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A global data-driven Bayesian network model for ship collision accident analysis

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ABSTRACT

Ship collision accidents remain one of the most frequent and severe types of maritime incidents worldwide, often resulting in significant property damage, loss of life, and pollution. Despite extensive regulatory and technological advancements, the underlying risk mechanisms and consequence formation processes of collision accidents are not yet fully understood, particularly from a global and data-driven perspective. To address this gap, this study develops a data-driven Bayesian Network framework to analyze and predict the consequences of ship collision accidents on a global scale. The proposed model is constructed using a Tree-Augmented Naive Bayes (TAN) structure and is trained on a long-term dataset of collision accident investigation reports covering the period 1978–2024, compiled from multiple international maritime bodies. Unlike most previous studies that primarily focus on causal factors or rely on expert judgment, this research simultaneously investigates accident related, environmental, ship related, and bridge operator related risk influencing factors (RIFs), while explicitly accounting for the characteristics of both vessels involved in a collision. In addition, spatial analysis based on accident coordinates reveals distinct geographical clustering patterns in high traffic coastal and port areas. The findings of the study provide practical value for maritime administrations, ship operators, and policy makers by supporting evidence-based decision making in collision prevention, risk informed regulation, targeted training strategies, and the prioritization of proactive safety measures at both operational and strategic levels.

1. Introduction

Maritime transport is growing at an average rate of 2.3% annually in line with global demand. Although there have been decreases in accidents during certain periods, the general trend is an increase in the number of accidents [1]. This growth in maritime transport inevitably leads to a higher likelihood of accidents [2]. The increased frequency of maritime accidents not only leads to significant loss of life and property but also poses a serious threat to the marine ecosystem and environment due to the nature of different types of accidents [3]. Accidents with catastrophic consequences typically occur when vessels are underway [4]. Ship navigation is a dynamic and complex process that requires cooperation between humans and machinery [5]. To fully understand the potential hazards and risks associated with maritime navigation, it is necessary to carefully examine the factors affecting ship safety and the consequences of adverse situations [6]. These factors generally encompass human, technical, and environmental elements. A sensitive analysis of these components can enable the development of strategic objectives to proactively control and prevent maritime accidents [7].

When examining the types of accidents occurring at sea, collision and allision accidents together account for 34.05% of all maritime accidents, making them the most common type [8]. Despite extensive efforts to improve safety measures, the frequency of such accidents remains a matter of concern. Ship collision accidents are significantly different from other types of maritime accidents by their very nature. Unlike incidents involving a single vessel, collisions typically involve two or more ships, making them multilateral events with potentially severe consequences. In terms of fatalities, environmental damage, and economic losses, collision accidents often result in more serious outcomes than other accident types. This situation highlights the need to place greater emphasis on collision accidents within maritime safety research and practice. Consequently, stakeholders across the maritime community are increasingly focusing on identifying the underlying causes of ship collision accidents. Numerous studies have developed risk factor analysis models that make significant contributions to understanding the causal factors of ship collision accidents these include the Technique for

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the Retrospective and Predictive Analysis of Cognitive Errors (TRACEr) [9], Functional Resonance Analysis Method [10], association rule mining [11], The Human Error and Reduction Technique (HEART) [12], Human Factor Analysis and Classification System (HFACS) [13], and Bayesian networks (BNs) [14]. However, these approaches focus primarily on human factors. In reality, accidents emerge from the interaction between Human and Organizational Factors and Operational Conditions including both internal and external environmental factors. Internal environmental conditions refer to factors directly related to the vessel's own structure, systems, and operational capabilities. External environmental conditions, on the other hand, represent natural and environmental factors outside the vessel. These conditions do not directly involve the ship's crew or organizational structure, but rather describe the surrounding operational context, such as sea state, weather conditions, daylight or nighttime operations, and the navigational environment (e.g., coastal waters, open sea, or port areas). Therefore, within the scope of accident analysis, many models have limitations in comprehensively analyzing the causes and formation mechanisms of vessel collision accidents.

Although studies on ship collision accidents in the literature have mainly focused on determining the causes of accidents, the fact that collision accidents remain one of the most frequently encountered accident types in maritime transportation demonstrates the continued relevance of this topic. The majority of existing studies have adopted approaches based on expert opinions, with accident outcomes mostly addressed at a secondary level. This study, however, develops a data-driven risk analysis and accident prediction model based on the consequences of collision accidents. Relying on a extensive, long-term accident dataset, this approach enables the analysis of both the causes and consequences of collision accidents by separately considering the type and technical/operational characteristics of each vessel involved in the accident. Thus, unlike the subjective assessments common in the literature, this study aims to fill an important methodological gap in this field by obtaining more objective, comparable, and generalizable findings regarding collision accidents.

2. Literature review

2.1. Ship collision accident analysis methods and applications

Ship collision accidents are evaluated from a wide range of perspectives in the literature. The most commonly employed approaches in the analysis of collision accidents are cause-effect analysis, risk analysis, and accident prediction modeling. Additionally, numerous studies examine different variables such as ship type, ship length, and navigation area.

The majority of studies examining the causes and consequences of ship collision accidents analyze risk factors through probabilistic models developed based on accident reports and emphasize the role of human error in accident formation. In this context, 304 collision accidents that occurred in China were examined using the N-K model and BNs; the interaction among human, ship, environmental, and management factors quantitatively evaluated [15]. Lan et al. [16] used a combination of association rule mining, complex network analysis, and random forest methods to investigate the correlations between risk factors in collision accidents; they found that poor crew communication was the factor that most affected the severity of accidents. In another study, accident reports from the United Kingdom and Canada were analyzed by adapting the HFACS model, highlighting decision-making errors, inadequate visibility conditions, lack of attention, and deficiencies in bridge resource management as the main causes of collision accidents [17]. In a study by Zhang et al. [18], which statistically analyzed 477 standardized collision reports, it was found that vessel speed was strongly correlated with fatalities and injuries, while oil spills varied depending on the collision position.

Various methods have been employed in the literature to address uncertainty in modeling ship collision risks. In a study focusing on modeling collision risks in narrow waters, fuzzy BNs were applied [19]. Integrating physical knowledge with data-driven approaches, Meng et al. [15] constructed a BN structure using the PC algorithm and identified that management systems, supervision, and crew training were primary risk factors in terms of preventive measures. Ma et al. [20] developed a semi-automatic complex network model based on 322 accident reports, ranked risk propagation pathways using the 3-WLR algorithm, and presented recommendations for ship management and supervision mechanisms. Chen et al. [21] identified critical risk factors through a deep learning-based triple inference method by combining knowledge graphs and complex network theory. The dynamic BN and navigation simulations developed by Wang and Fu [22] modeled the process of seafarers' unsafe actions transforming into collision risk within a three-stage structure. In risk assessment studies, validation and sensitivity analyses are widely used to enhance model reliability. Goerlandt and Montewka [23] proposed a BN-based framework for oil spills resulting from tanker collisions and managed uncertainty through a two-stage approach. Wu et al. [24] modeled collision consequences in the lower reaches of the Yangtze River using BNs and elaborated on the integration of emergency management. Jia et al. [25] analyzed collision causes by transforming fault trees into BNs, while Peng [26] developed a scenario-based risk assessment model.

Some studies address the dynamics of collision accidents in specific maritime areas within a geographical context. Research conducted in Chinese waters emphasized that the most likely risk scenario involves human–vessel–environment–management interactions [15]. In research focusing on the Yangtze River, perception, decision, and implementation errors were classified under human and organizational factors using HFACS and BNs methods [27]. Examining accidents off the Zhejiang coast, Tian et al. [28] identified improper lookout, underestimation of collision risk, and inadequate emergency response as the primary causal chain. Hänninen and Kujala [29] investigated the impact of weather conditions and human factors in the Gulf of Finland using a Bayesian belief network, revealing that course alteration decisions and officer of the watch (OOW) actions were decisive factors. Focusing on the Black Sea, Uğurlu et al. [30] analyzed 20 years of accident data, emphasizing the role of older vessels and those operating in inland waters in accidents concentrated in coastal areas such as the Kerch Strait and Novorossiysk. In a study addressing ship collisions occurred in congested waterways, the probabilities of root causes related to human error were determined using the Cognitive Reliability and Error Analysis Method (CREAM) method, while other causes were assessed using fuzzy logic; the findings were integrated into a comprehensive risk assessment using Fault Tree Analysis [31]. In research analyzing ship collisions occurring in Taiwanese waters, collision accidents were evaluated using a combined approach of Rough Set Theory and Bow-Tie Analysis [32].

Several studies address collision risks specifically for certain types of vessels. Ung [33] calculated the contribution of human error in oil tanker collisions using the modified fuzzy Bayesian CREAM approach, demonstrating that deficiencies in bridge communication and fatigue were high-probability factors. Zhang [34] found that small vessels (under 100 m) carried higher risk compared to large vessels in Tianjin Port and that collision risk increased significantly during navigation without a pilot. In a study focusing on LNG carriers in Arctic waters revealed that human and environmental factors forming the most critical risk scenarios in the East Siberian Sea [35]. In the study by Hsu [32], collision accidents that may occur during oil tanker operations were analyzed using Bayesian Belief Networks with a focus on human reliability. Uğurlu et al. [36] examined oil tanker accidents recorded in the Global Integrated Shipping Information System (GISIS) database using fault tree analysis and identified violations of International Regulations for Preventing Collisions at Sea (COLREG) and lack of inter-ship communication as prominent factors in collision accidents.

2.2. Application of Bayesian models in accident analysis

Although the use of statistical and data-driven methods in the analysis of maritime accidents has increased in recent years, classical statistical approaches often fail to adequately represent causal dependencies and uncertainties among variables. In this context, BNs have been increasingly adopted in maritime safety research due to their ability to model complex systems under uncertainty, explicitly reveal causal relationships among variables, and enable scenario-based analyses.

Moreover, BNs offer the advantage of evaluating interactions among human factors, ship-specific characteristics, environmental conditions, and operational variables within a unified analytical framework.

When examining existing BN-based maritime studies, it is observed that research has largely concentrated on grounding, fire/explosion, and general accident probability prediction [37–39]; whereas studies focusing on collision accidents have predominantly addressed causal analysis [40,41]. Moreover, research systematically evaluating the relative importance of risk factors involved in collision accidents from a network structure perspective remains insufficiently represented in the literature. In most studies, risk factors are examined individually; however, the structural interactions these factors create collectively and the critical nodes within the network are not investigated in detail. In many studies where collision accidents are analyzed using BNs, risk factors have been categorized with expressions such as present-absent or yes-no, which do not adequately represent qualitative data [40,42]. Another limitation in existing studies is that the constructed models attempt to explain multiple accident types with relatively limited data [43].

In recent studies, risk analysis of maritime accidents has been made more comprehensive and reliable through the use of multi-source Data-driven Bayesian network (DDBN) approaches [44]. In particular, a study analyzing 833 maritime accidents that occurred between 2017 and 2022 validated the predictive performance of a BN model using log loss, quadratic loss, and spherical payoff metrics [45]. Similarly, Uğurlu [77] developed a data-driven Tree-Augmented Naive Bayesian Network (TAN-BN) model to examine risk-influencing factors associated with disappearance and man-overboard (MOB) accidents, achieving 87.18% predictive accuracy in classifying accidents across 187 incidents from 2005 to 2024.

A significant portion of studies on maritime accidents in the literature focuses on identifying risk factors affecting accidents and quantitatively demonstrating the effects of these factors on accident type, severity, and consequences. In this context, Fan et al. [37] examined the effects of human factors on maritime safety, aiming to identify critical human errors and behavioral risk factors across different accident types. Another research focused on navigation risk prediction and analyzed the role of ship characteristics and environmental factors in accident occurrence [39]. Particularly in research on tanker accidents, the objective has been to predict the probability of oil spillage and reveal the key factors affecting spillage [46]. A regional study focusing on congested and complex waterways such as the Istanbul Strait was conducted to determine the frequency of accident types and quantitatively evaluate factors affecting accident formation [47].

Additionally, several research has aimed to improve the accuracy of risk prediction models by analyzing fundamental risk factors associated with maritime accidents [38,42], while others have focused on predicting accident severity and evaluating risk patterns changing over time [48]. Among more comprehensive approaches, Ma et al. [49] examined the effects of individual and collective accident influencing factors (AIF) on different accident types, while Jiang et al. [50] addressed the relationship of these factors with accident severity and loss levels together. In their study on collision accidents, Li et al. [43] developed collision risk models on a global scale and analyzed the root causes of these accidents. Time-oriented research by Zhou et al. [51] investigated the temporal evolution of maritime accidents and fatalities.

Research such as [41], particularly focusing on collision accidents between merchant and fishing vessels, have aimed to characterize collision-specific risk structures by jointly modeling organizational and human factors. In their study conducted under data constraints, Meng et al. [42] aimed to prioritize critical risk factors for preventive measures and emergency responses by developing maritime accident risk assessment networks using methods such as BN. Finally, studies examining the individual and interactive effects of human factors and operational conditions on accident severity [40,44] have aimed to identify key risk combinations and causal pathways for reducing accident severity. An overview of researches employing BNs to explain the causes and consequences of maritime accidents is provided in Table 1.

In this context, a review of the literature indicates that ship collision accidents are often addressed through subjective assessments, limited variable sets, and without explicit consideration of spatial dimensions, while the technical and operational characteristics of the vessels involved are commonly treated as homogeneous structure. Furthermore, it is understood that the effects of regulatory and technological developments on collision accidents are mostly examined in the literature through specific periods or individual regulations, while long-term and holistic data-based analyses remain limited. This study presents an in-depth risk analysis focusing solely on ship collision accidents based on an extensive and original accident dataset, developing a data-driven Bayesian Network model that separately considers the characteristics of both vessels involved in the accident. In doing so, the study quantitatively reveals spatial concentration patterns, ship-type-specific critical risk factors, and the temporal effects of regulatory and technological developments, thereby contributing to the mitigation of key methodological limitations identified in the existing literature.

3. Methodology

This study compiles and analyzes ship collision accident records covering the period 1978–2024 obtained from multiple maritime accident databases, including the Marine Accident Investigation Branch (MAIB), United States Coast Guard (USCG), Japan Transport Safety Board (JTSB), Transport Safety Investigation Bureau (TSIB), and GISIS. By integrating these datasets, the study aims to develop proactive accident risk predictions through a systematic evaluation of ship characteristics and environmental conditions. In line with this objective, a Tree-Augmented Naive Bayes (TAN)-based Bayesian network model was employed in this study. Bayesian networks are among the commonly used methods in maritime safety research because of their ability to model probabilistic dependency relationships among factors that influence accident occurrence [59,60].

Maritime risk analyses employing BNs are typically conducted through a sequence of well-established stages, including data collection, variable identification, structure learning, model validation, and sensitivity analysis [44]. The methodological approach proposed in this study provides a holistic analytical framework aimed at analyzing collision accidents from a multidimensional and global perspective. The TAN structure enables the modeling of not only conditional dependencies related to the target variable but also secondary dependency relationships among risk variables. The proposed methodological framework aims to systematically analyze the factors affecting ship collision risk and to estimate risk levels using a BN model. The methodological contribution of this study lies in the auxiliary procedures and analyses implemented at each stage of the research process. For instance, the spatial distribution of collision events was evaluated using the coordinates reported in accident records, which helped to analyze the dataset in a more comprehensive manner. Fig. 1 presents the overall workflow of the proposed approach, including the stages of data collection, model development, model validation, and interpretation of the outputs. In line with the general workflow summarized in Fig. 1, the methodological steps followed in the study are systematically described in the following sections.

Table 1
The comprehensive comparison of the screened papers.

