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Research paper

Bulk carrier accident severity analysis in Australian waters using a data-driven Bayesian network

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A R T I C L E I N F O

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A B S T R A C T

Maritime accident consequences often entail substantial property losses, environmental contamination, and even loss of life. To investigate the consequences of maritime accidents in Australian waters, this paper develops a data-driven Bayesian network (BN) model with new features derived from a new accident database. The localised vital risk factors influencing bulk carrier safety in Australian waters are generated, which can help develop new measures for consequence mitigation. Compared to the previous relevant research, this article makes new contributions in that 1) manual analysis of each ATSB maritime accident report to formulate a new comprehensive database containing the key influential factors (IFs) influencing bulk carrier accident consequences. Maritime risk analysis and safety management suffer from insufficient accident databases and hence, this development will address the research gap and stimulate data-driven maritime risk analysis in future; 2) the development of a new data-driven BN model to investigate the accident consequences in Australian waters which attracts little attention compared to the other regions of high maritime traffic. The results aid in formulating a new baseline to benchmark Australian maritime accident consequences research; 3) the raw data is trained to configure and quantify the interdependence and dynamics of all the IFs. Given the country's crucial role in international dry bulk trade, this paper contributes to ensuring maritime safety from Australian national and global bulk carrier perspectives. The results reveal that the critical IFs are accident type, emergency handling, navigational condition, ship speed, visibility, safe act, time of the day, loaded or ballast condition, and lookout. Furthermore, the new BN can realise the real-time analysis of a ship's consequence severity in Australian waters and provide valuable insights for transport authorities to mitigate the consequences of accidents.

1. Introduction

Maritime accidents often cause serious consequences, posing significant threats to maritime industry safety. Lloyd's List Intelligence Casualty Statistics report shows that 26,707 maritime accidents occurred worldwide between 2012 and 2021, with an average of 2671 annually. Among the 26,707 accidents, 892 led to a total loss consequence, reaching an average of 89.2 per year (Allianz Commercial, 2022). Therefore, it is crucial to develop strategies to prevent them from happening or minimise their impacts.

The IFs, called root causes of maritime accidents, vary depending on ship types and geographical locations. For example, container ship accidents (Wan et al., 2022) are often caused by mechanical failure and human errors; general cargo ship accidents (Tunç et al., 2021a) are usually influenced by violating the Convention on the International Regulations for Preventing Collisions (COLREG) and communication failure; passenger ship accidents (Gundic et al., 2021) are highly associated with human errors; tanker accidents (Wang et al., 2022a) are mainly contributed by foundered or fire/explosion. Maritime accidents, such as Derbyshire (Editor, 2021) and Estonia (HISTORY, 2021), demonstrate that a single IF does not necessarily cause these disasters; two or more IFs are often involved, and so are their associated consequences. These situations imply the necessity of investigating maritime accidents, focusing on specific types of ships in particular regions to develop meaningful insights and prevention measures. Australia is the world's leading exporter of iron ore and met coal; nearly 60% of the

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global exported iron ore originates from this country (Salisu and Adediran, 2019). These mining cargoes (e.g., iron ore fines) are transported mainly by bulk carriers. However, the liquefaction of iron ore fines can make the bulk carriers easier to list, capsize, and thus become total-loss accidents; these accidents and subsequent consequences show unique risk characteristics on one hand, and vital research needs to address the high risk on the other hand (Munro and Mohajerani, 2015). It justifies the necessity and emphasises the novelty of this study. Furthermore, reports from the ATSB (https://www.atsb.gov.au/marine-investigation-reports) reveal that, as of 2022, 38% of maritime accidents in the past decade were bulk carrier-related accidents (see Fig. 1). Therefore, ensuring the safe operation of bulk carriers in Australian waters is crucial for the global iron ore trade and transportation.

Although maritime accident analysis studies are conducted in Europe (Montewka et al., 2022) (Jon et al., 2021), Asia (Xue et al., 2021) (Özaydı et al., 2022) (Hanafiah et al., 2022), Arctic waters (Kum and Sahin, 2015), and global waterways (Wang et al., 2021a) (Yildiz et al., 2021) (Chen et al., 2020a) (Wang et al., 2022b) (Zhang et al., 2021a). It does not reveal risk levels in international dry bulk trade. Given the crucial role of Australia in global bulk carriers, new solutions are needed to address dry bulk carrier accidents in Australian waters. This paper develops a new data-driven BN model to quantify the interdependence of IFs and analyses accident consequences in Australian waters, which serves as a baseline to benchmark Australian maritime accident consequences research.

The ATSB maritime accident reports are gathered to build a database supporting the development of a new BN risk analysis model. Statistical analysis of the raw ATSB data reveals the unique risk characteristics of bulk carriers in Australia that differ from those in other waters, which stimulates in-depth risk analysis using BN to generate new insightful findings beyond the state-of-the-art in the current literature. The main contributions are summarised below and detailed in the ensuing section.

- Manual analysis of each ATSB maritime accident report collected from 2000 to 2022 to formulate a new comprehensive database containing the key IFs influencing bulk carrier accident consequences that fit the need of this study. Maritime risk analysis and safety management suffer from insufficient accident databases (e.g. (Wang and Yang, 2018) (Li et al., 2023)) and hence, this development will address the research gap and stimulate data-driven maritime risk analysis in future;
- The development of a new data-driven BN model to investigate the accident consequences in Australian waters, which attracts little attention compared to other regions of high maritime traffic. The results will initiate a new baseline to benchmark Australian maritime accident consequences research in the future.

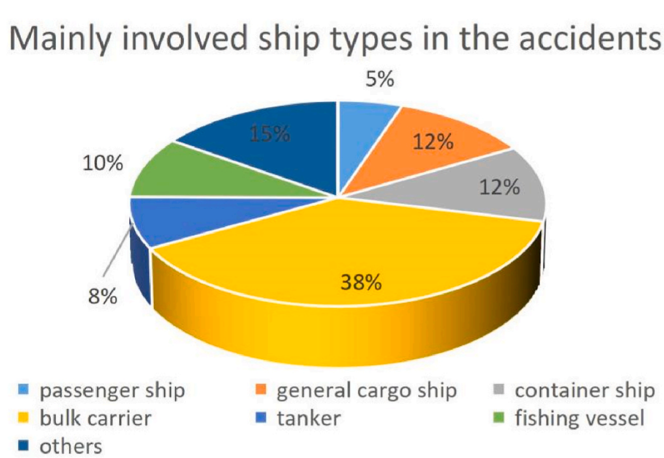

Fig. 1. Mainly involved ship types in ATSB accident reports.

