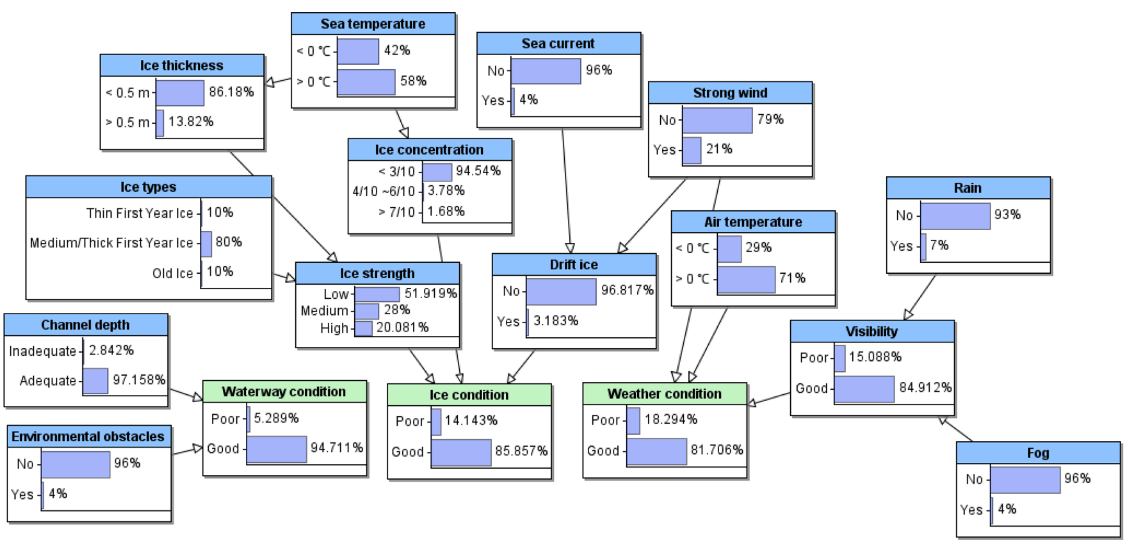

Fig. 4. Probability of environment (Level 1).

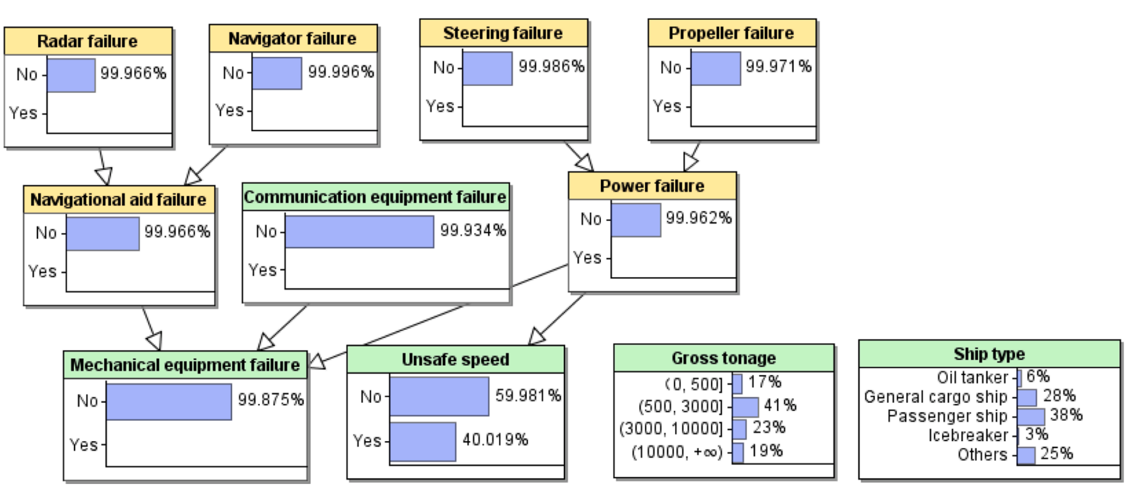

Fig. 5. Probability of unsafe condition (Level 2).