Accident types	Reports	RIFs	Research area	Years	Research objectives	Limitations	References
9	161	25	Global	2012-2017	To investigate human factors' impact on safety, identify critical human factors by accident type.	Lack of objective criteria in RIFs categorization (speed, weather etc.). Each accident type's distinct causal dynamics may not be fully captured by a unified BN.	[37]
6	583	10	Taiwan	2014-2019	Estimate navigation risk and identify vessel and environmental risk factors.	Accidents are analyzed over a short period, using limited RIFs to analyze risk factors of multiple accident types.	[39]
6	2080	18	USA	1997-2015	Predict oil spills after tanker accidents, identify key factors influencing oil spill probability.	RIFs are not clearly defined (e.g., ship length, season), only tankers included, outcomes focus solely on pollution.	[46]
9	418	13	Istanbul Strait	2016-2021	Quantitatively assess accidents in Istanbul Strait, determine most frequent accident types, identify factors influencing accident occurrence.	Accidents are analyzed over a short period, using limited RIFs to analyze risk factors of multiple accident types.	[47]
11	462	23	Global	2017-2021	To analyze key maritime risk factors, improve prediction accuracy in risk analysis.	The model's represent-ativeness is limited due to a short study period and a relatively small dataset for each accident type.	[38]
9	362	23	Global	2012-2021	To evaluate prediction accuracy of accident severity, identify changing risk patterns over time.	Two four-year periods are compared, but one lacks sufficient data for the first period, accident samples per type are limited.	[48]
6	908	20	China	2000-2023	To analyze individual & collective AIF impacts, identify key factors affecting accident types.	Despite insufficient number of accidents in recent years, a large number of accidents represented in the model.	[49]
8	55,469	7	Global	2002-2022	Capture individual and collective AIF impacts, analyze accident type, severity and loss.	The number of RIFs is very limited, and accident reports were not subjected to systematic classification.	[50]
1	402	23	Global	2017-2021	To develop a global collision risk model, identify root causes of collision accidents.	The analyzed period is short and some RIFs include un-identified categories that may influence results significantly.	[43]
11	402	24	Global	2017-2021	Analyze temporal evolution of maritime casualties.	The model's represent-ativeness is limited due to a short research period & a relatively small dataset for each accident type.	[51]
1	258	14	China	2013-2023	To identify & model the key organizational and human factors contributing to collision accidents between merchant & fishing vessels.	All RIFs are paired into just two categories, and the research is limited exclusively to the Chinese waters.	[41]
1	327	24	China	n/a	To develop a network for maritime accident risk assessment under limited data. To prioritize key risk factors to support prevention and emergency response decisions.	The research covers only Chinese waters, and the temporal coverage of the data is not specified.	[42]
11	472	17	Global	2005-	To identify key factors	Only high seas accidents	[44]

(*continued on next page*)

Table 1 (*continued*)

Accident types	Reports	RIFs	Research area	Years	Research objectives	Limitations	References
				2022	influencing HSMAs, enhance prediction accuracy for maritime accidents, support proactive HSMA risk assessment.	are considered, and data volume is limited relative to accident types, reducing model reliability.	
1	318	11	Chinese	2014-2023	To examine the effects of operating conditions and human factors on maritime accident severity. To identify key risk combinations & causal pathways to reduce accident severity.	The research covers only Chinese waters.	[40]

3.1. Data collection and processing

The initial stage of the study involves the collection of collision accident data from 34 national and international competent and reliable maritime accident investigation bodies, including, but not limited to, the BSU, MAIB, and USCG. Reports obtained from these institutions provide comprehensive accident data records containing vessel information, accident causes, meteorological data, and other relevant information. To ensure transparency in data inclusion and exclusion criteria, the PRISMA 2000 framework was adopted [52]. In total, 896 collision accident cases were collected, screened, and organized for use in the BN model in accordance with PRISMA 2000. Unlike most comparable studies in the literature, all data used in this research were extracted directly from official investigation reports, and no records with missing information (100% observed data) were included. The term '100% observed data' indicates that no record contained missing RIF values requiring imputation. However, this does not imply that every possible state combination in the resulting Conditional Probability Tables (CPTs) was observed; rather, it reflects the inherent sparsity of high-dimensional categorical variables. The detailed steps involved in constructing the filtered dataset are outlined below.

(1) Original data collection from maritime accident investigation bodies.

Basic information regarding maritime accidents was collected through data mining from the official records published by accident analysis institutions, including vessel name, location, voyage segments where accidents occurred, time of accidents, and a brief description of their causes.

(2) Data processing

A total of 896 collision accident records were compiled from reports issued by national and international maritime accident investigation authorities. To ensure data accuracy and consistency, records containing missing information, duplicate cases investigated by multiple authorities, and collision accidents deemed unsuitable through manual screening were excluded from the analysis. Following the initial data cleaning process, 566 accident records remained.

(3) Final filtering

The dataset was further refined by applying additional criteria, retaining only collision accidents involving vessels above 300 Gross Tonnage (GT), excluding non-commercial vessels, and restricting the temporal scope to the period between 1978 and 2024. This step was critical to ensuring the validity and robustness of the final dataset.

PRISMA 2000 is a standardized approach that ensures meta-analyses and systematic reviews are conducted and reported in a transparent, reproducible, and scientifically rigorous manner. It provides a structured protocol for documenting all stages of the evidence process including data collection, screening, inclusion, and analysis. The complete selection workflow for each event type is shown in PRISMA 2000 flow diagrams (Fig. 2). Following this process, a total of 361 ship collision accidents were included in the analysis.

The final dataset of 361 cases represents a substantial reduction from the 896 initially identified collisions. This reduction resulted from three critical quality constraints: (i) requirement for complete data on all 17 Risk Influencing Factors (RIFs), official reports frequently lack detailed operational variables such as precise speed at collision moment or bridge watch period; (ii) exclusion of non-merchant vessels and those under 300 GT to ensure regulatory and operational comparability; and (iii) temporal scope limitation to 1978–2024. We acknowledge this sample size as a study limitation; however, the application of PRISMA 2000 protocols, exclusive reliance on official investigation reports, and comprehensive validation support the reliability of findings. The dataset remains among the largest for global collision-focused BN analysis, particularly given the 46-year temporal span and 17-variable multidimensional characterization, exceeding typical studies that analyze 4–6-year windows with 7–14 RIFs.

3.2. Model construction

3.2.1. Identification of RIF's

Factors affecting the safety of maritime transportation are commonly referred to in the literature as RIFs [43,61]. In data-driven analyses of maritime accidents, the systematic identification of RIFs is critically important for accurately modeling the causal relationships underlying accident occurrences. For this reason, a multi-stage procedure was followed in this study to determine the RIFs used in the analysis, including a literature review, accident report analysis, and data availability assessment. The RIF identification process consisted of five main stages.

In the first stage, recent literature was systematically reviewed in order to identify the risk factors commonly used in the analysis of ship collision accidents. In this context, studies employing data-driven accident analysis and Bayesian networks were examined, and the most frequently used risk factors in the literature were identified [20,21,27,34,38,42,48,50]. In the second stage, official accident reports published by national maritime accident investigation bodies such as the MAIB, the USCG, the JTSB, and the TSIB were examined in detail. During this process, accident-related factors, environmental factors, ship-related factors, and bridge operator-related factors contributing to collision accidents were systematically evaluated. In the third stage, the information obtained from the literature review and accident reports was combined to develop a candidate list of RIFs. In the fourth stage, the candidate variables were evaluated in terms of data availability and sample size, and variables with insufficient observations or missing data were excluded from the analysis. In the final stage, the selected variables were categorized based on their operational relevance, and the final set

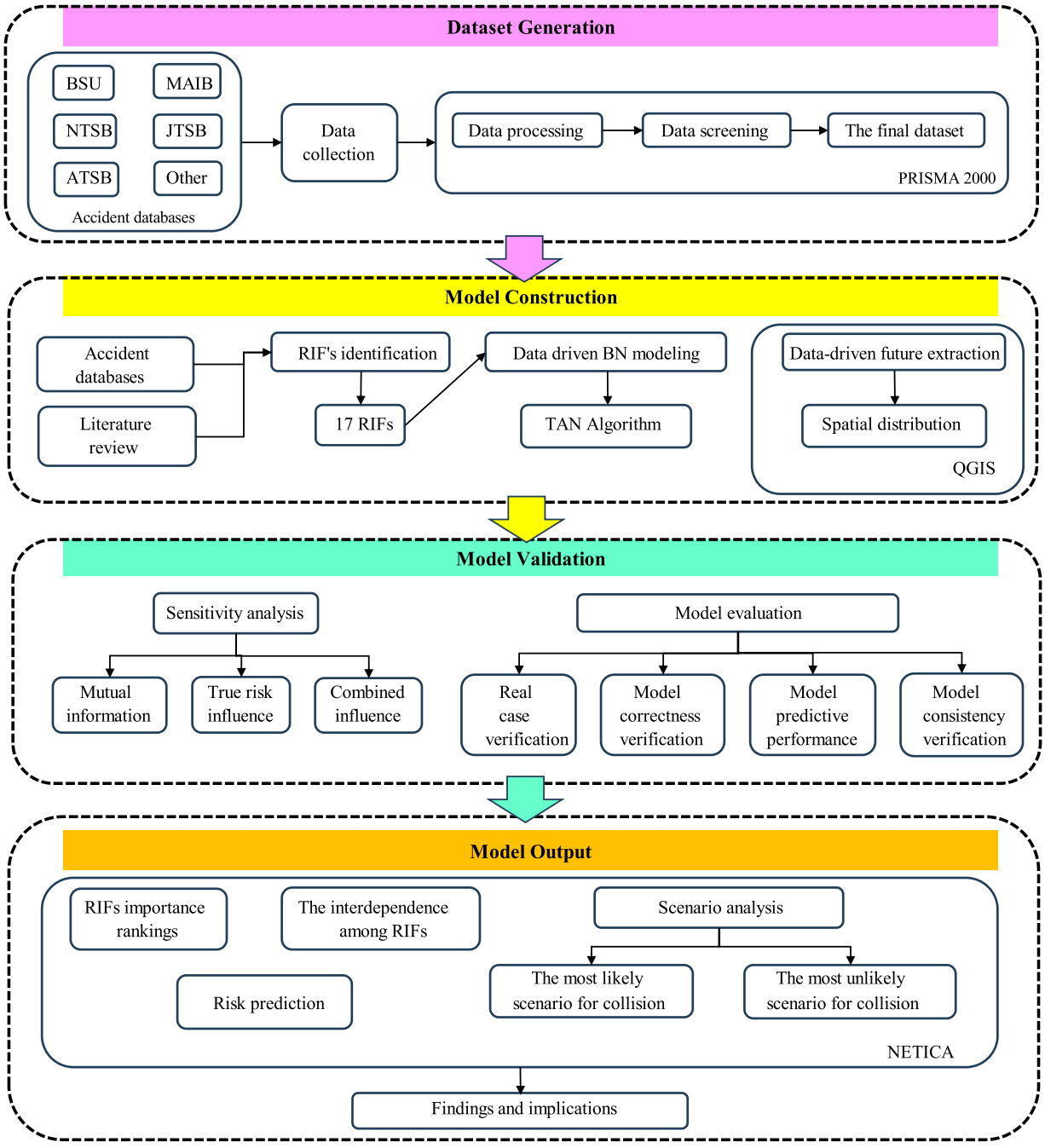


Fig. 1. Methodological framework for data-driven analysis of ship collision risks.

of 16 RIFs to be used in the model was determined. Following the identification of RIFs, the state definitions of these factors were simplified and presented in tabular form (Table 2) to reduce the amount of data required for quantifying dependencies (e.g., CPTs). As a result, the RIFs identified in this study were classified into four main categories: accident-related factors, environmental factors, ship-related factors, and bridge operator-related factors.

Following the identification of the RIFs, the state definitions of these factors were simplified and presented in tabular form by defining them as categorical variables. This approach was adopted to reduce the amount of data required to quantify the dependency relationships within the model. In addition, to more comprehensively represent the characteristics of the analyzed collision events, several variables that have received limited attention in previous studies were also incorporated into the model. In particular, variables such as collision consequences and the rank of the bridge operator were included in the analysis to enhance the explanatory capability of the model.

One of the distinguishing features of this study is that the variables were defined in a way that considers the operational characteristics of both vessels involved in the collision. Ship-related variables were not defined based on a single vessel; instead, they were structured to represent the characteristics of both ships involved in the collision. This approach made it possible to analyze potential interactions between vessel characteristics. The International Maritime Organization (IMO) proposes a detailed classification for the voyage segment variable, including anchorage areas, archipelagos, berths, channels, straits, coastal waters, inland waters, open seas, ports, port approach areas, and rivers. However, due to limitations in data availability, a more general

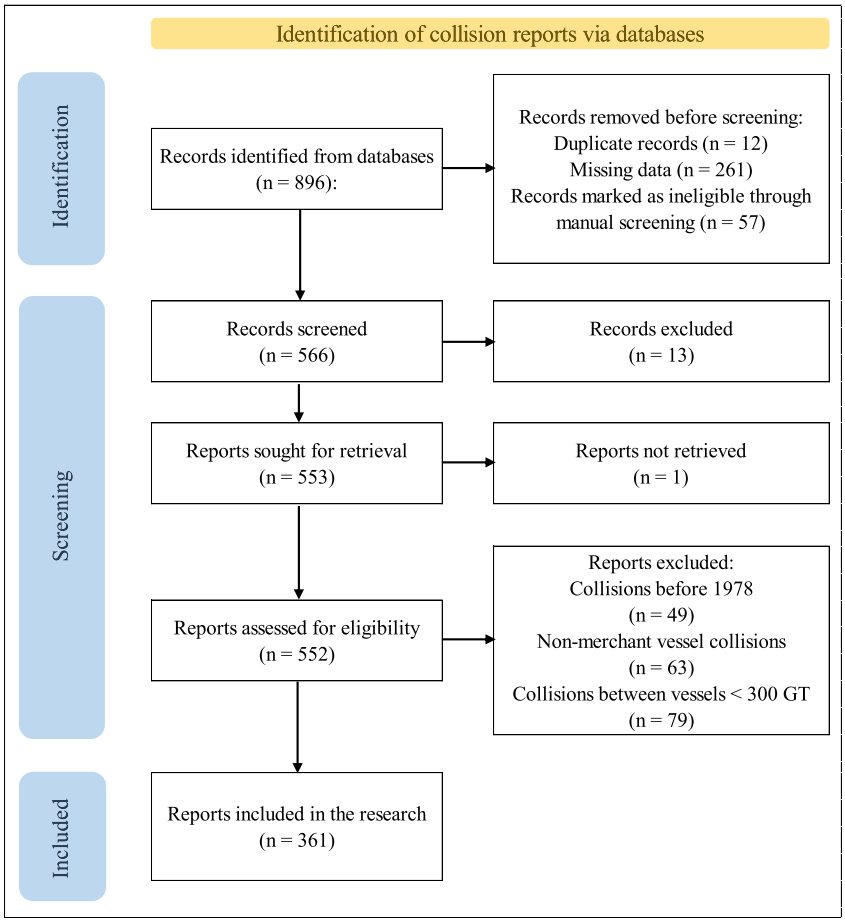


Fig. 2. PRISMA 2000 data processing flowchart for collision accidents.

classification was adopted in this study, and the voyage segment variable was categorized into broader groups: open sea, coastal area, port area, and narrow channel/river.

Compared with previous studies, this research adopts a more methodological approach in determining the day/night condition. Instead of using approximate time intervals, the recorded time of each accident was matched with the geographical location of the vessel, and the sunrise and sunset times for the corresponding latitude and longitude on the relevant date were calculated. Thus, accidents were coded as day or night based on actual astronomical times rather than fixed hourly intervals. Visibility conditions were evaluated using a classification commonly adopted in the literature. A visibility distance of less than two nautical miles was classified as restricted visibility, whereas visibility greater than two nautical miles was considered good visibility [38]. In Table 2, the values for ship type, ship speed, ship age, navigational status, gross tonnage, loading condition, and the rank of the bridge operator are presented separately for each of the two vessels involved in the collision. Ship speed, ship age, and gross tonnage are expressed as interval ranges.

Additionally, the effects of the 16 identified RIFs were examined in terms of collision consequences. As collision outcome is influenced by all covariates in the model, it provides a richer and more discriminative basis for sensitivity analysis. However, some variables under "Ship type" and "Rank" did not achieve sufficient sample size. Therefore, these variables were merged and evaluated under the "Other" category.