- The raw data is trained to configure and quantify the interdependence and dynamics of all the IFs. As a result, the new BN can realise the real-time analysis of a ship's consequence severity in Australian waters. It can then help generate rational mitigation strategies and provide other valuable insights for enhancing the safety of bulk carrier transport in Australian waters.

The generic theoretical aspect of this study could be adapted to investigate maritime accident consequences of other ships in other regions and inspire effective risk control measures to ensure safety at sea as a whole. The rest of the paper is structured into five sections. Section 2 describes a review and summary of the pertinent literature. The research methodology is detailed in Section 3. Section 4 elaborates on the modelling process, the validation of the model, the results and findings, and the generated implications. Finally, Section 5 concludes the paper.

2. Literature review

This section conducts a systematic literature review from the perspective of maritime accident severity. Because of its bidirectional analysis abilities, BNs have been utilised in risk analysis-based studies, and their popularity is increasing, including maritime accident risks. According to accident causation theory, complex risk IFs trigger the happening of maritime accidents, and the accidents result in different severity of consequences. Therefore, the literature review of this paper highlights three parts: maritime accident risk analysis, BN-based maritime risk analysis, and maritime accident consequence analysis.

2.1. Maritime accident risk analysis

Many shipping companies witness different financial standings, significantly influencing their risk tolerance and the potential consequences of maritime accidents. Gucma and Androjna (Gucma et al., 2021) analyse maritime accidents through a causal-effect model and deliver a simplified model, resulting in an arguable accuracy. With a partial proportional odds logistic model, Chen et al. (2019) undertake risk analysis for total-loss maritime accidents. Similarly, Browne and Taylor (Browne et al., 2022) analyse the total loss of maritime accidents, specifically on Arctic shipping routes. Fu and Goerlandt (Fu et al., 2021) summarise the risk analysis related articles focusing on Arctic routes and identifying the related IFs. Ma and Deng (Ma et al., 2022) build a framework, combining an event tree, an improved K-shell algorithm, and a complex network to mine the IFs mechanism of maritime grounding accidents. Similarly, Chen and Pei (Chen et al., 2020b) analyse the human factor mechanism in maritime accidents using the reason-SHEL and the multidimensional association rule. Coraddu and Oneto (Coraddu et al., 2020) determine significant human factors contributing to maritime accidents. However, the results are arguable since there is evidence revealing that the related crew tends to conceal some information. Tzannatos (2009) and Paolo et al. (2021) focus on human factors influencing maritime accidents. Specifically, Uğurlu and Yıldırım (Uğ et al., 2015) concentrate on human errors related to grounding accidents. Kum and Sahin (2015) analyse the IFs contributing to accidents using a fuzzy fault tree model, revealing a significant IF of crew carelessness.

Various IFs trigger maritime accidents, and these IFs have garnered significant attention from scholars, leading to the publication of numerous related articles. Eliopoulou et al. (2016), Xu et al. (2019), and Yildiz et al. (2022) analyse maritime accidents using statistical methods but fail to identify interdependencies among IFs. Bye et al. (Bye and Almklov, 2019) (Bye and Aalberg, 2018a) utilise AIS data to investigate maritime accident characteristics without human-related IFs. Maya and Kurt (2020) determine IFs of bulk carrier accidents using Maritime Accident Learning through Fuzzy Cognitive Maps (MALFCMs), which largely rely on expert knowledge. Puisa and Lin (Puisa et al., 2018) analyse passenger ship accidents in the past ten years and reveal that the significant IF is the interaction between the navigators and shore-based supports. Wang et al. (2021a) utilise an ordered logistic regression model to mine the IFs contributing to the severity of maritime accidents. Weng et al. (Weng and Yang, 2015) use a regression model to analyse the world shipping accidents and determine the severity of maritime accidents. Bye and Aalberg (2018b) systematically analyse the IFs contributing to maritime accidents in Norwegian waters. Ship's type, length, and visibility are the identified critical IFs. In addition, Luo and Shin (2019) summarise the research status of global maritime accidents for the last fifty years. Kulkarni and Goerlandt (Kulkarni et al., 2020) conduct a literature review of shipping accident prevention for the Baltic Sea area.

The safe operation of bulk carriers significantly affects global maritime safety. Research (UNCTAD, 2023) shows that bulk carriers delivered 70.2% of global maritime trade in 2022. According to Tuncel et al. (Tunç et al., 2023), fire and explosion are the most frequent bulk carrier accidents. Besides that, collision and grounding accidents are also identified in (Tunç et al., 2021b) as frequent consequence types. Psarros and Vassalos (2010) focus on the foundering and sinking accidents in bulk carriers. Kretschmann et al. (2017) comprehensively analyse the costs of running an autonomous bulk carrier compared with conventional vessels and conclude that profitability is the primary consideration. Besides that, an auto-discharging bulk carrier shows differences from traditional bulk carriers regarding accident IFs (Agamy and Youssef (Agamy et al., 2022)). Regarding human error-related risks, Kaptan (2021) analyses bulk carriers involving steel cargo transport with a hybrid model to get the significant IFs. Nwigwe et al. (Nwigwe and Kiyokazu, 2022) conduct a systematic review of bulk carrier accidents, in which statistical analysis is performed.

Despite the significance of Australian waters in maritime activities, there is a noticeable lack of studies focusing on accident risk analysis in this region, particularly concerning bulk carrier accidents.

2.2. BN-based maritime risk analysis

The IMO has recognised BN modelling and intends to incorporate it into the formal safety assessment (FSA) (Yang et al., 2013). The advantages of its forward prediction, backward diagnosis, and ability to update the results when new information is available without significantly changing the original network make it popular in risk analysis applications. Zhang et al. (2016) focus on assessing the risks associated with maritime transportation at the Tianjin Port in China with a BN model. In addition, they (Zhang et al., 2018) also study collision accidents in the same area. Park et al. (2023) use a BN approach to determining the IFs of maritime cybersecurity. Wang et al. (Wang and Yang, 2018) develop an augmented BN (ABN) model to determine the IFs that influence the accident severity in China maritime transportation. Jiang and Lu (Jiang et al., 2020) use a BN-based model to conduct accident prevention analysis within the maritime Silk Road. Chang et al. (2021) utilise BN and evidential reasoning to develop an evaluation model to study the risks of Maritime Autonomous Surface Ships (MASS). Nonetheless, expert evaluation plays a pivotal role in the studies and arguably causes subject biases in finding accuracy.