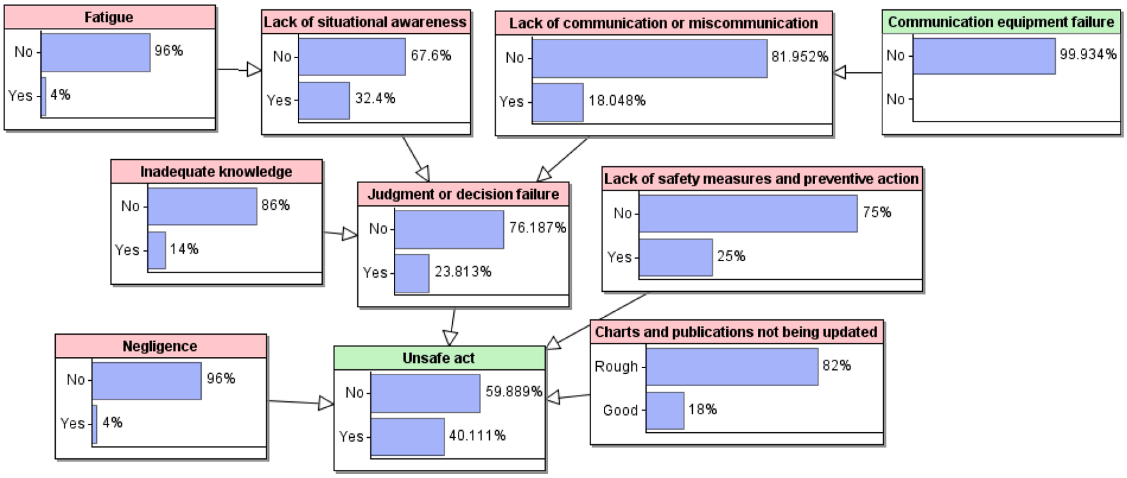

Fig. 6. Probability of an unsafe act (Level 3).

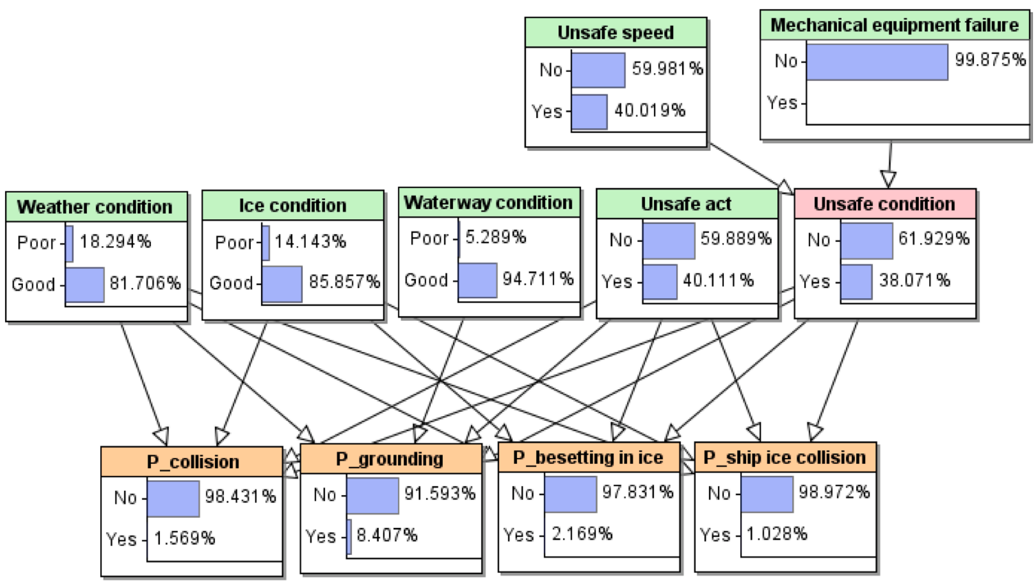

Fig. 7. Probability of a navigational accident (Level 4).