3.2.2. Data driven BN model

A BN provides a robust theoretical framework for representation and reasoning under uncertainty and is therefore a valuable tool in areas such as risk assessment, decision-making, and accident analysis. A BN consists of nodes and directed edges, where each node represents a random variable and each directed edge denoted a direct probabilistic dependency between variables. The learning process of a BN typically comprises two main components: parameter learning and structure learning. In parameter learning, each node is assigned a CPT that defines the conditional probability distribution of that node given its parent nodes. In structure learning, a directed acyclic graph (DAG) is constructed by identifying dependency relationships among variables. When developing a BN model for maritime accident risk assessment, either subjective or objective approaches may be employed. While the subjective approach relies on expert judgements and domain knowledge, the objective or data-driven approach derives BN structures directly from datasets using machine learning (ML) algorithms [43].

The BN structure in this study was constructed based on a data-driven approach. In a data-driven approach, ML algorithms are employed to automatically extract and generate the BN structure directly from the dataset. Various BN classification types are available for training a DDBN model, including Augmented Bayesian Networks (ABN), Naive Bayes Networks (NBN), and TAN. The ABN model can typically experience issues such as increasing structural complexity, greater data requirements, intensive computation, overfitting risk, and low interpretability. On the other hand, NBN assumes conditional independence among variables; however, since this assumption is rarely satisfied in real-world conditions, it limits the model's applicability. The TAN approach addresses these limitations by relaxing the independence assumption of NBN and capturing dependencies among variables more accurately, while still preserving the computational efficiency and simplicity of the naive structure. The TAN structure constrains each RIF to have at most two parents, limiting CPT size explosion. The largest CPT in our model corresponds to the "Ship Type" node with 21 states,

Table 2
Definition and status of RIFs.

No	Main factors	RIFs	Notation	Description	Corresponding values
	Collision related				
1		Collision consequences	C	(Structural damage), (Total loss), (Structural damage + Pollution), (Structural damage + Total loss), (Total loss + Pollution), (S. damage + T. loss + Pollution)	1, 2, 3, 4, 5, 6
2		Collision situation	R1	(Crossing), (Overtaking), (Head-on), (Moored), (Anchored), (Maneuver)	1, 2, 3, 4, 5, 6
3		Date of collision	R2	(1978–1994), (1995–2000), (2001–2006), (2007–2012), (2013–2018), (2019–2022)	1, 2, 3, 4, 5, 6
4		Fatality	R3	(Yes), (No)	1, 2
5		Injury	R4	(Yes), (No)	1, 2
	Environmentally related				
6		Day/Night condition	R5	(Day), (Night)	1, 2
7		Voyage segment	R6	(Open sea), (Coastal area), (Port area), (Narrow channel/ River)	1, 2, 3, 4
8		Visibility condition	R7	(Good), (Restricted)	1, 2
9		Wind force	R8	Beaufort (0–4), (5–7), (8–12)	1, 2, 3
	Ship related				
10		Ship type	R9	(Tanker-Tanker), (Tanker-Dry cargo), (Tanker-Container), (Tanker-Fishing) (Tanker-RoRo/ Passenger), (Tanker-Other), (Dry cargo -Dry cargo), (Dry cargo -Container), (Dry cargo-Fishing), (Dry cargo- RoRo/ Pass.), (Dry cargo -Other), (Container-Container), (Container-Fishing), (Container-RoRo/ Passenger), (Container-Other), (RoRo/ Passenger-RoRo/ Passenger), (RoRo/ Passenger-Other), (RoRo/ Passenger-Fishing), (Other-Other), (Other-Fishing), (Fishing - Fishing)	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21
11		Ship speed	R10	(0–10 / 0–10), (0–10 / 11–15), (0–10 / >15), (11–15 / 11–15), (11–15 / >15), (>15 / >15)	1, 2, 3, 4, 5, 6
12		Gross tonnage	R11	(300–3k / 300–3k), (300–3k / 3001–10k), (300–3k / 10,001–20k), (300–3k / >20k), (3001–10k / 3001–10k), (3001–10k / 10,001–20k), (3001–10k / >20k), (10,001–20k / 10,001–20k), (10,001–20k / >20k), (>20k / >20k)	1, 2, 3, 4, 5, 6, 7, 8, 9, 10
13		Ship age	R12	(0–10 / 0–10), (0–10 / 11–20), (0–10 / >20), (11–20 / 11–20), (11–20 / >20), (> 20 / > 20)	1, 2, 3, 4, 5, 6
14		Navigation status	R13	(Underway-Underway), (Underway-Restricted maneuver),	1, 2, 3, 4, 5, 6, 7, 8

(*continued on next page*)

Table 2 (*continued*)

No	Main factors	RIFs	Notation	Description	Corresponding values
				(Underway-Moored), (Underway-Engaged in fishing), (Underway-Anchored), (Underway-Not under command), (Anchored-Anchored), (Anchored-Restricted maneuver)	
15		Loading condition	R14	(Loaded-Loaded), (Loaded-Ballast), (Ballast-Ballast)	1, 2, 3
	Bridge operator related				
16		Rank of OOW	R15	(Master-Master), (Master-Chief off.), (Master-2nd off.), (Master-3rd off.), (Master-Other), (Chief off.-Chief off.), (Chief off.−2nd off.), (Chief off.−3rd off.), (Chief off.-Other), (2nd off.−2nd off.), (2nd off.−3rd off.), (2nd off.-Other), (3rd off.−3rd off.), (3rd off.-Other), (Other-Other)	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15
17		Bridge watch period	R16	(0000–0400), (0400–0800), (0800–1200), (1200–1600), (1600–2000), (2000–0000)	1, 2, 3, 4, 5, 6

requiring 126 conditional probability entries given the class variable. The tree-augmented edges add minimal complexity, with the maximum joint CPT size being the product of child states, six class states, and one parent RIF states. This structural constraint ensures computational tractability while capturing essential dependencies among RIFs. The TAN model has been shown to provide higher accuracy and greater efficiency compared to other data-driven BN structure construction methods [37]. For these reasons, TAN was selected in this study to train the BN for the severity analysis of ship collision accidents.

The Naive Bayes network is an annotated structure represented in the form of a DAG that specifies a joint probability distribution over the variable set U (in this study U = {C, R_1,…, R_{16}}). If the class variable "Collision consequence" C is taken as the sole parent of each risk variable in the set R = {R_1,…,R_{16}} (i.e., $\Pi_(R_i) = \{C\}$, $1 \leq i \leq 16$) and C has no parent nodes ($\Pi_C = \varnothing$), then the Naive Bayes architecture is fully defined. The factorization of the joint probability distribution associated with the Naive Bayes model is given in Eq. (1).

$$P_{TAN}(C,\ R_1,\ldots R_{16}) = P_{TAN}(C)\prod_{i=1}^{16} P_{TAN}(R_i|C) \tag{1}$$

In contrast to the Naive Bayes structure, which links only the "Collision consequence" class to individual risk variables, the TAN model enriches the model by establishing a tree structure among risk variables. This extension allows additional edges to be learned from the data and captures mutual dependencies among RIFs [38]. A directed edge added from R_i to R_j indicates that the effect of R_i on "Collision consequence" can be modified by R_j. The TAN structure employed in this study fundamentally differs from traditional causal BNs used in risk assessment. In conventional BNs, arcs typically represent causal relationships directed from risk factors (parent nodes) to accident outcomes (child nodes), simulating how various hazards lead to specific consequences. In contrast, TAN is a classification-oriented BN classifier where the class variable (Collision consequences) serves as the parent of all feature variables (RIFs). This reversed structure does not imply that collision outcomes causally influence vessel characteristics or environmental conditions; rather, it follows the standard generative classifier formulation where the class variable 'explains' the joint probability distribution of features. The mathematical foundation P(R_i|C) enables efficient computation of posterior probabilities P(C|R_1,…,R_n) through Bayes' theorem, optimized for predictive accuracy rather than causal inference. This approach is consistent with established maritime safety studies employing TAN for accident severity analysis [37,44,50].

Within this framework, the function π: {1,…,16} → {0,…,16} can be used to encode a tree structure over the risk variables R_1,…,R_{16}. This tree must satisfy the following three properties:

(1) There exists only one index i where $\pi(i) = 0$ (the root node).
(2) Every non-root risk variable has exactly one parent.
(3) No cycles exist among the risk variables; that is, for a sequence i_1, …,i_k, no loop is formed satisfying the conditions $\pi(i_j)=i_{j+1}$ for $1 \leq j < k$ and $\pi(i_k)=i_1$.

The requirement that every non-root risk variable has exactly one parent (Property 2) is fundamental to the tree structure and distinguishes TAN from more complex network structures such as general BNs or ABNs. In graph-theoretic terms, a tree structure ensures that there exists exactly one unique path between any two nodes, thereby preventing cycles and maintaining computational tractability. This constraint is deliberately imposed by the Construct-TAN algorithm [58] to balance model complexity and predictive accuracy. Specifically, limiting each risk variable to a single parent within the tree structure (in addition to the class node - Collision consequence) ensures that: (i) the model remains computationally efficient with polynomial-time inference; (ii) the risk of overfitting is mitigated by restricting the number of parameters to be estimated; and (iii) the conditional dependencies among risk variables are captured without introducing the complexity of full network structures. While this assumption simplifies the representation of relationships among risk variables compared to unrestricted networks, it has been demonstrated to provide superior classification performance relative to Naive Bayes while maintaining greater computational efficiency than general BNs [38]. In the context of maritime accident analysis, this property ensures that the influence of any given risk variable on collision consequences is transmitted through a single pathway within the tree, facilitating interpretability and enabling clear identification of the most influential dependency relationships among risk factors.

Accordingly, when $\Pi_C = \varnothing$ and a π function satisfying the conditions given in Eq. (2) is specified, a TAN-BN can be constructed over the variable set *U*. Furthermore, the posterior probability of collision consequence in the TAN-BN model is expressed in Eq. (3).

$$\prod_{R_i} = \begin{cases} \{C,\ R_{\pi(i)}\},\ \pi(i) > 0 \\ \{C\},\ \pi(i) = 0 \end{cases} \quad (2)$$

$$P\ (C|R_1, \ldots, R_{16}) = P(C)\ .P(R_{root}|C) \prod_{i=1}^{16} P\ (R_i|C) \quad (3)$$

Learning the TAN-BN structure is an optimization problem that can be accomplished through the Construct-TAN procedure [47]. In this approach, the conditional mutual information (CMI) given in Eq. (4) quantitatively defines the relationship between two RIFs conditional on "Collision consequence." The magnitude of the CMI is used as weight of candidate edges, and the maximum weighted spanning tree with the highest total edge weight is selected.

$$I_p(R_i, R_j|C) = \sum P(r_{ii}, r_{ji}, c_i)\ \log_b \frac{P(r_{ii}, r_{ji}|c_i)}{P(r_{ii}|c_i)\ P(r_{ji}|c_i)}\ i \neq j \quad (4)$$

Here, I_P denotes the CMI value between risk variables R_i and R_j conditional on "Collision consequence." The terms r_{ii} and r_{ji} represents the i th state of R_i and R_j, respectively and c_i denotes the i th state of "Collision consequence." The logarithm base b is typically taken as 2. For example, if "Fatality" and "Visibility" each have two states and the "Collision consequence" variable has six states, I_P for this pair consists of a total of 24 terms ($2 \times 2 \times 6$).

After CMI values are calculated, the Construct-TAN algorithm is applied to construct the structure of the proposed TAN-BN model. The learning process consists of five main steps [53]:

(1) Calculate CMI I_P values to identify dependencies among variables.
(2) Construct a fully connected undirected graph where each node represents a risk variable by assigning I_P values corresponding to connections between R_i and R_j as weights.
(3) Construct a maximum weighted spanning tree ensuring that the sum of weights of all edges exceeds all other possible tree structures.
(4) Selecting one of the risk variables as the root and transform the undirected tree into a directed structure by directing all edges outward from the root.
(5) Incorporate the class variable C ("Collision consequence") into the network and complete the TAN-BN structure by creating directed edges from C to all risk variables.

Parameter learning was conducted using Netica's counting-learning algorithm with Laplace smoothing ($\alpha = 1$) to eliminate zero probabilities and ensure numerical stability. This Bayesian approach applies a uniform Dirichlet prior to all conditional probability entries, effectively adding one pseudo-count to each observed state combination. For a CPT entry θ_{ijk} representing $P(X_i = k \mid \text{Parents} = j)$, the estimated probability is computed as:

$$\widehat{\theta} = \frac{N_{ijk} + \alpha}{N_{ij} + \alpha . r_i} \quad (5)$$

where N_{ijk} represents the observed count for state k of node X_i given parent configuration j, N_{ij} is the total count for parent configuration j, r_i is the number of states for node X_i, and $\alpha = 1$ is the smoothing parameter. This approach ensures that no conditional probability is exactly zero, enabling the model to handle evidence combinations not present in the training data while maintaining statistical validity.

It is important to note that while the ratio of CPT entries to observations exceeds unity for high-cardinality nodes (e.g., Ship Type: 1260 entries vs. 361 cases), the TAN structure's constraint of at most two parents per node, combined with Laplace smoothing ($\alpha = 1$), provides effective regularization against overfitting. The model's strong generalization performance on the held-out test set (Accuracy = 93.06%, Kappa = 0.832) and its successful prediction of an unseen real-case accident (91.0% consistency) empirically demonstrate that data sparsity in individual CPTs does not compromise the rationality or reliability of the network outputs.

The TAN structure constrains each RIF to have at most two parents. While most nodes require modest CPT sizes (e.g., Ship Type needs 126 entries) tree-augmented edges can increase complexity significantly. TAN structure automatically learned by the Construct-TAN algorithm may create large CPTs for certain RIF combinations. Rank of OOW exemplifies this: with two parents (Collision consequences and Gross tonnage), its CPT contains 900 entries ($15 \times 6 \times 10$). Given 361 accidents, this yields severe data sparsity (0.4 observations per cell). Laplace smoothing addresses this by ensuring even unobserved combinations receive probability mass of approximately 0.0027, preventing numerical instability during inference.

The constructed ship collision accident BN model is illustrated in Fig. 3. In Fig. 3, the 16 distinct boxes surrounding the edges represent the 16 RIFs that function as child nodes in the BN. The box in the center denotes the collision consequences, which is the research objective serving as the parent node in the BN. On the left side of each box, state partitions for the corresponding RIF are listed, with collision consequences selected as the parent node. Directed edges among RIFs (excluding edges from Collision consequences) represent statistical dependencies identified by the Construct-TAN algorithm based on CMI, not assumed causal relationships. The tree structure is optimized to maximize predictive accuracy while maintaining computational efficiency. It is important to emphasize that the TAN structure illustrated in Fig. 3 is entirely data-driven. Unlike traditional BNs where arcs often represent hypothesized causal relationships, the connections among RIFs in this TAN model reflect statistical dependencies automatically extracted from 361 collision accident records. The Construct-TAN algorithm selects edges that maximize the CMI between RIFs given the collision consequence, thereby optimizing the network's predictive performance. Consequently, some connections may appear counterintuitive from a causal perspective (e.g., environmental factors linked to ship characteristics), yet they capture genuine co-occurrence patterns in maritime accident data that improve the model's classification accuracy. This data-driven approach ensures objectivity and reproducibility, though we acknowledge that the resulting structure may differ from expert-elicited causal models.

3.3. Model validation

3.3.1. Sensitivity analysis

Sensitivity analysis is a widely used approach for dealing with uncertainty. In BN-based ship collision accident risk analysis, the primary objective is to identify the RIFs that have the greatest impact on the target variable, namely the "Collision consequence." This identification enables the implementation of cost-effective risk mitigation measures focused on the most critical factors [50]. To ensure a comprehensive evaluation, the study employs mutual information (MI), joint probability, and True Risk Impact (TRI) methods to conduct sensitivity analysis from both individual and combined variable perspectives.