To reduce the subjectivity of BN modelling, scholars have built new accident databases and developed data-driven BN models for improved results. Li et al. (2023) analyse the global maritime accident risks using a data-driven BN. Fan and Yang (Fan et al., 2022) build a TAN model to ultimately identify the critical IFs in confined waters. Similarly, Kamal and Çakır (2022) quantitatively analyse maritime accidents in the Istanbul strait with a TAN-BN model. To help the authority better allocate the PSC inspection, Yang et al. (2018a) collect the previous inspection data under the Paris MoU to develop a data-driven BN model to figure out the critical IFs for PSC inspections and calculate the detention rate. Wang et al. (2021b) disclose the most significant IFs contributing to port state control (PSC) detention are the ship safety status. By collecting numerous tankship accidents as a database, Sevgili et al. (2022) propose a data-driven BN to analyse the oil spill occurrences.

The above analysis reveals that BN modelling's powerful ability in safety science makes it popular in various applied fields, including canal/strait traffic risks, PSC inspections, and oil spill risks. Comparatively speaking, few studies have been conducted to analyse the consequences of bulk carrier accidents, and fewer have been conducted in Australian waters.

2.3. Maritime accident consequence analysis

While maritime accident risk analysis is relatively common, consequence analysis is less prevalent and relatively scarce. Maritime accidents can trigger catastrophic consequences such as loss of life, property loss, and environmental damage. Therefore, research in this field is vital to maritime safety. Furthermore, many maritime accidents are often followed by secondary and even tertiary accidents, exacerbating the situation. According to the statistical analyses from IMO, European Maritime Safety Agency, and Allianz Global Corporate & Specialty, only an initial accident is typically counted; subsequent accidents are considered a consequence. Suppose accident risk analysis aims to prevent or reduce accidents, thereby establishing the primary safety barrier (s). In that case, accident consequence analysis aims to devise optimal mitigation strategies to minimise human or property losses, effectively forming the secondary safety barrier(s). Siddiqui and Verma (2013) propose an assessment method to analyse the consequences of an oil spill accident. They found that a short route did not necessarily lead to a less severe consequence. Expert knowledge is required since a single accident can lead to multiple consequences, e.g., ship damage and oil spill. Pitblado et al. (2005) focus on the consequence severity of LNG carrier accidents. Wu and Yip (Wu et al., 2019a) use a BN model to analyse the consequences of maritime accidents; the mutual information and the belief bar are calculated from historical accident records. However, subjective judgments by expert evaluations are necessary for this approach. To help with emergency response handling, Li and Lu (Li et al., 2021) develop a decision tree model to analyse the IFs that contribute to accident consequences. Zhang and Wang (Zhang et al., 2019) use the statistical research method to determine the IFs contributing to the accident consequence. Wu and Tian (Wu et al., 2019b) utilise a BN model to analyse the consequence of collision accidents, and the BN structure is built based on expert judgments. Based on the statistical analysis, Ventikos et al. (Ventikos and Giannopoulos, 2013) develop a cost-benefit approach to quantitatively assessing the consequences of maritime accidents in Greece.

Previous studies on maritime accident consequences have employed different models and methods. Although distinctive insights have been generated, most studies rely partly or entirely on expert evaluations. Expert judgments can arguably introduce subjectivity and uncertainty (Li et al., 2023), which stimulates advanced methods and good improvement to address the possible subjective bias by expert knowledge or at least make it minimal. Data-driven BN can generate the research model and analyse results without needing expert subjective input, thus becoming a choice for maritime accident consequence analysis. On the other hand, the consequences of maritime accidents are associated with ship types and often show some unique characteristics. For instance, tanker accidents easily result in oil spill consequences, while gas carrier accidents are prone to explosion. Within this context, few articles in the literature have been found to analyse the consequences of bulk carrier accidents.

Further, many studies have been carried out to analyse the accidents in geographical areas, such as British waters (Chauvin et al., 2013), Istanbul strait (Aydogdu, 2013), Suez Canal (Fan et al., 2022), and China coastal waters (Liu et al., 2021), but yet Australian waters. According to the research (Wu et al., 2019a) (Wu et al., 2019b) (Aydogdu, 2013), location (i.e. geographical area) is an essential factor that can influence maritime accidents and their associated consequences. It is, therefore, necessary to conduct a study on the consequences of bulk carrier

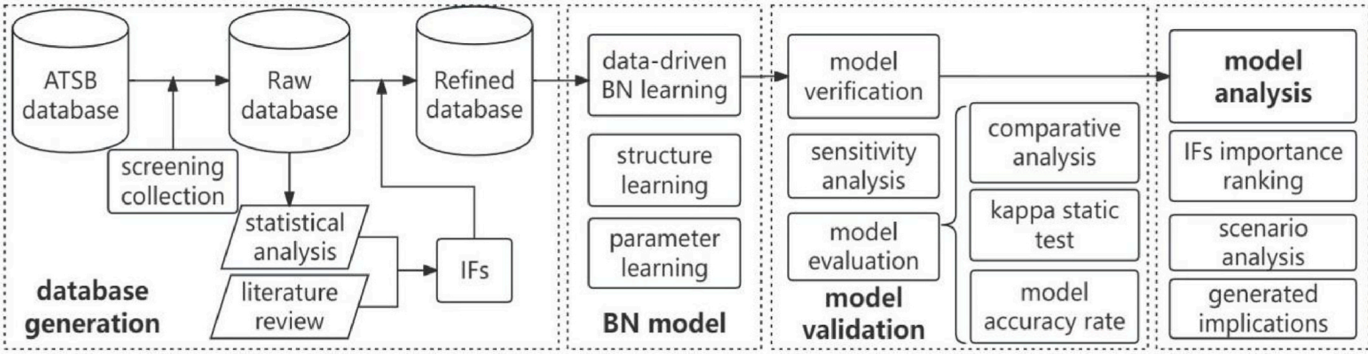

Fig. 2. The framework of BN modelling.

accidents in Australian waters.