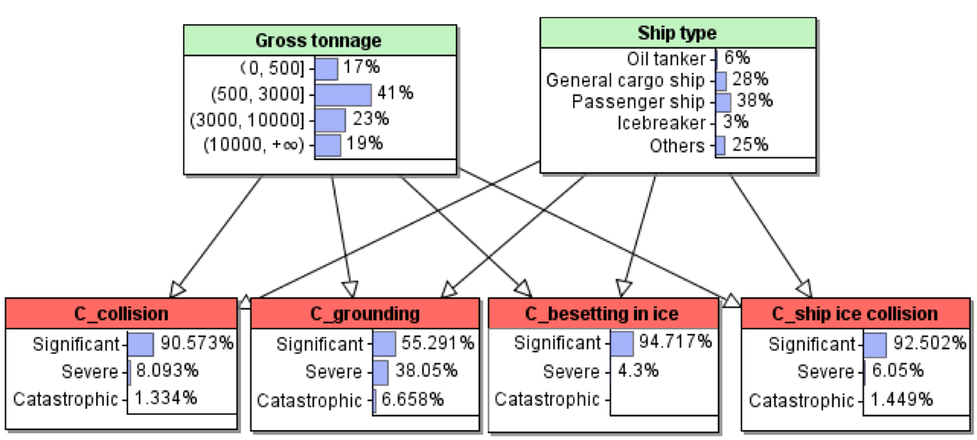

Fig. 8. Probability of the consequence of a navigational accident (Level 5).

of the output nodes of mechanical equipment failure and unsafe speed are 0.0125%, and 40.019%, respectively.

For Level 3, Fig. 6 presents the resulting probabilities of unsafe act nodes in the OOBN model. The resulting negative probability of the output node of unsafe act are 40.1115%.

For Level 4, Fig. 7 presents the resulting probabilities of navigational

Table 9
Maximum absolute sensitivity values for the variables and corresponding parameters in the OOBN model when P_collision is set as the target variable.

Rank	RIFs	Maximum sensitivity
1	Unsafe speed	0.01
2	Unsafe condition	0.008
3	Lack of safety measures and preventive action	0.007
	Charts and publications not being updated	0.007
5	Negligence	0.006
	Propeller failure	0.006
	Steering failure	0.006
	Communication equipment failure	0.006
	Ice condition	0.006
10	Radar failure	0.005
	Navigator failure	0.005
	Visibility	0.005
	Weather condition	0.005

accidents nodes in the OOBN model. The resulting negative probabilities of the output nodes of P_collision, P_grounding, P_besetting in ice, and P_ship ice collision are 1.569%, 8.407%, 2.169%, and 1.028%, respectively.

For Level 5, Fig. 8 presents the resulting probabilities of the consequences of navigational accident nodes in the OOBN model. The resulting probabilities for the (significant, severe, catastrophic) states of the output nodes of C_collision, C_grounding, C_besetting in ice, and C_ship ice collision are (90.573%, 8.093%, 1.334%), (55.291%, 38.05%, 6.658%), (94.717%, 4.3%, 0.983%), and (92.502%, 6.05%, 1.449%), respectively.

4. Results

4.1. Validation

Validation is a critical component of any modeling methodology as it serves to confirm the accuracy of the data analysis and the soundness of the model design. In this section, the paper presents a comprehensive validation of the OOBN model proposed in Section 3, which entails scrutinizing both the data and the model itself. By subjecting the model to a rigorous validation process, the paper establishes the model's reliability and robustness in accurately capturing the intricate relationships among various risk factors and estimating the probability and consequences of different types of navigational accidents in ice-covered Arctic waters.

4.1.1. Data validation

The reliability of data constitutes a fundamental aspect of conducting rigorous risk assessment modeling studies. In this paper, objective data sources such as MAIRs and relevant literature were primarily utilized. As opposed to subjective data, such as expert knowledge, objective data has the capacity to reflect the evolution of an accident more accurately. By avoiding the potential influence of subjective data on the model results, objective data can enhance the validity and reliability of the model. To ensure the authenticity, accuracy, and integrity of the data, a total of 28 MAIRs were collected from official investigation organizations. The detailed information regarding these MAIRs is listed in Appendix A. The use of official MAIRs in this study can provide greater confidence in the reliability of the data sources and enhance the credibility of the study's findings. By employing objective data sources, this study reinforces the importance of employing a rigorous and systematic approach to data collection and analysis in risk assessment modeling studies.

4.1.2. Model validation

Sensitivity analysis is a commonly used method to assess the validity and reliability of a model, by evaluating the degree of influence of the relevant variables on the target variable [42,18]. In this study, sensitivity analysis was conducted to verify the reliability of the proposed

Table 10
Maximum absolute sensitivity values for the variables and corresponding parameters in the OOBN model when P_grounding is set as the target variable.