3.3.1.1. Mutual information (MI). Mutual information is an entropy-based measure that quantifies the statistical dependence between two variables by determining the extent to which knowing one variable reduces the uncertainty of the other. It is an information-theoretic indicator showing the strength of the relationship between two variables: Higher MI signifies a greater reduction in entropy and thus a stronger relationship. In this study, MI was used to systematically evaluate the informativeness of each RIF on "Collision accident" and to comparatively assess their explanatory contributions.

One of the main objectives of this research is to determine how each relevant RIF is associated with a particular collision consequence. Therefore, in the MI analysis, "Collision consequence" was designated as

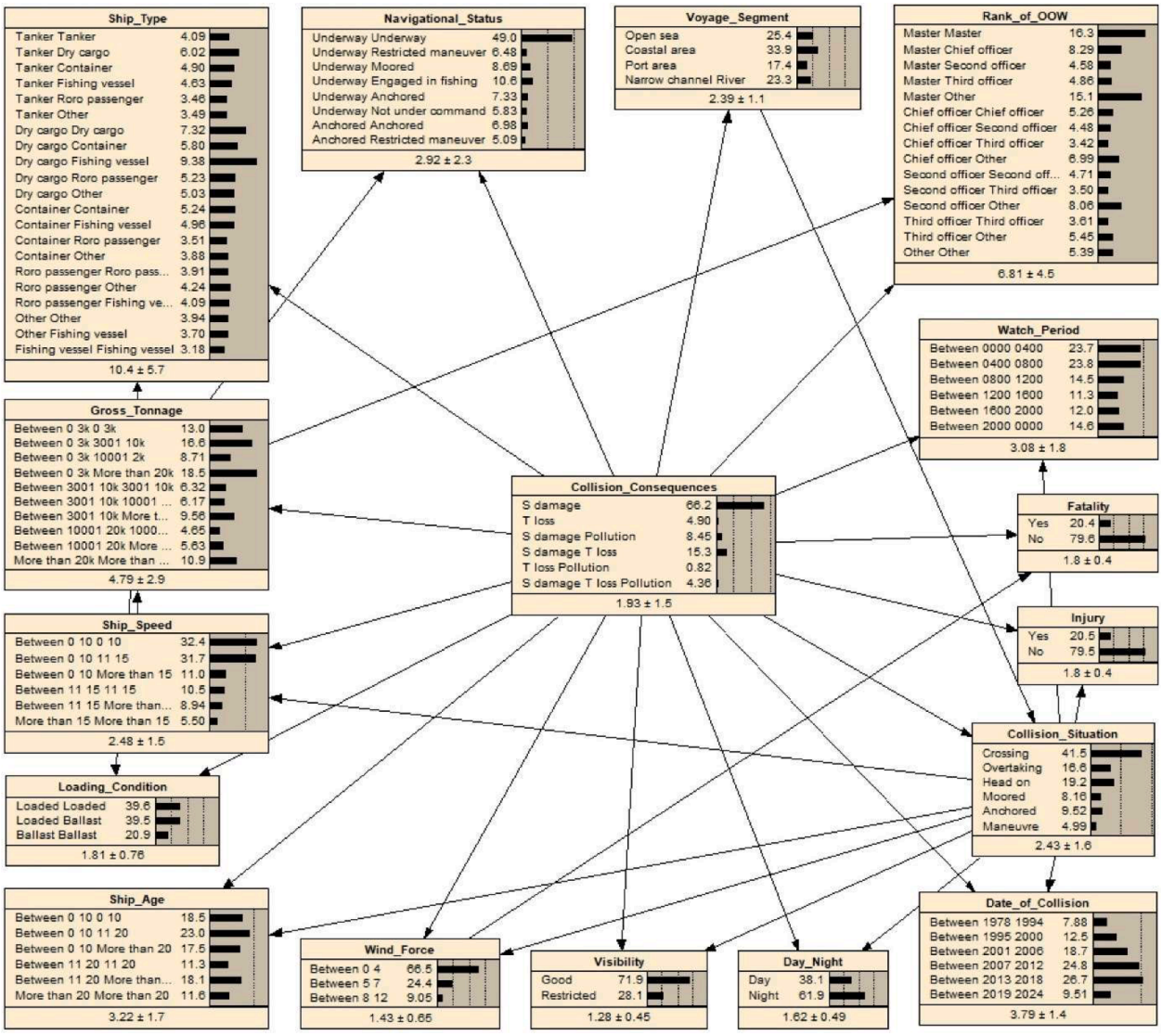


Fig. 3. The automatically learned TAN-BN structure and parameters.

the fixed (target) variable. Accordingly, the MI between collision consequence and related risk factors is formulated as follows:

$$I(C,R_i) = -\sum_{c,j} P(c,\ r_{ij}) \log_a \frac{P(c,\ r_{ij})}{P(c)P(r_{ij})}\ i \neq j \tag{6}$$

Here, C denotes "Collision consequence," R_i represents the i th risk variable, and r_{ij} denotes the j-th state of R_i. $I(C,R_i)$ indicate the MI value between collision consequence and the i th risk variable; the logarithm bases a is typically set to 2. When the MI between each risk factor and collision consequence is calculated, key variables with significant impact on accident outcome can be identified and selected for use in subsequent analyses. Subsequently, TRI and joint probability approaches are applied to examine the interactions and detailed effects among RIFs.

3.3.1.2. Joint probability. The first additional sensitivity analysis method used to better understand the detailed effects of the most important RIFs identified through MI analysis is the joint probability approach. Joint probability evaluates how each state of a RIF affects different collision consequence categories. To demonstrate how each state of a single variable influence's collision consequence, the probability of "Collision consequence" is calculated when each of the significant risk variables occurs. When other risk variables are held constant, the probability distribution of the "Collision consequence" variable under different conditions can be estimated using the TAN-BN model. In this process, a probability of 100% is assigned to the state of the risk variable being examined [38]. At this point, the total probability of all outcomes under a particular state of the analyzed variable equals one. The computational procedure is presented in Eq. (7). Accordingly, when a specific significant risk variable occurs, the probability of an event occurring for a specific collision consequence is defined as follows:

$$P(C=C_i|R=R_i) = \frac{P(R=R_i|C=C_i) \times P(C=C_i)}{P(R=R_i)} \tag{7}$$

where C and R denote collision consequence and any risk variable, respectively. R_i represents the i th state of R, and C_j represents the j-th state of C. $P(R{=}R_i|C{=}C_j)$ indicates the probability of R being in state R_i given that C is in state C_j.

It is important to note that joint probability analysis examines the effect of a single RIF state on the target variable, with other variables integrated out through marginalization. For assessment of combined effects from multiple RIFs, readers should refer to the TRI analysis (Section 3.3.1.3) and scenario analysis (Section 3.5).

3.3.1.3. True risk influence (TRI). After RIFs are identified through MI analysis, a complementary sensitivity analysis can typically be conducted using scenario-based simulations to evaluate their combined effects. In the conventional approach, all nodes except those being analyzed are fixed, and then the conditions of the class node are progressively updated. While this method is effective for binary variables, it becomes inadequate when multi-state variables are involved. Therefore, when RIFs have more than two states, the traditional scenario simulation framework fails to capture the complex mutual dependencies among variables.

To address this limitation, Alyami et al. [54] proposed an alternative approach known as TRI. This technique provides an effective framework for evaluating the joint sensitivity of multiple variables identified through MI analysis. The TRI method consists of the following steps:

(1) According to the TAN-based model, initial impact values are obtained for eight ship types. Subsequently, the joint probabilities between the class node and each variable are calculated by setting each factor state to 100%.
(2) High Risk Impact (HRI) is calculated as the difference between the maximum occurrence probability for a given state and the corresponding initial impact value.
(3) Low Risk Impact (LRI) is calculated as the difference between the initial impact value and the minimum occurrence probability for the same state.
(4) Finally, the TRI value is calculated as follows:

$$TRI = \frac{HRI + LRI}{2} \tag{8}$$

A higher TRI value indicates that the corresponding RIF has a stronger impact on "Collision consequence." This measure enables a more detailed examination of how key RIFs affect the target node and provides deeper insight into their relative impacts on different collision consequences.

3.4. Model evaluation

The data-driven BN risk model must be validated before being applied in risk assessment or predictive analyses. In this section, four different methods are employed to validate the proposed model. First, two axioms are applied to assess the structural accuracy of the developed TAN-BN model. Second, the model's predictive performance and reliability are analyzed using ML-based evaluation metrics. Third, the model's consistency in predicting accident occurrences is examined to verify its robustness across different scenarios. Finally, the model's predictive effectiveness is tested through the implementation of a real case study, thereby evaluating the model's practical applicability and reliability in the maritime context.

3.4.1. Model correctness verification

To verify the correctness of the constructed BN-based model, it must comply with two fundamental axioms used to assess the model's robustness, as specified below [38]:

Axiom 1: A small change in the prior probability of each RIF, whether an increase or decrease, should lead to a corresponding decrease or increase in the posterior probability of the target node.

Axiom 2: The total effect obtained from integrating probability changes over all x parameters should be greater than the effect generated by any subset of RIFs ($y \in x$).

3.4.2. Model predictive performance

The reliability and predictive accuracy of the model proposed in this study are evaluated using a confusion matrix (Fig. 4) and a set of performance metrics. The dataset was randomly classified with 80% of observations as the training set and the remaining 20% as the test set for the BN model.

	Actual positive	Actual negative
Predicted positive	True positive (TP)	False positive (FP)
Predicted negative	False negative (FN)	True negative (TN)

Fig. 4. The confusion matrix.

Accuracy measures the proportion of correctly classified instances among all cases, providing a simple overview of performance; however, it can be misleading in cases of class imbalance. To overcome this limitation and evaluate validity, reliability, and robustness more comprehensively, the following metrics were employed: Recall, Precision, F-measure, True Positive Rate (TPR), False Positive Rate (FPR), Recall macro, Precision macro and F-measure macro.

As an F-measure value approaches 1, overall performance improves [51]. Model quality increases with high TPR and low FPR. The computational definitions for each metric are provided in Eqs. (9)–(15).

$$Recall = \frac{T_P}{T_P + F_N} \tag{9}$$

$$Precision = \frac{T_P}{T_P + F_P} \tag{10}$$

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{11}$$

$$F - measure = \frac{2 \times Recall \times Precision}{Recall + Precision} \tag{12}$$

$$TPR = \frac{T_N}{T_N + F_P} \tag{13}$$

$$FPR = \frac{F_P}{T_N + F_P} \tag{14}$$

$$Macro\ avarage = \frac{1}{n}\sum_{i=1}^{n}. \tag{15}$$

3.4.3. Model consistency verification

In this research, the distribution of collision consequences in the dataset is imbalanced; for example, the "Total loss + Pollution" category accounts for only approximately 0.82% of total records. Therefore, Cohen's Kappa statistic was used to assess the consistency of the model's predictive performance across different collision consequences. The computational result of the Kappa statistic ranges within $k \in [-1, 1]$. A Kappa value (k) approaching 1 indicates a higher level of agreement and stronger model consistency [48]. The calculation of the Kappa statistic is based on the confusion matrix (Table 4), and is expressed as follows:

$$k = \frac{p_0 + p_e}{1 - p_e} \tag{16}$$

Here, k represents the Kappa coefficient, and p_0 denotes the overall prediction accuracy. Given n as the total number of samples in the test dataset, the actual number of samples for each collision consequence is denoted by $a_1, a_2, \ldots, a_n$, and the predicted number of samples for each collision consequence is represented by $b_1, b_2, \ldots, b_n$. In this case, the expected agreement value p_e is calculated as follows:

$$p_e = \frac{(a_1 \times b_1) + (a_2 \times b_2) + \ldots + (a_n \times b_n)}{n \times n} \quad (17)$$

3.4.4. Real case verification

To validate the robustness of the proposed data-driven BN risk assessment model, real-case verification was conducted using an accident investigation report from 2024. This accident was not included in the training or test datasets used in this study. For the real-case analysis, data from the collision accident investigation report of the vessels Damgracht and AP Revelin, which occurred on August 21, 2022, obtained from the NTSB database, were considered. This accident was selected as the real-case verification example because it was the first collision case identified through a web search that was not present in the dataset analyzed in this study. Therefore, the case was not chosen based on any specific characteristics but rather to provide a random and unbiased example for evaluating the model's predictive capability on previously unseen data.

3.5. Spatial distribution of ship collision accidents

To further examine the spatial characteristics of ship collision accidents, latitude and longitude data were extracted from accident investigation reports. This detailed dataset enabled a focused spatial analysis of collision accidents. Fig. 5 maps the global spatial distribution of ship collision accidents over the 1978–2024. The key spatial characteristics derived from these data are summarized below.

(1) Geographical distribution

Collisions are not evenly distributed across oceans but are concentrated along major shipping routes and in coastal regions near ports with high traffic density.

(2) Regions with concentrated collision accidents

Collision accidents are distinctly clustered in certain regions. Particularly, collision accidents are frequently observed along the North and Northwest European coasts, East Asian coasts around China, Japan, and Korea, the eastern coasts of Australia, the Atlantic coasts of North America, and more specifically around Singapore and the western coasts of Turkey.

(3) Comparison between coastal waters and open seas

Most collisions occur in areas close to the coast rather than in the open ocean. This situation indicates that navigational complexity and higher vessel density in coastal navigation have a greater impact on collisions. These finding is consistent with the results reported by [48].

These spatial patterns are particularly evident in the voyage segment RIF and demonstrate the close relationship between geographical areas and navigated waters. The findings also confirm the critical importance of the "voyage segment" RIF in ship collision risk analysis.

4. Results, discussion, and implications

Based on the TAN mechanism for ship collision accidents, a 17-node BN model was constructed in accordance with Eq. (4). Subsequently, the counting-learning algorithm implemented in Netica Version 7.01 [55] software was employed to estimate the parameters for each node in the network. This process enabled the derivation of CPTs for all nodes and allowed for the computation of corresponding probability distributions for the relevant variable nodes.

4.1. Sensitivity analysis

4.1.1. Mutual information

The degree of relationship between variables increases with higher MI values. One of the primary objectives of this study is to examine the relationship between different risk variables and "Collision consequences" to identify factors with stronger influence on collision accidents. The MI values between collision consequences and 16 risk variables-along with entropy reduction percentages and belief variance-are presented in Table 3. The importance ranking of risk variables was obtained from this table.

As shown in the MI column, the "Fatality" node has the highest impact on the target node (0.1947), followed by "Voyage segment"

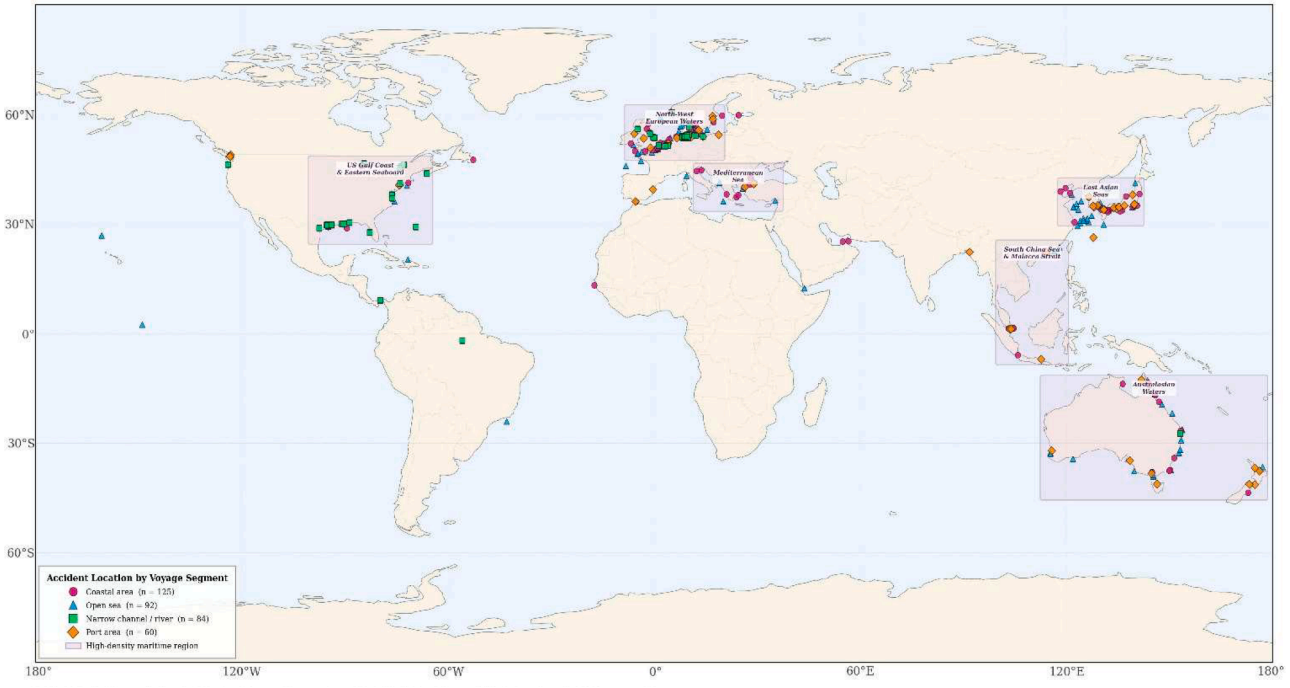


Fig. 5. The spatial distribution of global ship collision accidents between 1978–2024 period.