3. Methodology

This section outlines the methodology, as shown in Fig. 2. First, all the accident reports relating to bulk carriers in 2000–2022 from the ATSB database are screened, and the relevant accident data are collected to form the raw database for model generation; secondly, with statistical analysis and literature review, the IFs and their states are identified; thirdly, based on the recognised IFs, the raw database is further refined; fourthly, with the refined database, the BN structure is constructed and the parameters of the nodes are determined through the data-driven learning process; fifthly, the model validation process is performed; lastly the analysis of the generated results and the implication output takes place.

3.1. Data collection

The data are collected from the ATSB maritime investigation reports (Atsb.gov.au, 2023) from January 2000 to December 2022. The ATSB database categorises accident reports into five states: pending, interim, preliminary, discontinued, and final. Only the final reports are considered, given the impact of information completeness in terms of identifying IFs. Only those classified as accidents, incidents, and serious incidents are included regarding occurrence categories. Following this filtering process, 189 reports involving 220 vessels were collected. The distribution of the 220 vessels is shown in Fig. 1. It indicates the involved ship types based on the collected accident reports. Bulk carriers hold the highest frequency, followed by container ships, general cargo ships, and fishing vessels. Therefore, it further justifies the choice of bulk carriers as the target ship type in this work. The final database has 80 accident reports involving 99 vessels. Fig. 3 depicts the distribution of these accidents. The 'collision' occupies the first position, followed by 'accident to person', 'grounding', 'fire/explosion', and 'mechanical failure'. Therefore, the accident type in this article is identified based on Fig. 3. Furthermore, the refined database is divided into two subsets at a ratio of 80:20: the training set (i.e. 64) and the test set (i.e. 16). The test set is reserved explicitly for model validation.

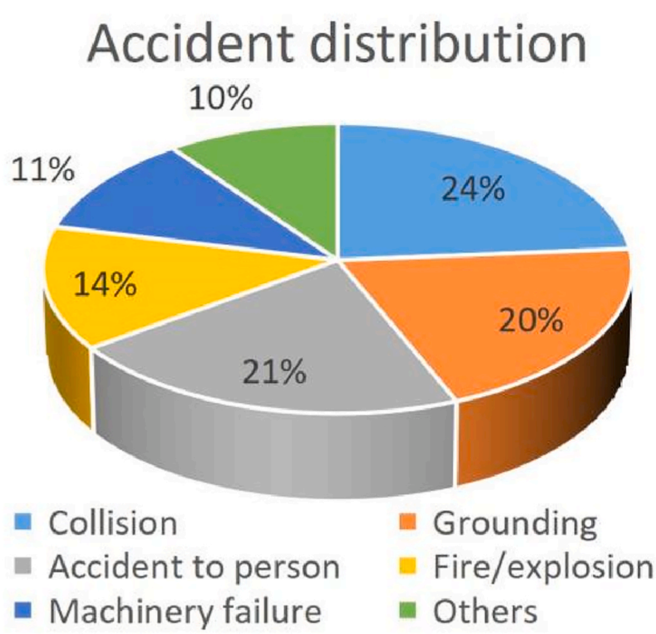

Fig. 3. The accident distribution of bulk carrier.

3.2. Identify the IFs

The IFs are identified through a two steps process: 1) screening the IFs from maritime accident reports and the literature review, as shown in the Appendix at the end of the manuscript; 2) selecting the significant IFs using the Chi-square test, which is a statistical test for determining relationships between variables. The key indicators for this Chi-square test are given as follows: dependent variable: consequence severity; independent variable: IFs from the Appendix table; sample size: 80; significance level: $p < 0.01$. The Chi-square test is performed through SPSS (version 29.0.1.0).

With the results of the Chi-square test, the IFs that exhibit substantial correlations with consequence severity are accident type (χ^2(15, 23.97, $p < 0.007$)), navigational condition (χ^2(20, 62.88, $p < 0.001$)), emergency handling (χ^2(6, 11.43, $p < 0.007$)), ship speed (χ^2(10, 26.91, $p = 0.003$)), time of the day (χ^2(5, 30.79, $p < 0.001$)), safe act (χ^2(5, 18.54, $p = 0.002$)), lookout (χ^2(5, 64.53, $p < 0.001$)), visibility (χ^2(5, 17.44, $p = 0.004$)), loaded or ballast condition (χ^2(5, 17.48, $p = 0.004$)).

The states of the IFs are determined based on the database in section

Table 1
Selected IFs.

NO.	IFs	States
1	Lookout	Proper, improper
2	Safe act	Yes, no
3	Loaded or ballast condition	Loaded, ballast
4	Navigational condition	Berthed, departure, sea passage, anchored, arrival
5	Visibility	Good, not good
6	Emergency handling	Good, bad
7	Ship speed	Safe speed, unsafe speed
8	Time of the day	Day (07:00/18:59), night (19:00/06:59)
9	Accident type	Collision, grounding, accident to person, fire/explosion, machinery failure, others
10	Consequence severity	Minor, significant, severe, catastrophic

Table 2
Navigational condition.

State	Description
Berthed	As per the practices of good seamanship, when the first mooring line fastens, the 'berthed' condition starts; when the last mooring line unfastens, the 'berthed' condition ends.
Departure	This condition starts from the last mooring line unfastens (i.e. the berthed condition end) and ends when the vessel exceeds the port limit.
Sea passage	This condition is between the 'departure' and the 'arrival'.
Anchored	This is a special condition, which could happen in 'departure', 'sea passage', and 'arrival' conditions, but not a part of them. If it is 'anchored' condition, the accident reports will specify it.
Arrival	This condition starts when the vessel enters the port limit and ends when the first mooring line fastens.

3.1 and the previous research (see Table 1). Regarding the time of the accident, research (Fan et al., 2022) (Li et al., 2021) defines the states as day (07:00/18:59) and night (19:00/06:59), irrespective of the season. So does this research.

The navigational condition of a vessel often correlates with its geographical location. Generally, a berthed vessel is typically found in a port, while a grounded ship is likely in shallow water. Rule 3 in COLREGs defines 'underway' as a vessel not at anchor or made fast to the shore or aground. However, 'underway' encompasses various conditions and lacks the specificity needed for defining the states of navigational conditions. A panel of experts, including a maritime risk assessment specialist, a maritime accident researcher, and an experienced shipmaster, were consulted to address this. Based on the operational procedures of commercial vessels, they recommended 'berthed', 'departure', 'sea passage', 'anchored', and 'arrival' as the states of the navigational condition, see Table 2.