Rank	RIFs	Maximum sensitivity
1	Channel depth	0.050
2	Environmental obstacles	0.039
3	Visibility	0.036
4	Weather condition	0.034
	Unsafe speed	0.034
6	Unsafe condition	0.029
7	Fog	0.028
	Lack of safety measures and preventive action	0.028
9	Charts and publications not being updated	0.026
10	Rain	0.024

Table 11
Maximum absolute sensitivity values for the variables and corresponding parameters in the OOBN model when P_besetting in ice is set as the target variable.

Rank	RIFs	Maximum sensitivity
1	Ice condition	0.033
2	Unsafe speed	0.025
3	Unsafe condition	0.021
4	Ice concentration	0.018
5	Steering failure	0.016
	Propeller failure	0.016
7	Communication equipment failure	0.015
8	Radar failure	0.013
	Navigator failure	0.013
10	Ice strength	0.011

Table 12
Maximum absolute sensitivity values for the variables and corresponding parameters in the OOBN model when P_ship–ice collision is set as the target variable.

Rank	RIFs	Maximum sensitivity
1	Ice condition	0.025
2	Ice concentration	0.014
3	Ice strength	0.008
4	Unsafe speed	0.007
5	Unsafe condition	0.006
	Ice type	0.006
7	Drift ice	0.004
	Sea temperature	0.004
	Steering failure	0.004
	Propeller failure	0.004
	Navigator failure	0.004
	Radar failure	0.004
	Communication equipment failure	0.004

model by assessing the impact of various parameters on the target variable, namely, P_collision, P_grounding, P_besetting in ice, and P_ship-ice collision. The top 10 parameters with the highest absolute sensitivity values and their corresponding values are presented in Tables 9–12.

Table 9 demonstrates that unsafe speed and unsafe condition have the most significant impact on P_collision, which are direct causes of accidents. Organizational factors such as the lack of safety measures and preventive action and outdated charts and publications also have a substantial influence. Negligence, ship equipment failure, ice condition, and weather conditions such as visibility also contribute to the probability of a collision. Table 10 reveals that channel depth is the most important parameter affecting P_grounding, followed by environmental obstacles, visibility, weather conditions, and unsafe speed. These factors are also major contributors to grounding accidents. In Table 11, ice condition, unsafe speed, and unsafe condition are the most significant factors that cause besetting in ice accidents, followed by ice concentration, steering failure, and propeller failure. Finally, Table 12 shows

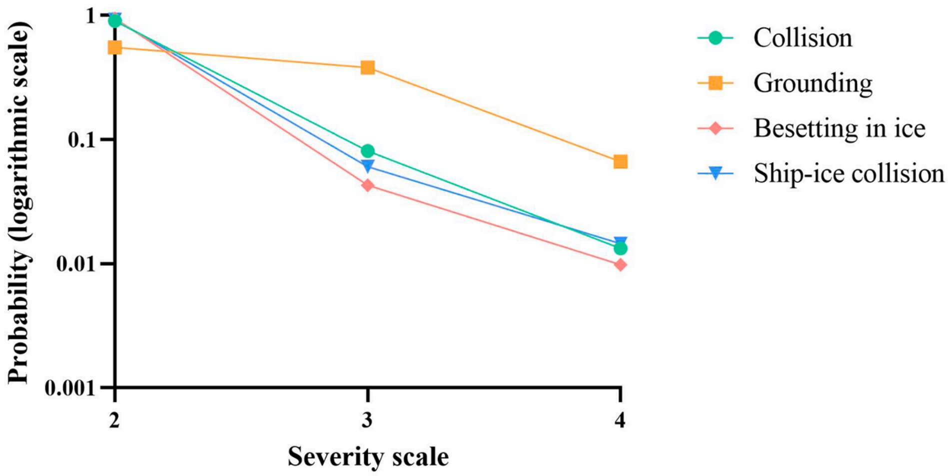

Fig. 9. Probability curve of accident consequence severity.

Table 13
Occurrence probability and risk index of different consequence severities (RI_i).