Table 3
Mutual information between "Collision consequences" and RIFs.

Node	Mutual info	Percent	Variance reduction	Percent	Variance of beliefs
Collision consequences	1.5759	100	2.123	100	0.3482
Fatality	0.1947	12.40	0.436	20.60	0.0267
Voyage segment	0.0619	3.93	0.048	2.28	0.0058
Navigational status	0.0554	3.51	0.103	4.86	0.0093
Rank of OOW	0.0540	3.42	0.115	5.41	0.0105
Ship's speed	0.0411	2.61	0.066	3.13	0.0057
Gross tonnage	0.0251	1.60	0.025	1.18	0.0021
Date of collision	0.0243	1.54	0.030	1.44	0.0021
Collision situation	0.0237	1.50	0.024	1.15	0.0017
Wind force	0.0225	1.42	0.041	1.92	0.0032
Injury	0.0219	1.39	0.054	2.56	0.0035
Ship's age	0.0176	1.12	0.028	1.31	0.0018
Ship type	0.0161	1.02	0.020	0.94	0.0019
Bridge watch period	0.0128	0.81	0.011	0.50	0.0010
Day/Night condition	0.0092	0.58	0.003	0.14	0.0003
Visibility	0.0072	0.46	0.015	0.71	0.0008
Loading condition	0.0068	0.43	0.005	0.25	0.0007

(0.0619) and "Navigational status" (0.0554). However, the strong influence observed for the Fatality node does not represent a direct causal effect. In the BN structure, the fatality variable is not a cause of collision outcomes but rather an outcome variable representing the severity of the accident. Therefore, the high MI value between fatality and collision outcomes reflects the strong statistical relationship between these two variables and indicates the severity of the accident. In other words, fatalities tend to occur in scenarios where collision consequences are more severe, which leads to a higher MI value between these variables.

The high MI value of the voyage segment variable indicates that collision risk varies significantly depending on the operational environment in which the vessel is navigating. In this study, the voyage segment variable represents different navigational environments such as open sea, coastal area, port area, and narrow channel/river. The primary differences among these environments relate to traffic density, available maneuvering space, and navigational constraints. For instance, vessels operating in the open sea generally have greater maneuvering space, whereas in areas such as ports and narrow channels or rivers, both traffic density increases and physical maneuvering space becomes limited. This situation reduces the time and distance available for vessels to perform avoidance maneuvers and may increase the likelihood of collision [56]. Therefore, the high MI value of the voyage segment variable suggests that collision outcomes are strongly influenced by the navigational context in which the vessel operates.

The navigation status variable represents the operational conditions of the vessels involved in the collision. In the dataset, situations such as "underway-underway," "underway-restricted maneuver," and "underway-not under command" indicate scenarios in which vessels are simultaneously in motion or where maneuverability is limited. Particularly in situations where both vessels are underway, the interaction between vessels increases and the correct interpretation and application of the COLREGs become critical. When encountering vessels with restricted maneuverability or vessels not under command, avoidance maneuvers may become more complex, which may contribute to more severe collision outcomes. According to MI values, other influential variables, namely Rank of OOW, Ship's speed, and Gross tonnage, were identified as the most effective risk factors on collision consequence and were therefore included in subsequent sensitivity analysis. The emergence of the OOW rank as an important variable highlights the role of the human factor in collision accidents. The dataset includes encounter combinations involving bridge officers of different ranks such as captain, chief officer, second officer, and third officer. When officers with different levels of experience and responsibility encounter each other, differences may arise in terms of situational awareness, risk perception, and the interpretation and application of COLREGs. In complex traffic environments, officers with lower levels of experience may face greater challenges during the decision-making process. This finding indicates that bridge resource management and the level of training play an important role in reducing collision risk.

4.1.2. Joint probability

Table 4 summarizes how each state of the examined variables affects the distribution of collision consequences categories. Accordingly, the analysis provides novel and practically relevant insights. The main findings can be summarized as follows:

From the perspective of fatality, it was found that the highest proportion of fatalities (46.8%) occurred in accidents involving both structural damage and total loss. In contrast, the lowest proportion of fatalities (22.5%) was observed in collision accidents resulting in structural damage only.

The most striking result obtained according to rank is that the most severe collision consequences occur when the bridge was manned by the 1st Officer or 4th Officer at the time of the accident. The experience level and operational responsibilities of OOW can be particularly decisive in terms of situational awareness and the application of COLREGs, especially under heavy traffic conditions or complex navigational environments. Officers with lower levels of experience may face greater cognitive workload during the decision-making process in complex encounter scenarios, which may increase the severity of collision outcomes. In situations where collision consequences have the lowest impact, ship's master was present on the bridge.

As expected, the analysis of ship speed indicates that collision consequences become more severe as vessel speed increases. The influence of vessel speed on collision consequences is closely related to ship dynamics and maneuverability. As speed increases, the stopping distance of the vessel becomes longer and the reaction time required for avoidance maneuvers decreases. Particularly in encounter situations involving vessels traveling at high speed, the time available for bridge personnel to make situationally informed decisions becomes shorter. At the same time, the higher kinetic energy present at the moment of collision may lead to more severe damage and loss outcomes.

Collisions occurring in open seas tend to result in more severe consequences, whereas collisions in port areas lead to the least severe outcomes. In open seas, vessels generally operate at higher speeds, resulting in greater kinetic energy at the moment of collision. In contrast, vessels in port areas typically operate at lower speeds due to speed restrictions, pilotage practices, and traffic management systems. Consequently, collisions occurring in port areas often result in limited structural damage, whereas collisions in open seas may lead to more severe damage or total loss scenarios.

Ship age does not create a significant difference in terms of collision consequence.

For the collision situation variable, the most severe collision consequences observed in maneuvering situations, while the least severe outcomes occurred in overtaking situations.

An evaluation of watch periods shows that the time interval between 08:00 and 12:00 is associated with the lowest impact in terms of collision consequences.

Furthermore, this analysis emphasizes the methodological importance of applying the joint probability approach in BNs; it demonstrates that it is an effective tool for evaluating the individual effect of each RIF state on collision consequences. Unlike scenario analysis where multiple factors are varied simultaneously, joint probability isolates the impact of single variables while marginalizing over other factors. This provides a foundational understanding of how specific states of individual risk factors influence outcomes, complementing the multi-factorial assessment provided by TRI and scenario-based methods.

Table 4
The joint probability of single RIF states and collision consequences.

Initial	C1	C2	C3	C4	C5	C6
Fatality						
1	22.30	12.80	6.03	46.80	2.40	9.62
2	77.50	2.88	9.07	7.17	0.41	3.01
Rank of OOW						
1	83.40	1.74	5.35	6.64	0.37	2.48
2	71.10	3.94	6.67	14.20	0.65	3.48
3	56.60	7.14	11.00	18.30	1.17	5.74
4	56.00	5.83	11.60	19.60	1.10	5.97
5	78.90	2.32	5.48	11.10	0.36	1.92
6	52.40	5.39	8.72	26.90	1.02	5.52
7	54.50	6.33	10.20	21.90	1.20	5.87
8	46.80	8.29	13.40	22.20	1.57	7.69
9	62.40	5.15	8.89	17.80	0.77	4.97
10	51.10	6.59	13.40	21.00	1.14	6.76
11	49.90	8.10	13.10	19.90	1.54	7.52
12	70.70	6.50	6.80	12.10	0.67	3.26
13	49.10	7.85	14.30	19.20	1.49	8.03
14	60.80	6.80	8.42	18.20	0.99	4.83
15	63.30	6.49	9.58	14.60	1.10	4.88
Navigational status						
1	77.60	2.39	4.97	12.50	0.22	2.27
2	53.30	7.58	14.00	16.60	1.54	7.06
3	62.80	6.28	11.50	12.40	1.27	5.80
4	59.50	6.32	7.95	20.90	0.94	4.32
5	53.00	7.54	12.50	19.40	1.36	6.24
6	48.80	8.43	13.00	20.30	1.71	7.84
7	57.70	7.03	11.90	15.40	1.43	6.55
8	43.50	9.65	14.80	21.10	1.96	8.98
Ship's speed						
1	77.80	2.69	7.96	8.49	0.47	2.61
2	63.10	4.93	6.59	21.70	0.48	3.21
3	61.00	7.52	9.10	15.20	1.16	6.08
4	57.40	6.00	8.42	18.80	1.23	8.23
5	64.00	5.65	11.40	12.20	1.44	5.38
6	47.40	9.20	16.00	16.30	2.34	8.76
Injury						
1	50.70	7.52	12.30	19.50	2.00	8.04
2	70.20	4.23	7.47	14.20	0.51	3.41
Voyage segment						
1	58.20	7.35	5.86	24.40	0.54	3.61
2	61.20	6.90	6.60	19.10	0.80	5.42
3	80.60	1.35	7.16	7.45	0.78	2.64
4	71.50	2.00	14.90	5.54	1.17	4.91
Wind force						
1	70.70	4.04	7.10	14.10	0.49	3.55
2	61.60	5.14	9.37	18.00	1.00	4.90
3	45.60	10.60	15.90	16.30	2.71	8.85
Date of collision						
1	54.60	11.10	11.00	13.50	1.63	8.20
2	70.30	6.02	7.09	11.70	1.03	3.87
3	67.10	3.36	6.83	18.90	0.69	3.15
4	66.40	4.66	7.26	18.00	0.52	3.14
5	71.10	3.27	9.33	12.40	0.57	3.31
6	54.50	6.60	11.90	15.10	1.59	10.30
Ship's age						
1	71.00	5.38	8.36	10.40	0.69	4.21
2	71.30	4.14	9.04	11.50	0.56	3.49
3	61.50	4.10	7.21	21.30	0.74	5.07
4	65.40	5.85	8.98	14.40	1.14	4.26
5	65.60	3.90	9.92	17.20	0.71	2.66
6	57.30	7.53	6.43	19.20	1.51	8.02
Gross tonnage						
1	66.20	4.86	4.15	20.10	0.61	4.07
2	66.40	3.63	7.73	18.80	0.56	2.84
3	65.50	4.22	7.40	16.60	0.91	5.33
4	73.50	5.64	5.09	12.70	0.50	2.52
5	57.90	6.72	10.20	18.40	1.25	5.41
6	59.80	5.96	13.60	11.70	1.28	7.65
7	69.20	3.84	9.02	12.90	0.83	4.22
8	55.90	7.91	11.60	15.50	1.70	7.36
9	57.00	6.53	14.90	12.80	1.40	7.28
10	69.00	3.36	12.10	10.70	0.72	4.21
Collision situation						
1	66.60	5.30	5.86	17.80	0.30	4.14
2	73.70	4.25	6.59	12.20	0.74	2.55
3	66.00	2.92	10.70	15.70	0.84	3.86
4	63.70	5.78	14.10	8.43	1.99	5.99
5	62.80	5.89	11.60	14.00	1.29	4.45
6	49.70	8.12	12.10	16.40	2.47	11.30
Ship type						
1	63.90	5.11	10.30	15.10	0.94	4.71
2	68.60	3.48	10.90	12.50	0.64	3.88
3	72.20	4.27	7.77	11.00	0.79	3.94
4	66.40	6.57	8.44	13.50	0.92	4.17
5	60.30	6.04	9.95	17.00	1.11	5.57
6	53.60	6.00	12.20	20.40	1.10	6.69
7	68.10	2.86	5.20	20.30	0.53	2.94
8	69.00	3.94	8.53	12.90	0.66	5.01
9	72.10	3.98	4.07	17.20	0.41	2.29
10	73.20	4.00	6.59	11.40	0.74	4.08
11	65.40	4.66	10.10	14.80	0.77	4.24
12	73.20	3.99	8.11	10.30	0.73	3.68
13	66.30	5.42	7.87	15.80	0.78	3.89
14	59.90	5.96	10.80	16.80	1.10	5.50
15	63.20	5.40	9.65	15.80	0.99	4.98
16	66.10	5.36	8.83	13.80	0.99	4.94
17	67.00	4.94	8.13	14.50	0.91	4.55
18	59.40	7.44	8.43	19.10	0.94	4.72
19	63.10	5.31	10.80	13.70	1.08	5.98
20	58.40	7.03	9.32	19.00	1.04	5.22
21	58.30	6.58	10.80	17.00	1.21	6.07
Visibility						
1	68.20	5.12	8.59	13.60	0.49	3.98
2	61.10	4.35	8.08	19.50	1.64	5.33
Bridge watch period						
1	68.70	4.39	6.55	16.10	0.54	3.73
2	67.90	3.94	6.95	17.30	0.64	3.27
3	70.20	4.32	8.76	12.10	0.88	3.79
4	64.90	7.07	11.40	9.01	1.35	6.19
5	63.40	6.25	8.35	15.30	1.07	5.59
6	58.80	5.12	11.40	18.50	0.88	5.31
Loading condition						
1	70.10	3.31	8.38	13.10	0.65	4.41
2	63.70	5.83	8.90	17.20	0.71	3.66
3	63.50	6.19	7.72	15.60	1.34	5.58
Day/Night condition						
1	67.60	6.23	9.62	10.70	1.07	4.76
2	65.40	4.09	7.72	18.00	0.66	4.11

4.1.3. True risk influence

Based on the probabilities presented in Table 4, TRI values were calculated for all RIFs with respect to the target node "Collision consequence." As shown in Table 5, the TRI results indicate that the contribution of RIFs to accident risk varies depending on the specific collision

Table 5
TRI of RIFs for collision consequences.

	C1	C2	C3	C4	C5	C6	Average
Fatality	27.60	4.96	1.52	19.82	1.00	3.31	9.70
Rank of OOW	18.30	3.28	4.48	10.13	0.61	3.06	6.64
Navigational status	17.05	3.63	4.92	4.35	0.87	3.36	5.70
Ship's speed	15.20	3.26	4.71	6.61	0.94	3.08	5.63
Injury	9.75	1.65	2.42	2.65	0.75	2.32	3.35
Voyage segment	11.20	3.00	4.52	9.43	0.32	1.39	4.98
Wind force	12.55	3.28	4.40	1.95	1.11	2.65	4.32
Date of collision	8.30	3.92	2.54	3.60	0.56	3.58	3.75
Ship's age	7.00	1.82	1.75	5.45	0.48	2.68	3.19
Gross tonnage	8.80	2.28	5.38	4.70	0.60	2.57	4.05
Collision situation	12.00	2.60	4.12	4.69	1.09	4.38	4.81
Ship type	9.80	2.29	4.07	5.05	0.40	2.20	3.97
Visibility	3.55	0.39	0.26	2.95	0.58	0.68	1.40
Bridge watch period	5.70	1.57	2.43	4.75	0.41	1.46	2.72
Loading condition	3.30	1.44	0.59	2.05	0.35	0.96	1.45
Day night condition	1.10	1.07	0.95	3.65	0.21	0.33	1.22

outcome. These findings indicate that collision accidents arise not from a single dominant cause but from the interaction of multiple operational and human factors. In particular, the high TRI values of variables such as OOW rank, navigation status, and vessel speed suggest that collision outcomes are largely shaped by bridge decision-making processes and operational navigational conditions.