The states of loaded or ballast conditions are determined based on a combination of expert advice and widely accepted industry practices. 'Loaded' and 'ballast' are essential conditions for commercially traded vessels.

Regarding ship speed, Rule 6 in COLREGs states that every vessel shall always proceed at a safe speed so that it can take proper and effective action to avoid a collision and be stopped within a distance appropriate to the prevailing circumstances and conditions. Consequently, this research prefers 'safe speed' over 'normal speed'. In addition to 'safe speed', 'unsafe speed' is another fitting state to demonstrate the situation when a ship breaches Rule 6.

Rule 5 in COLREGs defines lookout as every vessel shall at all times maintain a proper lookout by sight and hearing as well as by all available means appropriate to the prevailing circumstances and conditions to appraise the situation and the risk of collision fully. Therefore, the states of lookout can be given as 'proper' and 'improper'. It is noteworthy that Rules 3, 5, and 6 determine the states of relevant IFs. This does not imply the other rules in COLREGs are less critical; all the regulations in COLREGs are essential for ship safety.

Referring to articles (Kamal et al., 2022) (Met Office, 2021), visibility in maritime accident research has two states: not good (less than five nautical miles) and good (not less than five nautical miles).

According to the International Safety Management (ISM) code, every vessel shall have a safety management system. All the crew working onboard should comply with safe working practices and procedures. Therefore, it is considered safe when the crew complies with the ship's safety management system; otherwise, it is unsafe.

Table 3
Consequence severity.

Minor	Significant	Severe	Catastrophic
No fatality, single or minor injuries, local equipment damage	No fatality, multiple or severe injuries, non-severe ship damage, economic loss	Single fatality or multiple severe injuries, severe damage, big economic loss	Multiple fatalities, total loss of ship, huge economic loss

The IMO document (IMO, 2018) established guidelines for consequence severity, categorising states as minor, significant, severe, and catastrophic, as detailed in Table 3. Firstly, it clearly expresses human injuries and fatalities. If the accident report declares no fatality and only finds single or minor injuries, it is 'minor' severity; if multiple or severe injuries are found, it is 'significant' severity; similarly, the other severity can be determined. Secondly, the ship and its equipment should be considered if human injuries and fatalities are not involved. If the accident only involves non-critical equipment damage, e.g., lifeboat damage, fire pump damage, it is 'minor' severity; if the ship hull suffers damage, but is not severe (i.e. still seaworthy), it is 'significant' severity; if the ship hull suffers severe damage and lead to the ship being not in seaworthy condition, it is 'severe' severity; and when it becomes total loss of the ship, it is 'catastrophic' severity. Consequence severity is defined as a dependent node in the BN modelling. The change of IFs will affect the accident consequences, as further demonstrated in Section 4.

3.3. BN training-TAN

A BN is a directed acyclic graph formed by nodes and links. This research generates nodes through statistical analysis and literature review, while the links are generated through the TAN learning process. In terms of objectivity and reliability, the results generated by TAN show better consistency compared to the standard BN modelling methods such as the K2 algorithm, Naïve BN (NBN), ABN, Markov Chain Monte Carlo (MCMC) (Fan et al., 2022) (Sevgili et al., 2022) (Siddiqui and Verma, 2013).

TAN learning, introduced by Friedman et al. (1997), is considered an optimisation process; its outline and calculation procedures are initiated by Chou et al. (Chow and Liu, 1968). In this study, the optimisation aims to identify a tree that defines function π over $X_1, X_2, \ldots, X_n$ such that it maximises its log-likelihood. With this procedure, the TAN model is the target BN structure model. The Netica (Norsys Software Corp) is used to assist the BN modelling process (i.e. BN structure learning, conditional probability table (CPT) learning). For structure learning, the interrelationship of the IFs can be configured by learning the training dataset through TAN. After TAN learning, the obtained BN structure is thoroughly checked for rationality based on the ATSB accident reports, previous similar research (Kamal et al., 2022) (Fan et al., 2020b) and industrial standard practices. No change has been made in this research because of its reasonability. Three algorithms (counting, expectation maximisation, and gradient descent) are available for CPT learning. Fan et al. (2022) have outlined their characteristics. According to references (Fan et al., 2022) (Yang et al., 2018b), gradient descent is selected to perform this learning process to get the CPTs of all the IFs.

3.4. Model validation

3.4.1. Sensitivity analysis

The sensitivity analysis is used to examine the detailed results generated by the model and help to evaluate its rationality. Mutual information (MI) and True Risk Influence (TRI) (Alyami et al., 2019) are standard methods. MI can quantitatively measure the information one variable gets from another variable and thus examine their interdependence. The value of MI represents the relationship between the variables (i.e. IFs and consequence severity); a larger value means a stronger dependence or correlation. The calculation of an MI value is well documented in the literature (Li et al., 2023) (Fan et al., 2022) (Kamal et al., 2022).

The TRI analysis, introduced by Alyami et al. (2019), is also a sensitivity analysis. The TRI value represents the degree of effect that IF posed on the consequence severity. A larger TRI value tells a greater degree of influence that the IF has on the consequence severity.

Therefore, the value can help researchers screen out the most critical IFs contributing to certain consequence severity. The value of TRI is the average value of High-Risk Inference (HRI) and Low-Risk Inference (LRI). The HRI value can be obtained by setting the state of the selected IF, which has the most decisive influence on consequence severity (i.e. 'minor'), to 100%. The LRI value can be obtained by setting the state of the IF, which has the most negligible impact on 'minor', to 100%. The calculation of other corresponding TRI is similar until all TRI values are obtained.

3.4.2. Model evaluation

The model evaluation process involves comparative analysis, the D-separation method, the kappa statistic test, and scenario simulation.