Scenario	Probability	Severity	Risk index (RI)		
		Significant (Scale 2)	Severe (Scale 3)	Catastrophic (Scale 4)	
Collision	0.0157	0.9057	0.0809	0.0133	6.3031
Grounding	0.0841	0.5529	0.3805	0.0666	7.4383
Besetting in ice	0.0217	0.9472	0.0430	0.0098	6.3990
Ship–ice collision	0.0103	0.9250	0.0605	0.0145	6.1013

that ice condition and concentration are the primary factors responsible for ship–ice collision accidents, followed by ice strength, unsafe speed, unsafe condition, and ice type.

The results of the sensitivity analysis provide valuable insights into the model and highlight the significant factors that contribute to the target variables. These findings can assist in risk management decisions and prioritize strategies to reduce the probability and consequences of navigational accidents in ice-covered Arctic waters. The sensitivity analysis is a crucial step in verifying the reliability and accuracy of the proposed model and adds to the robustness of the study.

4.2. Risk metrics

The probability of consequence severity for different accidents is shown in Fig. 9. At the severity Scale 2 (significant), the ranking of the probability of the four navigational accidents is collision>besetting in ice>ship-ice collision>grounding. At the severity Scale 3 (severe), the ranking of the probability of the four navigational accidents is grounding>collision>besetting in ice>ship-ice collision. Finally, at the severity Scale 4 (catastrophic), the ranking of the probability of the four navigational accidents is grounding>ship-ice collision >collision >besetting in ice. It should be noted that the probability of grounding accident consequences is significantly higher than the other three accidents at each severity scale.

To classify the comprehensive accident risk levels, we calculated a risk index for each accident scenario based on the results of the OOBN model. The risk index for each navigational accident scenario can be calculated using Eq. (8). Taking a collision accident as an example, the calculation method of the risk index is shown in Eq. (9) and the risk indices for all accident scenarios are shown in Table 13.

$$RI = 0.0157 + (0.9057 * 2 + 0.0809 * 3 + 0.0133 * 4) = 6.3031 \tag{9}$$

It can be found that the risk of grounding accidents is the highest, followed by the risk of ship besetting in ice, collision, and ship–ice collision. This result is because environmental obstacles are difficult to

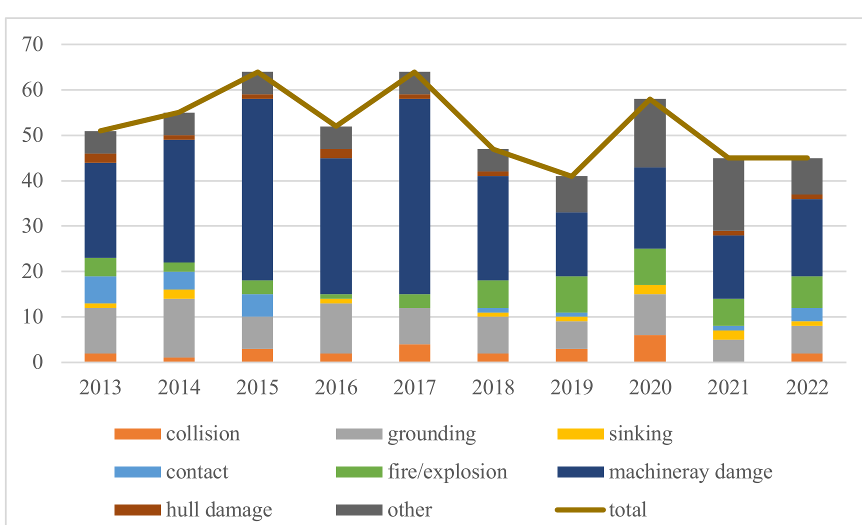

Fig. 10. Annual distribution of ship navigation accidents in in the ice-covered Arctic waters.

detect and ship traffic in the Arctic waters has a relatively low density. Moreover, although the ice concentration and thickness in Arctic summer waters are low, large sea ice or icebergs still exist in Arctic summer waters.