Based on these TRI scores, the importance of RIFs for six collision consequences was ranked between 1 (most influential) and 6 (least influential), and the resulting hierarchy is summarized in Table 6. This ranking enables a systematic evaluation of the relative contribution of critical RIFs on collision consequence. The findings indicate that "Fatality" has a greater impact on collision consequences compared to other factors. In contrast, the lowest impact on collision consequences is associated with the RIFs "Visibility," "Loading condition," and "Day/Night condition." Overall, the ranking of the most influential factors is as follows: fatality, rank of OOW, navigational status, ship speed, voyage segment, and collision situation. This ranking further demonstrates that collision outcomes are influenced not only by environmental factors but also by the interaction between operational context and human factors. The prominent positions of variables such as navigation status and voyage segment highlight that the navigational environment and encounter conditions in which vessels operate play a significant role in shaping collision risk.

The TAN-based BN model developed in this study differs from previous global and regional models used in the analysis of ship collision accidents in several methodological aspects. Many studies in the literature have employed statistical regression models, event tree analysis, or conventional BNs to evaluate collision risk [9,30,33]. However, these approaches often represent the dependency structure among variables only to a limited extent or rely solely on specific regional datasets. The TAN structure used in this study provides the advantage of modeling not only conditional dependencies related to the target node but also secondary dependency relationships among risk variables. This feature allows the interactions among operational conditions, vessel characteristics, and human factors to be represented more realistically compared with the classical Naïve Bayes approach. Furthermore, the model was trained using a dataset covering different operational contexts on a global scale, and the situations of all vessels involved in the accidents were incorporated into the analysis. As a result, the findings are not limited to a specific geographical region but can be interpreted within a broader maritime operational context. In this respect, the proposed model offers a more comprehensive analytical framework than previous approaches in the literature, both in terms of representing interdependencies among variables and evaluating collision risk under different operational conditions.

Table 6
The most important RIFs for collision consequences.

	C1	C2	C3	C4	C5	C6
Fatality	1	3	5	2	6	4
Rank of OOW	1	4	3	2	6	5
Navigational status	1	4	2	3	6	5
Ship's speed	1	4	3	2	6	5
Injury	1	5	3	2	6	4
Voyage segment	1	4	3	2	6	5
Wind force	1	3	2	5	6	4
Date of collision	1	2	5	3	6	4
Ship's age	1	4	5	2	6	3
Gross tonnage	1	5	2	3	6	4
Collision situation	1	5	4	2	6	3
Ship type	1	4	2	2	6	5
Visibility	1	5	6	2	4	3
Bridge watch period	1	4	3	2	6	5
Loading condition	1	3	5	2	6	4
Day/Night condition	1	3	4	2	6	5

4.2. Model evaluation

4.2.1. Model correctness verification

To demonstrate that the model satisfies both axioms, the six most influential RIFs were considered as a variable set, and small changes were introduced to their prior probabilities. Given that the target node consists of multiple states, this study calculates the variation in probability values for each state. To verify Axiom 1 and Axiom 2, the prior probability of each influential RIF is cumulatively increased in 5% increments, and the resulting changes in posterior probabilities are observed. Taking "Structural damage (C1)" as an illustrative example, "Fatality" is first selected as the initial node. This sequential procedure is then applied to all six critical RIFs, Fatality, Rank of OOW, Navigation status, Ship's speed, Voyage segment, and Collision situation, and the cumulative updates for all six collision consequence categories (C1-C6) are presented in Table 7. The first column of Table 7 presents the original probabilities for each collision consequence, while subsequent columns display the cumulative updated values after each successive modification.

Within this framework, the continuous decrease or increase observed in the posterior probabilities of the class node in response to small increases or decreases in the prior probabilities of risk variables confirms the validity of Axiom 1. Furthermore, when the prior probabilities of RIFs were collectively increased by a small proportion (e.g., 5%), the occurrence probabilities of collision consequences under different states increased correspondingly, supporting Axiom 2. Overall, the obtained findings reveal that the proposed model complies with both Axiom 1 and Axiom 2, demonstrating the model's effectiveness.

The reduction observed in the single target node component "Structural damage (C1)" is primarily stems from conditional dependencies and class definitions in the BN. That is, +5% increases in RIFs often shift probability mass toward more severe combinations, which elevates combined outcomes while reducing the single "Structural damage" share.

4.2.2. Model predictive performance

To evaluate the model's predictive performance, 72 accident records (20% of the dataset) were randomly selected and used as the test dataset. Test results were presented in the form of a confusion matrix (Table 8). According to the confusion matrix, the overall accuracy of the model was obtained as 93.06% (67/72). As shown in Table 8, the model's prediction accuracy is 98.11% for C1, 75% for C2, 66.67% for C3, 80% for C4, and 100% for both C5 and C6. Minority classes C5 and C6 (0.82% and 4.36% of dataset, respectively) achieve 100% Recall and Precision.

Five predictive performance indicators for each collision consequence are presented in Table 9. The recall of the proposed BN model was calculated as 100% for C5 and C6. The precision value of the model reached 100% for C2, C3, C5, and C6. To address class imbalance concerns, macro-averaged metrics were calculated following recent BN-based accident prediction studies [57]. The macro-averaged F-measure score of 0.887 indicates balanced performance across all six consequence categories, complementing the overall Accuracy of 93.06%.

While the model achieves 100% prediction accuracy for C5 and C6, it is important to note that these results are based on limited test samples ($n = 1$ each for C5 and C6; $n = 4$ for C2). Therefore, statistical generalizability for these severe collision consequences is constrained. The model's reliability for minority classes should be interpreted cautiously, with emphasis placed on macro-averaged metrics that provide balanced evaluation across all outcome categories.

The F-measure values exceeded 0.8 for all collision consequences. As a general rule, a higher specificity value indicates better model performance, while a lower FPR is desirable. According to Table 8, the specificity values of all collision consequences were above 90% (except C1), and the FPR values were below 10% (except C1). The comparative results of the five-performance metrics further demonstrate that the constructed BN model exhibits strong predictive capability and high

Table 7
The analysis result of minor changes in RIFs for all collision consequence categories (C1-C6).

Risk variables	Percentage change						
Fatality		+5%	+5%	+5%	+5%	+5%	+5%
Rank of OOW			+5%	+5%	+5%	+5%	+5%
Navigation status				+5%	+5%	+5%	+5%
Ship's speed					+5%	+5%	+5%
Voyage segment						+5%	+5%
Collision situation							+5%
Collision consequences	Initial probability	Changed probability					
C1	66.20	66.00	65.78	63.63	65.51	65.41	65.33
C2	4.90	5.04	5.15	5.24	5.31	5.36	5.40
C3	8.45	8.55	8.62	8.68	8.73	8.76	8.79
C4	15.30	15.58	15.80	15.97	16.10	16.19	16.26
C5	0.82	0.86	0.88	0.90	0.91	0.92	0.93
C6	4.36	4.50	4.63	4.77	4.86	4.93	4.98

Table 8
Confusion matrix of the predicted results.

Predicted	C1	C2	C3	C4	C5	C6	Actual total	Accuracy rate (%)
C1	52	0	0	1	0	0	53	98.11
C2	1	3	0	0	0	0	4	75
C3	0	0	2	1	0	0	3	66.67
C4	2	0	0	8	0	0	10	80
C5	0	0	0	0	1	0	1	100
C6	0	0	0	0	0	1	1	100
Total	55	3	2	10	1	1	72	93.06

Table 9
Performance results for each collision result.

	C1	C2	C3	C4	C5	C6 Macro-averaged
Recall	0.911	0.750	0.667	0.800	1	1 0.854
Precision	0.9455	1	1	0.800	1	1 0.946
F-measure	0.9630	0.8571	0.800	0.800	1	1 0.887
Specificity	0.8421	1	1	0.9677	1	1 0.968
FPR	0.1579	0	0	0.0323	0	0 0.032

reliability for overall classification performance (macro-averaged F-measure = 0.887), with the caveat that validation for rare catastrophic outcomes requires additional data.

4.2.3. Model consistency verification

According to the confusion matrix in Table 8 and Eq. (17), the expected agreement value was obtained as $p_e = 0.586$, while the observed agreement (overall accuracy) was calculated as $p_o = 0.931$. Substituting these values into Eq. (16), the Kappa coefficient was calculated as 0.832. According to the conventional interpretation scale, a kappa value in the range [0.81, 1] indicates that the model is considered "almost perfect." Accordingly, this validation reveals that the proposed model provides a high level of consistency. The Kappa coefficient ($\kappa = 0.832$) provides a conservative reliability estimate that is robust to class distribution skew, as it adjusts for chance agreement [37].

The multi-dimensional validation framework, including axiomatic correctness verification, Cohen's Kappa ($\kappa = 0.832$), and real-case verification (91.0% accuracy), mitigates overfitting concerns by validating model structure and generalizability beyond the confusion matrix.

4.2.4. Real case verification

The accident was simulated using the constructed BN-based risk prediction model, and details are illustrated in Fig. 6. When accident details were selected on the network constructed from the dataset, the model correctly predicted the accident outcome with a high consistency rate of 91.0%. The risk factors identified in the examined accident report were used as input data for the model, and the model output was validated by comparing it with the collision consequence specified in the same accident report.

This real case analysis further validates the reliability and robustness of the developed risk analysis model. Moreover, the risk model presented in this study can serve as a predictive tool; it can provide valuable insights and effective preventive measures for the mitigation of future collision accidents. The model constitutes a proactive tool that can be confidently used to prevent the recurrence of similar accidents by offering timely intervention opportunities, particularly when high probability values are calculated and detected in advance.

Another important advantage of the proposed model compared with many collision analysis models in the literature is that it not only identifies statistical relationships among risk factors but also enables scenario-based inference. Unlike regression or deterministic risk models, BNs allow the probabilities of all variables to be dynamically updated when observed evidence is entered into the network. The combination of TAN's structural simplicity and Bayesian smoothing ensures that high-dimensional nodes do not drive the model toward overfitting, as corroborated by robust test-set and real-case validation metrics. This capability makes it possible to analyze how collision risk changes under different operational conditions and to identify potential high-risk combinations of factors. Therefore, the proposed TAN-BN model can be used not only as an analytical tool for explaining past accidents but also as a decision-support tool capable of evaluating potential risk scenarios by considering variables such as vessel types, navigation patterns, and voyage conditions.

4.3. Scenario analysis

Scenario analysis examines how different collision consequences are influenced under specific conditions by adjusting the states of the relevant nodes. By analyzing selected critical scenarios, it becomes possible to identify the risk levels associated with various collision consequences, specific situations, and combinations of multiple RIFs. This approach provides valuable support to maritime authorities in developing informed and effective strategies for accident prevention. Scenario analysis is particularly important for evaluating the combined effects of different operational and environmental factors. In real maritime operations, accidents rarely result from a single factor; rather, they typically occur due to the simultaneous interaction of multiple risk variables. Therefore, this approach enables a more comprehensive understanding of the mechanisms underlying collision accidents.

With the activation of the Most Probable Explanation (MPE) function, the belief-bar of each variable is scaled such that the most probable state reaches the 100% level, and typically these bars are observed to be at lower levels in some RIFs. This situation reveals the most likely configuration by taking as basis the state where the bar appears at the 100% level for each variable. Shorter bars indicate that the relevant

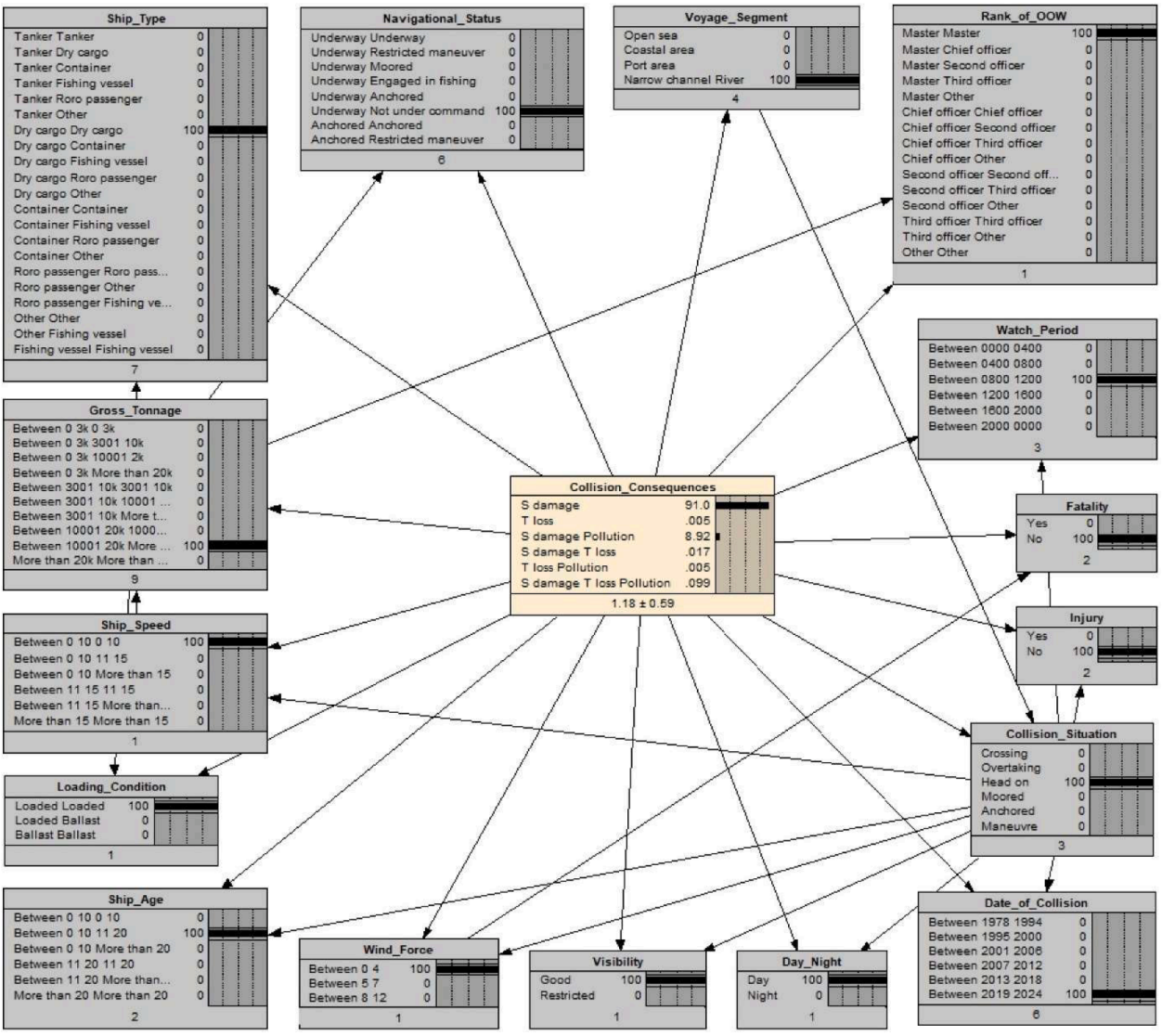


Fig. 6. Real case verification network structure.

state has a relatively lower probability when other variables are in their most probable configuration. Additionally, all belief bars are scaled using the same normalization factor applied to elevate the longest bar to the 100% level.

This section employs two distinct analytical approaches that yield different interpretive results. Scenarios 4.3.1 and 4.3.2 utilize the MPE function available in Netica software. The MPE algorithm identifies the single most likely joint configuration of all parent and child variables given a specified target node state. In MPE outputs, belief bars are scaled such that the most probable state for each variable reaches 100%, with other states displayed proportionally. Consequently, the probabilities shown do not represent normalized distributions (i.e., they do not sum to 100% across states), but rather indicate the relative likelihood of each variable's states within the most probable global explanation. This approach is particularly valuable for identifying high-risk combinations of factors that collectively maximize the probability of a specific outcome.