This research database reveals a series of statistical results, which can serve as a benchmark for verifying the predicted results after learning the BN structure and parameters. The D-separation method in BN modelling is to decide the conditional independence relationships between nodes in the BN structure. It helps identify whether two nodes are independent or not. The Kappa statistic test calibrates the consistency between the results generated by the BN model and the actual statistical results. This consistency is quantified by the kappa coefficient, donated by *c:*

$$c = \frac{k_0 - k_e}{1 - k_e} \tag{1}$$

Where k_0 is the accuracy rate between the two results (generated result and actual result). k_e is the likelihood in the hypothesis. In this research, c can be calculated through Eq. (1). The k_0 value can be obtained when the predicted number is divided by the actual number of the test set. The k_e value takes more steps. Take 'consequence severity' as an example; the predicted number of 'minor' consequences multiplied by the actual number of 'minor' consequences, then divided by the number of the test set; the 'significant', 'severe', and 'catastrophic' are calculated similarly to get the sum result of all accident types, finally, the sum result is divided by the number of the test set to obtain the k_e value.

Scenario simulation is useful in verifying the proposed model. On the one hand, real accident scenarios help evaluate the developed model. On the other hand, it allows analysts to model different hypothetical scenarios by assigning specific values to the nodes, providing insights into predicting future accidents, and helping stakeholders understand potential consequences under various conditions.

4. Results, discussion, and analysis

4.1. Results of BN modelling

Fig. 4 demonstrates the results of the trained BN model. Regarding the accident type, 'collision' and 'accident to person' are the most frequent, accounting for 23.7% and 21.2%, respectively. They are followed by 'grounding', 'fire/explosion', and 'machinery failure'. This ranking of types shows consistency with the prior probability of BN, as shown in Fig. 3.

Regarding consequence severity, the most frequent severity level is 'minor', with a 48.7% occurrence rate. Only 3.75% of them occur with 'catastrophic' consequences. Concerning human-related factors, consequence severity is influenced by improper 'lookout' (38.3%), inadequate 'emergency handling' (80%), and 'unsafe acts' (38.3%).

4.2. Model validation

4.2.1. Sensitivity analysis

A sensitivity analysis is conducted to validate the model. Firstly, MIs between each variable and the consequence severity are calculated, as shown in Table 4. The IF 'accident type', with an MI value of 0.21609, has the highest correlation with consequence severity, followed by 'navigational condition', 'emergency handling', 'visibility', and 'ship speed'. In particular, 'emergency handling' significantly influences the target node 'consequence severity'. This finding further justifies its selection based on the Chi-square test.

Table 5 presents the TRI value (i.e., 12.5) of 'minor' consequence concerning 'navigational condition'. The data in the first row represents

Table 4
MI between the IFs and consequence severity.

Node	MI	Percentage (%)	Variance of Belief
Accident type	0.21609	13.0	0.02819
Navigational condition	0.09283	5.58	0.00787
Emergency handling	0.08656	5.20	0.02063
Visibility	0.04824	2.90	0.00460
Ship speed	0.04565	2.74	0.00722
Safe act	0.03199	1.92	0.00221
Time of the day	0.02257	1.36	0.00126
Lookout	0.00942	0.566	0.00008
Loaded or ballast condition	0.00446	0.268	0.00019

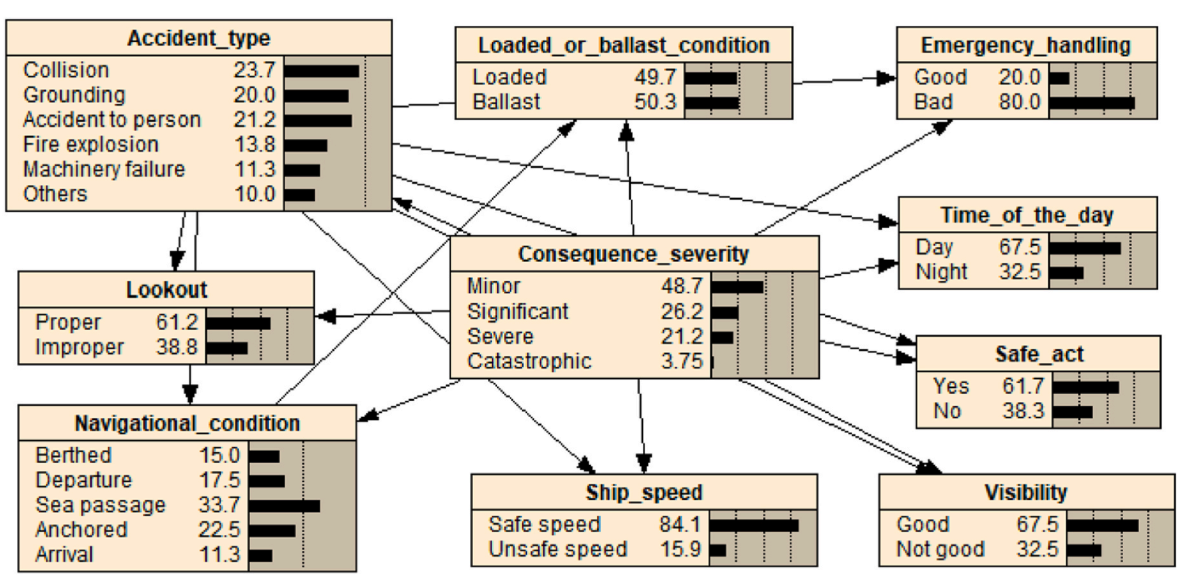

Fig. 4. BN modelling of bulk carrier accidents.

Table 5
TRI value between ‘navigational condition’ and ‘minor’ consequence.

Berthed	Departure	Sea passage	Anchored	Arrival	Minor	HRI	LRI	TRI
/	/	/	/	/	48.8	17.9	7.1	12.5
100%	0	0	0	0	41.7			
0	100%	0	0	0	57.1			
0	0	100%	0	0	44.4			
0	0	0	100%	0	44.4			
0	0	0	0	100%	66.7			

Table 6
TRI of IFs to all consequence severity.

TRI	Minor	Significant	Severe	Catastrophic	Average
Accident type	38.2	15.95	22.2	5.25	20.4
Navigational condition	12.5	11.6	11.23	3.57	9.725
Lookout	0.25	0.35	1.5	2.205	1.08
Time of the day	3.75	5.2	1.5	2.92	3.34
Ship speed	9.3	14.85	3.4	2.23	7.45
Emergency handling	20.2	8.6	9.38	2.35	20.27
Loaded or ballast condition	1.5	1.35	1.15	1.27	1.32
Visibility	7.6	9.05	1.35	2.78	5.20
Safe act	3.45	5.4	6.6	2.26	4.43

the initial state, while the subsequent rows indicate the values when each state of navigational condition adjusts to 100%. Moreover, Table 6 shows all TRI values for consequence severity. According to the explanation provided in section 3.4.1, ‘accident type’ appears as the most important IF for all levels of consequence severity (TRI value 38.2, 15.95, 22.2, 5.25, respectively). The IFs exert varying degrees of influence on different levels of consequence severity. Specifically, besides 'accident type', ‘emergency handling’ has the most decisive impact on ‘minor’ consequence (20.2); ‘ship speed’ contributes mainly to ‘significant’ consequence (14.85); ‘navigational condition’ has the most significant influence on ‘severe’ (11.23) and ‘catastrophic’ (3.57) consequence. Generally, for all levels of consequence severity, the most critical IFs are ranked as follows:

Accident type > emergency handling > navigational condition > ship speed > visibility > safe act > time of the day > loaded or ballast condition > lookout.