Based on Lloyd's maritime accident data from 2013-2022, the annual distribution of ship navigation accidents in the ice-coved Arctic waters can be obtained, as shown in Fig. 10. According to Fig. 10, it can be found that besides machinery damage accidents, the main accident scenario in the Arctic waters in the last 10 years were grounding with 83 in total, followed by fire/explosion, collision and contact accidents with 48, 25 and 21 accidents, respectively. According to the IMO definition of accident types, both ship besetting in ice and ship-ice collision are considered to be contact accidents. Thus, the results in Fig. 10 are consistent with the risk level of ship navigation accidents in the ice-coved Arctic waters calculated in this paper. It can also prove the validity and reasonableness of the risk assessment method proposed in this paper.

5. Conclusion

This paper developed a quantitative risk assessment method using the OOBN model to assess the risk of multiple navigational accidents in ice-covered Arctic waters. The OOBN model is decomposed into five levels of navigational accidents by the accident causation analysis: environment (Level 1), unsafe condition (Level 2), unsafe act (Level 3), probability of navigational accident (Level 4), and consequence of navigational accident (Level 5). Each level has a large number of RIFs, which are identified from 28 MAIRs and the related literature. First, the structure of each level is assessed in terms of the dependencies between the RIFs, which are determined from the literature. Then, the OOBN model is used to calculate the probability and consequence of multiple navigational accidents, including collision, grounding, ship besetting in ice, and ship–ice collision. Finally, the risk levels of multiple navigational accidents are further determined by a risk metrics analysis.

The results show that the risk is the highest of grounding accidents, followed by besetting in ice, collision and ship–ice collision in ice-covered Arctic waters. The critical factors for multiple navigational accidents are identified through a sensitivity analysis of the OOBN model. Unsafe speed and unsafe conditions, as direct accident causes, are the important factors for these four typical navigational accidents. In addition, HOFs—such as the lack of safety measures and preventive action, charts and publications not being updated, and negligence and ship equipment failures such as propeller and steering failures—are the critical factors for collision accidents. Channel depth, environmental obstacles, and visibility are the critical factors for grounding accidents. Ship besetting in ice and ship–ice collision accidents are mainly related to the ice conditions.

The risk level obtained through the proposed method can be used to make decisions that are beneficial to improving the safety level of ship navigation in ice-covered Arctic waters. Future work is needed to extend this model and integrate it with decision-making techniques for the evaluation of the effectiveness of risk control options in minimizing the risk of navigational accidents in ice-covered Arctic waters.

CRediT authorship contribution statement

Shanshan Fu: Conceptualization, Methodology, Data curation, Validation, Writing – original draft, Writing – review & editing, Funding acquisition. **Yue Zhang:** Methodology, Data curation, Software, Writing – original draft, Writing – review & editing. **Mingyang Zhang:** Conceptualization, Validation, Writing – review & editing. **Bing Han:** Funding acquisition. **Zhongdai Wu:** Funding acquisition.

Declaration of Competing Interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled, 'An object-oriented Bayesian network model for the quantitative risk assessment of navigational accidents in ice-covered Arctic waters'.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ress.2023.109459.

Appendix A

Table A.1.

Table A.1
The detail information of the MAIRs.

No.	Year	Accident scenario	Source	Link
1	2010	Grounding	TSB	*https://tsb.gc.ca/eng/incidents-occurrence/index.html*
2	2012	Grounding	TSB	
3	2014	Contact	TSB	
4	2016	Contact	TSB	
5	1994	Sinking	TSB	
6	1994	Contact	TSB	
7	1995	Other	TSB	
8	1995	Contact	TSB	
9	1995	Collision	TSB	
10	1996	Grounding	TSB	
11	1997	Contact	TSB	
12	1997	Grounding	TSB	
13	1997	Contact	TSB	
14	2012	Grounding	DMIAIB	*https://dmaib.com/*
15	2016	Sinking	DMIAIB	
16	2017	Fire or explosion	DMIAIB	
17	2007	Grounding	DMAIB	
18	2011	Other	DMAIB	
19	2012	Fire or explosion	MSIU	*https://www.mot.gov.sg/about-mot/transport-safety-investigation-bureau/msib/investigation-report/*
20	2014	Grounding	IMO	*https://www.imo.org/*
21	2015	Other	IMO	
22	2015	Other	IMO	
23	2012	Other	AIBN	*https://infogalactic.com/*
24	2017	Contact	AIBN	
25	2018	Contact	AIBN	
26	2013	Sinking	AIBN	
27	2015	Sinking	AIBN	
28	2014	Sinking	AIBN	

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