In contrast, Scenario 4.3.3 employs traditional Bayesian inference, where specific evidence is entered into selected nodes (e.g., adverse weather conditions), and the network propagates these observations to compute updated posterior probabilities for all other variables. In this approach, all probability distributions remain properly normalized (summing to 100%), reflecting standard conditional probability calculations given the observed evidence.

It is important to clarify the distinction between MPE and traditional probabilistic inference in BNs. MPE determines the most likely combination of variables for a given outcome, highlighting the dominant factor configuration. In contrast, traditional inference calculates conditional probabilities based on observed evidence and shows how specific conditions influence risk levels. These approaches are complementary: MPE identifies the most likely overall scenario, while standard inference explains how individual factors affect the outcome.

4.3.1. Scenario one: most probable scenario network for the worst collision consequence

The worst-case scenario, where all three collision consequences are observed together, was determined as the most probable scenario for a collision accident by setting the probability of the target node to 100% and activating the MPE function. This configuration represents the most probable scenario for a collision accident under the most severe conditions. The node corresponding to the worst-case scenario, together with the associated most probable states of the RIFs in the network, is illustrated in Fig. 7. Collisions involving Dry cargo-Ro and Dry cargo-Container vessels exhibit the highest risk levels.

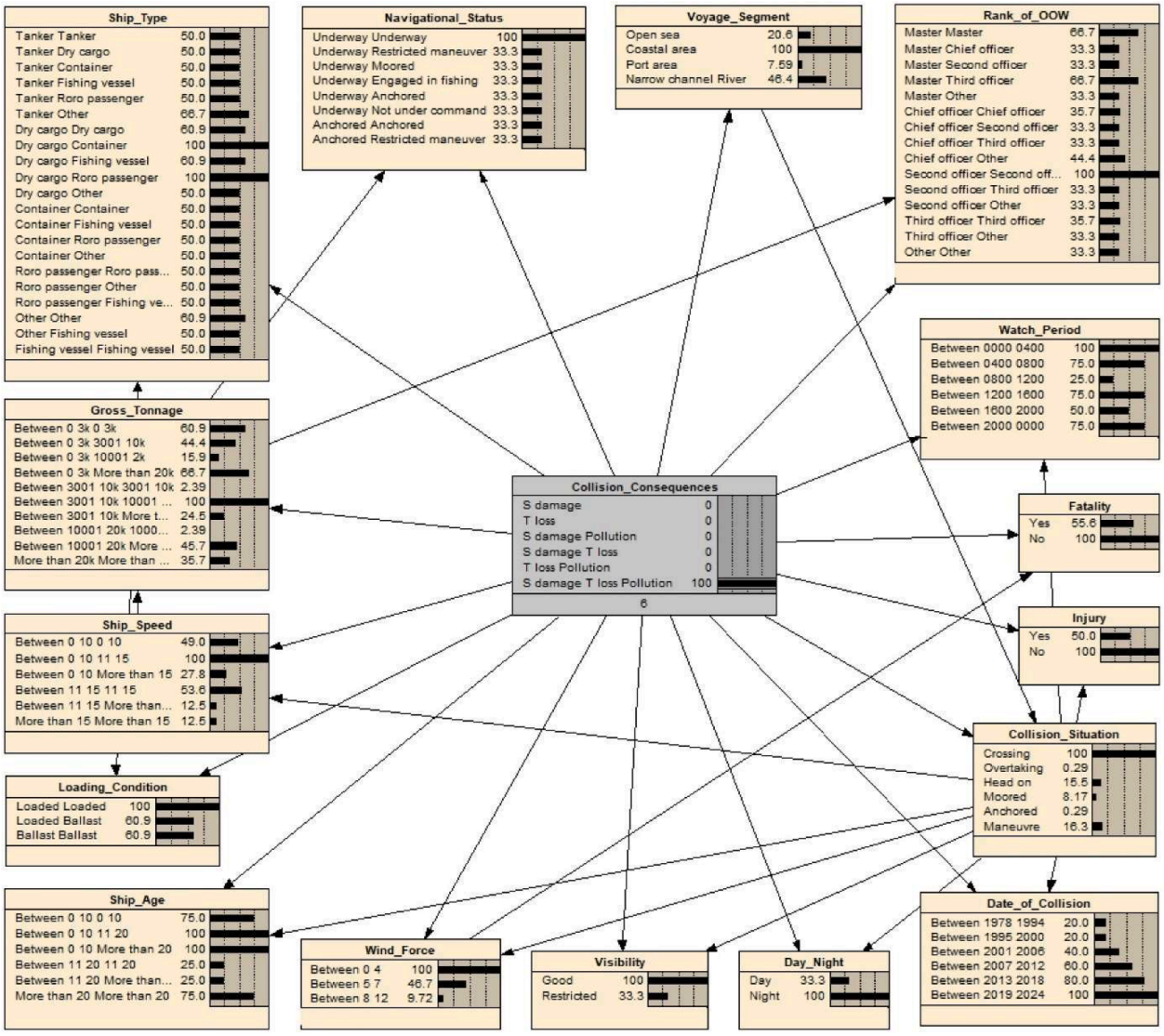


Fig. 7. Most probable scenario network for the worst collision consequence.

(1) Colliding ships with gross tonnages between 3001–10,000 GT and 10,001–20,000 GT, speeds between 0–10 and 11–15 knots, both laden, ages 0–10 and 0–10 or 0–10 and over 20, and both vessels underway are most prone to collision accidents with the worst outcome.
(2) The likelihood of the worst collision consequence is further increased when accidents occur in coastal waters, under wind conditions of 0–4 Beaufort, with good visibility, and during nighttime.
(3) The highest risk observed when 2nd Officers are on the bridge of both vessels, during the 0000–0400 watch, and the vessels are in a crossing situation.

These findings offer valuable insights for relevant authorities: fatal accidents are more likely to occur in conjunction with structural damage and total loss outcomes when both vessels are underway, collisions take place during nighttime watches, visibility conditions are good, and crossing situations are present simultaneously.

These findings are also consistent with collision risk patterns reported in the literature. Previous studies have shown that collision accidents are more likely to occur particularly in coastal waters, high-traffic areas, and during nighttime operations. In addition, human-factor-related errors such as maneuvering mistakes, violations of COLREGs, and loss of situational awareness by bridge teams have been emphasized as important contributors to severe collision outcomes [40, 62]. Similarly, decision-making errors of bridge teams combined with challenging operational conditions have been identified as critical factors increasing the severity of collision accidents [30,63].

4.3.2. *Scenario two: most probable scenario network for the least collision consequence*

The most probable situations for accidents with structural damage, representing the least severe scenario in the network, the most probable conditions are illustrated in Fig. 8. In this scenario, the probability value for the structural damage category was set at 100%, and the MPE function was activated. An examination of the nodes that most maximize the structural damage outcome, which represents the collision consequence with the lowest impact, the highest risk lies in collisions between dry cargo and fishing vessels. The impact of collisions between these two vessel types is minimized under the following conditions:

(1) Regarding vessel characteristics: gross tonnage ranges of 0–3000 GT and above 20,000 GT, vessel speeds of 0–10 and 11–15 knots, one vessel is laden while the other is in ballast condition, both vessels are aged between 0–10 years, and both vessels are underway;

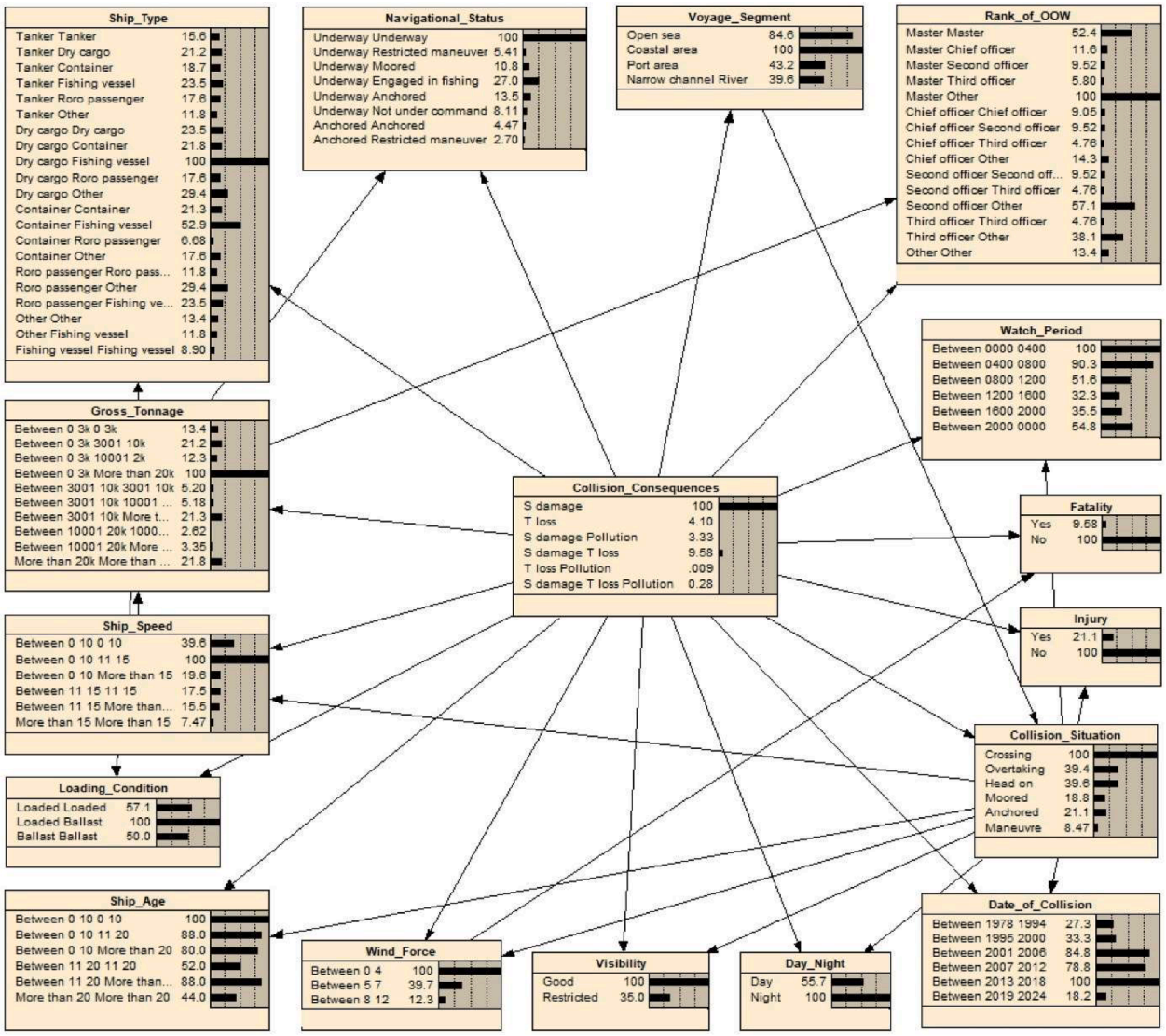


Fig. 8. Least probable scenario network for the worst collision consequence.

(2) Regarding environmental conditions: wind force is in the 0–4 Beaufort range, visibility is good, nighttime operation, and navigation within coastal waters;
(3) Regarding operational conditions: the presence of a master on the bridge of one vessel and other bridge personnel on the other vessel, during the 0000–0400 watch period, and in a head-on encounter situation.

A comparison of the nodes causing collision consequences with the lowest and highest impacts, the primary distinction between the two lies in gross tonnage, loading condition, and bridge personnel. No significant differences are observed among the remaining nodes.

These results are also consistent with the collision accident characteristics reported in the literature. Previous studies have indicated that collisions involving smaller vessels or fishing vessels often result in limited structural damage, and that vessel characteristics and operational conditions significantly influence the severity of collision outcomes [64,65]. Furthermore, effective communication between bridge teams and proper lookout practices have been highlighted as critical factors in reducing the severity of accident consequences [30,66].

4.3.3. *Scenario three: adverse weather scenario network for the collision consequence*

The model assessment in terms of adverse weather conditions is presented in Fig. 9. When nodes corresponding to adverse weather conditions are selected in the network, the probabilities of structural damage + total loss (15.3%→26.6%) and structural damage + total loss + pollution (4.36%→6.92%) collision consequences increase by over 50% compared to the initial state. Collision accidents occurring under adverse weather conditions are predominantly observed during nighttime watch periods.

Adverse weather conditions have also been widely reported in the literature as factors that increase both the likelihood of collision accidents and the severity of their outcomes. In particular, restricted visibility, severe weather conditions, and complex navigational environments are known to complicate the decision-making processes of bridge teams, thereby increasing collision risk [40]. In addition, previous studies have shown that the interaction of traffic characteristics, navigational behavior, and environmental conditions contributes to the formation of regions with a high risk of collision [30].

4.4. *Implications*

In the assessment conducted in terms of the years when accidents

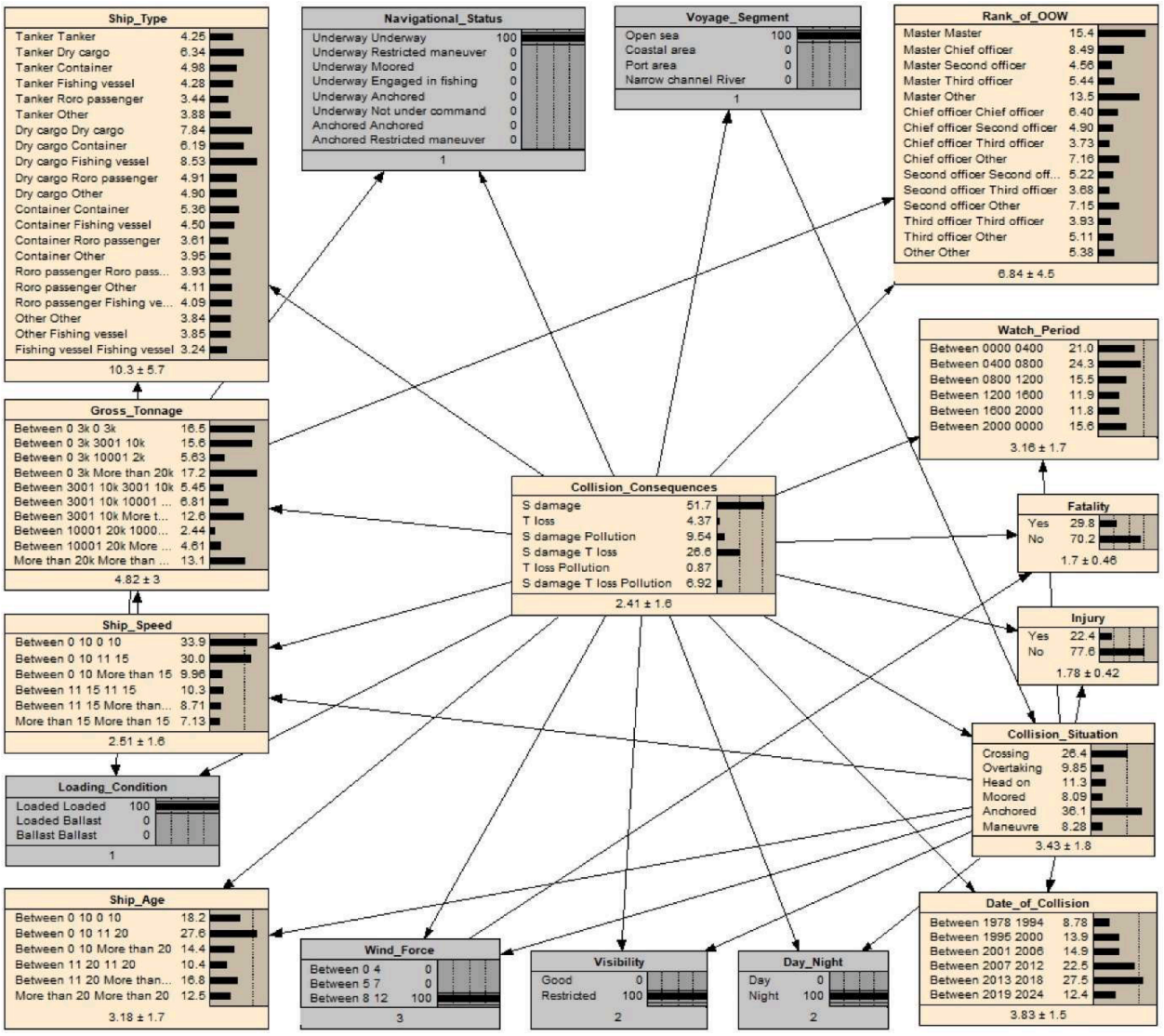


Fig. 9. Adverse weather scenario network for the collision consequence.

occurred, a notable improvement is observed in the impacts of accident consequences during the period between 1995–2000 (post- GMDSS). In contrast, during the 2001–2006 (post-AIS) and 2007–2012 (post-LRIT) periods, there is an increase in cases where the impacts of accident consequences are severe. A relative improvement in terms of the impacts of accident consequences was observed during the 2013–2018 period (post- BNWAS). However, between 2019–2024 (post-ECDIS), a significant rise has occurred in accident consequences with major impacts (Table 10).