4.2.2. Model evaluation

The BN structure is evaluated as per Section 3.4. Table 7 shows the statistical data derived from the database alongside the predicted results from the TAN-learned BN. Overall, the table indicates a high level of consistency to substantiate the learned BN model, proving the model's accuracy. The occurrence rates of ‘collision’ and ‘machinery failure’ display a minor discrepancy of 0.3%. Similarly, ‘accident to person’ and fire/explosion’ differ by 0.2%, while ‘grounding’ and ‘others’ share the same probability in this comparative analysis.

D-separation is applied to investigate the correlations between any two BN nodes. For instance, given the evidence of the ‘consequence severity’ node, the connection between the nodes ‘ship speed’ and ‘lookout’ is independent. Consequently, they are D-separated (conditionally independent), aligning with the concept of D-separation with coherent links and directions. Following similar investigations across other nodes and links, confidence is gained to support the rationality of the BN structure.

Table 7
Results from the database and learned BN.

Accident type	Database (%)	Learned BN (%)
Collision	24.0	23.7
Grounding	20.0	20.0
Accident to person	21.0	21.2
Fire/explosion	14.0	13.8
Machinery failure	11.0	11.3
Others	10.0	10.0
Total	100	100

As demonstrated in Table 8, a confusion matrix is obtained with the test set. Each column represents the predicted accident severity given one certain severity type. The bold numbers indicate that the predicted accident severity matched the reality. Overall, the prediction accuracy is 87.5%, which is a satisfactory model result. Then, the kappa coefficient value can be calculated using Eq. (2) ~ (4).

$$k_e = \frac{(5 \times 5 + 5 \times 6 + 6 \times 5)}{16 \times 16} = 0.3320 \tag{2}$$

$$k_0 = 0.875 \tag{3}$$

$$c = 0.8129 \tag{4}$$

Refer to research (Fleiss, 1971) (Richard and Koch, 1977) (Liang et al., 2022), when the c value is within the range of [0.61 0.8], it indicates substantial agreement, while the range of [0.81 1] is close to perfect agreement. This study obtained a c value of 0.8129, showing a satisfactory agreement strength.

4.3. Implications

Implications are generated from analysing real case scenarios alongside the most probable (MP) scenarios. The trained BN structure is applied to a real accident case (MO-2021-004, released on September 19, 2023, not included in the initially formulated database). It is a type of ‘accident to person’ involving the bulk carrier ‘Formosa bulk Clement’, anchored five nautical miles east of Caloundra, Queensland, on August 9, 2021. Based on the information provided in the accident report, the incident occurred at approximately 18:38 local time. The ship was in a ballast condition, and the departing chief mate accessed the pilot ladder without the master's order.

Meanwhile, the master manoeuvred the vessel to provide a lee for chief mate disembarkation. This situation indicates that the departing chief mate acted unsafely. Additionally, according to the report, the master's view of the disembarkation position from the bridge was restricted because it was located on the ship's side. Fig. 5 illustrates the outcome of the investigation analysis for updating the states of nodes accordingly. The trained model indicates a high probability (84.7%) of ‘accident to person’ and a 64.4% likelihood of ‘severe’ consequences, consistent with the accident report's details. Meanwhile, it also reveals the high likelihood of ‘accident to person’ due to unsafe acts; the significant risk of ‘severe’ consequences is associated with poor ‘emergency handling’ during onboard operations. Hence, it is imperative to maintain safe working practices and ensure proficiency in emergency handling skills.

Unlike the MI and TRI, which only focus on the relationship between each IF and consequence severity, Fig. 5 demonstrates how multiple IFs can generate a combined influence on a plausible outcome. Furthermore, the proposed BN model allows for the flexible adjustment of the number of IFs to generate a combined effect. For instance, an accident case (MO-2022-002, released on March 22, 2023, excluded from the database) is applied to the BN model. It involved a collision between the

Table 8
The confusion matrix.

Predicted	Minor	Significant	Severe	Catastrophic	Actual total	Accuracy (%)
Minor	**4**	0	1	0	5	80
Significant	1	**5**	0	0	6	83.33
Severe	0	0	**5**	0	5	100
Catastrophic	0	0	0	**0**	0	100
Predicted total	5	5	6	0	16	87.5