In the proposed model, fatal accidents are most frequently associated with collisions between dry cargo vessels and fishing vessels. At this point, it should also be considered that the international regulatory framework for fishing vessels differs in several respects from that applied to commercial ships. Many international safety regulations and technological requirements, particularly those developed under the conventions of the IMO, primarily apply to large commercial vessels, while a significant portion of small-scale fishing vessels may fall outside the scope of these regulations [41,62,64]. For example, major safety conventions such as the SOLAS Convention and the STCW Convention mainly target commercial vessels, whereas a separate regulatory framework, the International Convention on Standards of Training, Certification and Watchkeeping for Fishing Vessel Personnel (STCW-F), has been developed specifically for fishing vessels. However, in many countries small-tonnage fishing vessels operate under national legislation and may not be required to carry AIS, ECDIS, or other advanced bridge systems. This situation indicates that operational, technological, and training-related differences between fishing vessels and commercial ships may influence the development of collision risk. Therefore, when interpreting the collision patterns associated with fishing vessels in this study, these regulatory and operational differences should also be taken into consideration.

Table 10
Probability values of collision consequences by periods.

Period \ %	C1	C2	C3	C4	C5	C6
1978–1994	55.39	10.90	10.80	13.26	1.60	8.05
1995–2000	70.29	6.02	7.09	11.70	1.03	3.87
z2001–2006	67.08	3.36	6.83	18.90	0.69	3.15
2007–2012	66.41	4.66	7.26	18.00	0.52	3.14
2013–2018	71.11	3.27	9.33	12.40	0.57	3.31
2019–2024	54.51	6.60	11.90	15.10	1.59	10.30

In terms of navigation status, collisions involving vessels that are both underway present the highest probability, accounting for 39.2% of fatal cases. In fatal collision scenarios, the combined probability that at least one of the vessels has a gross tonnage below 3000 GT is 57.02%. When weather conditions and fatal collisions are evaluated together, the

results indicate that such accidents occur with a probability of 61.8% under wind forces of 0–4 on the Beaufort scale, 68% under good visibility conditions, and 64.7% during nighttime operations. The total probability of the master being present on the bridge of at least one of the vessels is 40.62%.

The spatial distribution results obtained in this study largely correspond with the global maritime accident patterns reported in the literature. Previous studies have shown that maritime accidents tend to cluster particularly in coastal regions with dense vessel traffic, port approaches, and narrow waterways. For example, global Geographic Information System (GIS)-based analyses have identified areas such as the Chinese coasts, the seas surrounding the United Kingdom, and the Singapore–Malacca Strait as regions with high accident density [69]. Similarly, the seas of Northern Europe and the Far East have also been reported as regions with elevated accident risk [73]. Studies focusing on narrow waterways further demonstrate that geographical conditions, traffic density, and vessel operational characteristics play important roles in accident occurrence [74]. In addition, earlier research has emphasized that a large proportion of accidents occur within 20–30 nautical miles from the coast, and that collision and grounding accidents are particularly concentrated in these areas [69,73,74]. Nevertheless, the accuracy of geographical coordinates and the integrity of the datasets used in spatial analyses can significantly influence the results of such analyses [75]. More recent studies indicate that spatial patterns of accidents are shaped not only by geographical factors but also by the combined effects of seasonal variables, human factors, and operational conditions [76]. In this context, the global collision distribution identified in the present study supports existing findings in the literature that maritime accidents are strongly associated with high-traffic areas and complex navigational environments.

Overall, the findings indicate that operational conditions, human factors, and vessel characteristics jointly play a decisive role in the occurrence of collision accidents. Previous studies have shown that ship collisions typically arise from the interaction between operational conditions and human factors [30,59,64,74]. In the present study, in addition to these factors, the potential influence of the vessel type variable on collision accidents has also been examined and evaluated. Therefore, future accident prevention strategies should adopt a comprehensive approach that extends beyond purely technical or operational measures and also includes bridge operations, training programs, and traffic management practices.

From a theoretical perspective, this study offers a methodological contribution to the literature on the analysis of maritime accidents using DDBN models. In particular, the integration of a TAN-based structure with multi-layered sensitivity analysis enables a more systematic examination of the cause-effect relationships underlying collision accidents. From a practical perspective, the findings may contribute to the identification of critical factors that increase collision risk and support the development of risk mitigation strategies targeting these factors. Therefore, the proposed model approach provides a comprehensive analytical framework that can be applied to risk assessment and decision-support processes in maritime safety management.

The TAN-based BN model developed in this study also offers potential applications not only for analyzing collision risk but also as a decision-support tool in maritime traffic management processes. In particular, within Vessel Traffic Services (VTS) operations, AIS data and operational parameters, such as navigation status, voyage segment, vessel speed, vessel type, and environmental conditions, can be integrated into the model to generate probabilistic collision risk estimates for encounter situations between vessels. Such an approach may assist VTS operators in identifying high-risk traffic situations at an early stage and, when necessary, providing navigational advice or speed reduction recommendations to vessels. In this way, potential collision situations could be managed through early warning mechanisms. Furthermore, the high-risk variable combinations identified by the model may contribute to the development of risk-based traffic management strategies for regions with dense vessel traffic.

In addition, the findings of this study provide important implications for the development of training programs for bridge teams. The analysis results indicate that encounter situations such as crossing, head-on, and overtaking represent critical operational contexts in the development of collision risk. Moreover, combinations of variables such as vessel speed, voyage segment, and traffic density were found to significantly increase risk levels. These findings provide an important basis for reviewing the content of existing bridge team training and simulation-based training programs and enriching them with a risk-oriented approach. In particular, operational situations such as crossing encounters at high speeds, encounters occurring in restricted navigation areas, and maneuvering decisions made under dense traffic conditions could be addressed more systematically within training curricula. Such data-driven improvements in training may enhance the situational awareness and risk assessment capabilities of bridge officers, thereby supporting safer and more effective decision-making processes during encounter situations.

4.5. Discussion

The majority of studies in the literature have not taken into account the entry-into-force dates of international rules and regulations when analyzing collision accidents. However, the systematic evaluation of the effects of IMO conventions and technological regulations such as Standards of Training Certification and Watchkeeping (STCW), Global Maritime Distress Safety System (GMDSS), Automatic Identification System (AIS), Long-Range Identification and Tracking (LRIT), Electronic Chart Display and Information System (ECDIS), Bridge Navigational Watch Alarm System (BNWAS), aimed at enhancing maritime safety on accident statistics is of critical importance for policymakers.

The findings of this study demonstrate that the use of the TAN structure in the analysis of ship collision accidents allows the conditional dependencies among risk variables to be represented in a more realistic and flexible manner. The results indicate that collision risk is shaped not by individual factors alone but by the interactions among multiple variables. This finding is consistent with results emphasized in recent DDBN studies. For example, the TAN-based model developed by Cao et al. [67] analyzed the effects of variables such as vessel type, engine power, and accident location on accident severity and revealed the multifactorial nature of collision risk. Similarly, Chang et al. [68] demonstrated that probabilistic relationships among weather conditions, vessel characteristics, and operational variables play an important role in explaining the mechanisms underlying accident occurrence. In addition, the studies of [37,69,70] presented data-driven risk assessments using BNs and Copula-based methods in specific navigational environments such as straits and channels, highlighting the importance of model–data relationships. The findings of the present study support these results and confirm that the TAN algorithm is an appropriate method for modeling complex causal relationships in maritime accidents. Furthermore, by applying the TAN approach to the evaluation of collision outcomes within an operational context, this study extends the methodological applications found in the existing literature.

One of the distinguishing aspects of this study is that the proposed model is evaluated within a multi-layered sensitivity analysis framework. In many BN–based collision studies, the importance of risk factors is typically assessed using a single sensitivity measure. In contrast, this study simultaneously employs MI, joint probability, and true risk impact analyses. This approach allows not only the relative importance of risk factors but also their effects on different collision outcomes to be evaluated in a more comprehensive manner. Similarly, the study conducted by Li et al. [43] reported that the combined use of TRI and sensitivity analyses contributes to a more reliable determination of the relative importance of risk factors. However, the present study further contributes to the literature by integrating these analytical tools with the evaluation of collision outcomes within an operational context.

Another important result of this study is that DDBNs can be used not

only as explanatory tools but also as predictive tools in the analysis of maritime accidents. The study by Meng et al. [42] emphasized that combining physical knowledge with data-driven approaches can contribute to a more reliable identification of factors influencing collision accidents. Similarly, the TAN-based model developed by Qiao and Fan [71] demonstrated that BNs can be used as decision-support tools in maritime safety studies by analyzing the relationships between human–machine interaction and operational factors. In addition, the studies of [60,72] showed that data-driven risk assessments using BNs can strengthen decision-support mechanisms in maritime safety applications, particularly in narrow waterways and high-traffic areas. The model developed in the present study further extends these approaches by incorporating scenario analysis and validation using real cases, demonstrating that BNs can provide both explanatory and predictive analytical frameworks.

Recent studies have emphasized that in DDBN models, the relationship between the model structure and the characteristics of the dataset used for training is critical for the reliability of the results. In particular, research in safety and risk analysis has demonstrated that the structural learning process of BNs is significantly influenced by factors such as data quality, sample size, and variable selection [67,71]. Similarly, studies examining global maritime collision risk using data-driven approaches have shown that the accuracy of model outputs depends on the representativeness of the dataset and the proper modeling of statistical dependencies among variables [27,36]. In this context, the accident dataset used in the present study, which covers a broad time period, together with the ability of the TAN structure to represent conditional dependencies, contributes to a more realistic explanation of collision risk. At the same time, this approach is consistent with recent literature demonstrating that DDBNs can be used as decision-support tools in maritime safety studies.

The spatial distribution of collisions in the present study is consistent with findings reported by Wang et al. [78] and Mou et al. [79], who identified the North Sea and the waters around the Korean Peninsula as global hotspots for maritime accidents, attributable to high traffic density and complex sea conditions. The predominance of coastal-area accidents (34.6%) aligns with the conclusions of Goerlandt and Kujala [80], who demonstrated that restricted-water environments significantly elevate collision risk due to reduced maneuvering margins. The share of narrow-channel/river accidents (23.3%) is similarly consistent with Bi et al. [76], who found that constrained waterways disproportionately contribute to collision frequency relative to their traffic volume.

5. Conclusion

The increasing volume of maritime transportation on a global scale and the progressively complex nature of operations necessitates the systematic handling of maritime accidents, particularly ship collision accidents involving multiple vessels that can potentially result in catastrophic consequences. This study emphasizes that collision accidents cannot be explained solely from a "single error" perspective; accidents mostly emerge as a result of the simultaneous accumulation and interaction of multiple factors. By addressing this reality, the research challenges the narrowly focused approaches frequently observed in the literature (predominantly human error-centered) and establishes the necessity of a more comprehensive and integrative analytical framework.

To investigate the influence of RIFs on collision consequences, this study develops a 17-node BN model based on the TAN structure. Model parameters were estimated using the counting-learning algorithm and CPTs were obtained for all nodes, and the relationships between the "Collision consequences" target node and RIFs were analyzed within a probabilistic framework. The findings demonstrate that, rather than focusing on isolated factors, a systematic assessment of both the relative importance of RIFs and their combined effects yields more informative and explanatory insights into collision accidents.

The implications of the study are significant on two levels. First, it is emphasized that most collision accident analyses in the literature do not consider the implementation timelines of international rules and regulations. However, the periodic and systematic evaluation of the effects of IMO conventions and technological regulations (STCW, GMDSS, AIS, LRIT, BNWAS, ECDIS) on accident consequences is of critical importance for policymakers. Indeed, temporal analysis reveals a marked improvement in 1995–2000 period (post-GMDSS), followed by an increase in severe outcomes during the 2001–2006 (post-AIS) and 2007–2012 (post-LRIT) periods, a subsequent improvement during 2013–2018 (post-BNWAS), and a notable rise in serious consequences during the 2019–2024 period (post-ECDIS). Second, the study identifies distinct patterns associated with fatal accidents including specific ship-type collision combinations; elevated probabilities under “vessel underway–vessel underway” navigation status; a high cumulative probability that at least one vessel involved in fatal collisions is below 3000 GT; combinations of wind force, visibility, and nighttime conditions; and the likelihood of the master being present on the bridge. These patterns have been shown to generate actionable signals for targeted safety assessments.

Furthermore, the study notes that existing BN-based collision research predominantly focuses on causal analysis, whereas systematic evaluation of the relative importance of risk factors from a network structure perspective remains limited. Some studies categorize RIFs in weakly representative binary formats (present–absent), and the effort to explain numerous accident types with limited data creates modeling constraints. By integrating RIF importance ranking methods (MI/TRI) with multifactorial analyses (joint probability and scenario analysis), this study offers a methodological contribution that addresses this gap in the literature.

Despite its contributions, this study has several limitations. The model evaluation was conducted using a single random 80/20 train-test split. Future work will incorporate k-fold cross-validation with multiple repetitions to further validate the robustness of findings across different data partitions, particularly for minority classes representing severe collision consequences. While, the TAN structure optimizes classification performance it does not capture causal relationships between RIFs and outcomes. Future studies may therefore consider hybrid approaches that balance predictive accuracy with causal interpretability. Additionally, future research should expand validation to multiple cases stratified by ship type combinations, consequence severity levels, and regulatory eras to strengthen generalizability.

Future research should focus on developing verifiable and updatable models that integrate human, technical, organizational, and environmental components within a unified framework to better explain collision accidents. Richer data architectures that combine accident reports with operational data sources such as AIS, VDR, meteorological data, traffic density indicators, and maintenance records will both enhance causal analysis accuracy and provide a more robust foundation for proactive risk management (early warning/preventive action). Additionally, testing the proposed frameworks through real-case analyses and conducting comparative evaluations across different ship types and operational profiles will strengthen the reliability and applicability of the approach.

In conclusion, this study establishes that approaches aimed at reducing ship collision accidents must move away from one-dimensional explanations and be based on a system-based and holistic framework. The proposed TAN-based BN model emerges as a predictive tool that can quantitatively rank the relative importance of risk factors in collision accidents, interpret the impact of multi-factorial combinations on collision consequences, and demonstrate high reliability through performance metrics and real case validation. Considering that sustainable improvement in safety performance require a management perspective that centers on the human factor while also addressing technical infrastructure, organizational decision processes, and

operational–environmental conditions, the primary contributions of this study can be summarized as follows: (1) providing analytical support to decision-makers through prioritization of critical RIFs, identification of high-risk combinations, and temporal effects of regulatory interventions; (2) laying the groundwork for proactive safety practices by offering timely intervention opportunities when high probability risk conditions are predetermined; and (3) contributing to the development of more effective preventive strategies for reducing ship collision accidents.

CRediT authorship contribution statement

Hasan Uğurlu: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Özkan Uğurlu:** Writing – review & editing, Supervision, Investigation, Conceptualization.

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.

Data availability

Data will be made available on request.

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