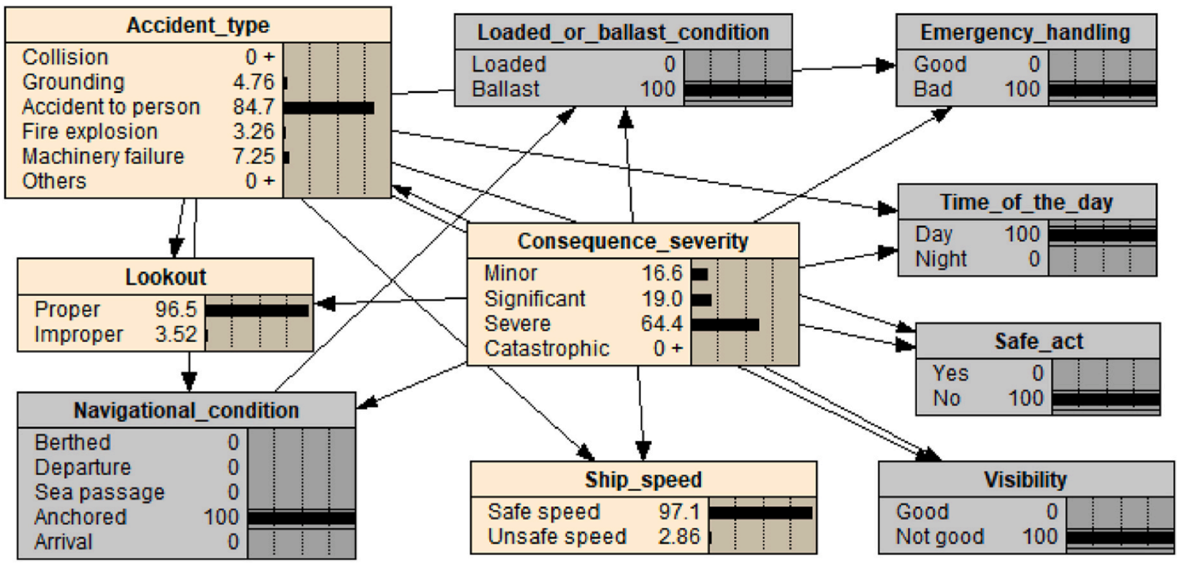

Fig. 5. Scenario A

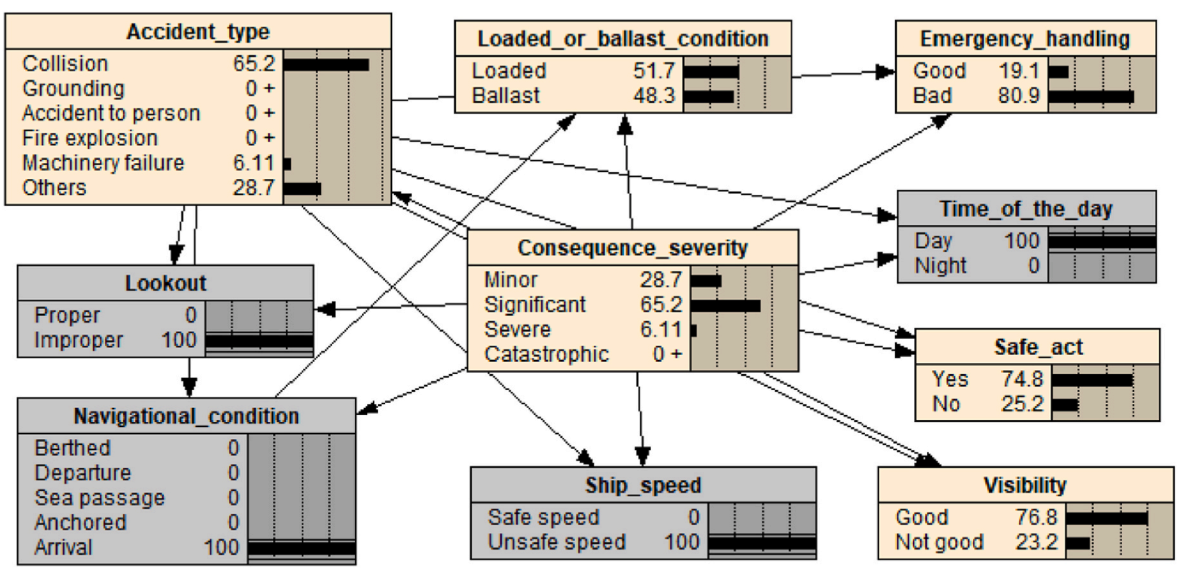

Fig. 6. MO-2022-002 (1).

bulk carrier Goliath and two tugs in Devonport, Tasmania, South Australia, on January 28, 2022. Some of the IFs' states can be inferred from the report, including:

(1) For the 'time of the day', 'day' is selected since the incident occurred shortly before noon. As for the 'navigational condition', 'arrival' is chosen as the vessel was within a port limit and manoeuvring for berthing, albeit not yet berthed.

(2) 'unsafe speed' is for ship speed because the bridge team could not halt the vessel upon observing the abnormal situation. Regarding 'lookout', 'improper' is selected because the bridge team failed to detect the abnormal condition promptly.

Fig. 6 displays the updated results, indicating a predictive probability of 65.2% for a 'significant' consequence. However, when the states of accident type (i.e. collision) are updated, as illustrated in Fig. 7, the results show a 100% probability of 'significant' consequence. It is noted

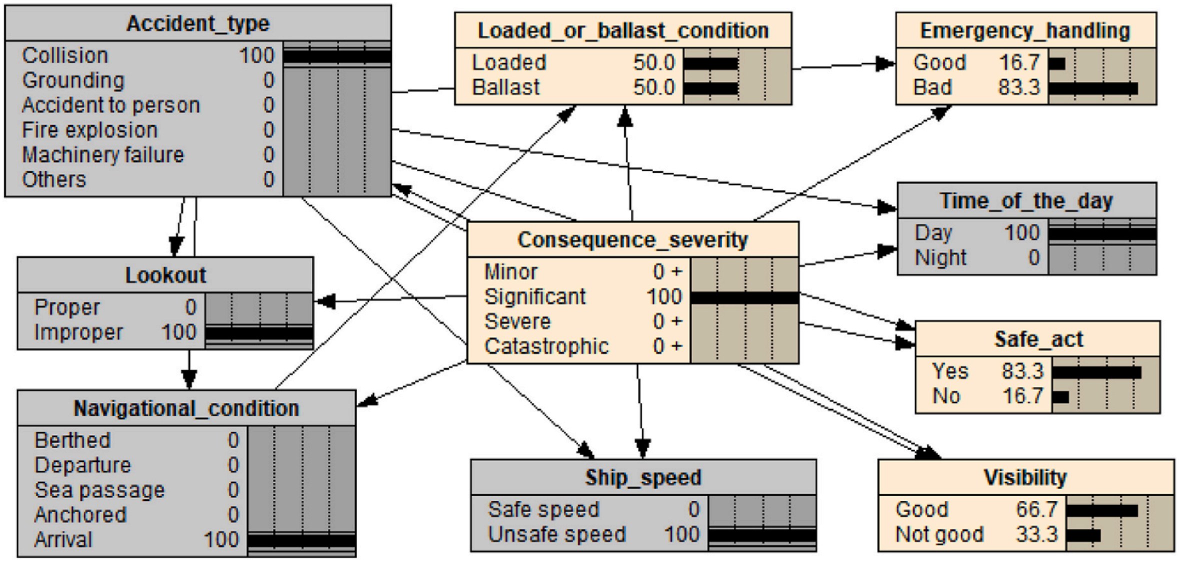

Fig. 7. MO-2022-002 (2).

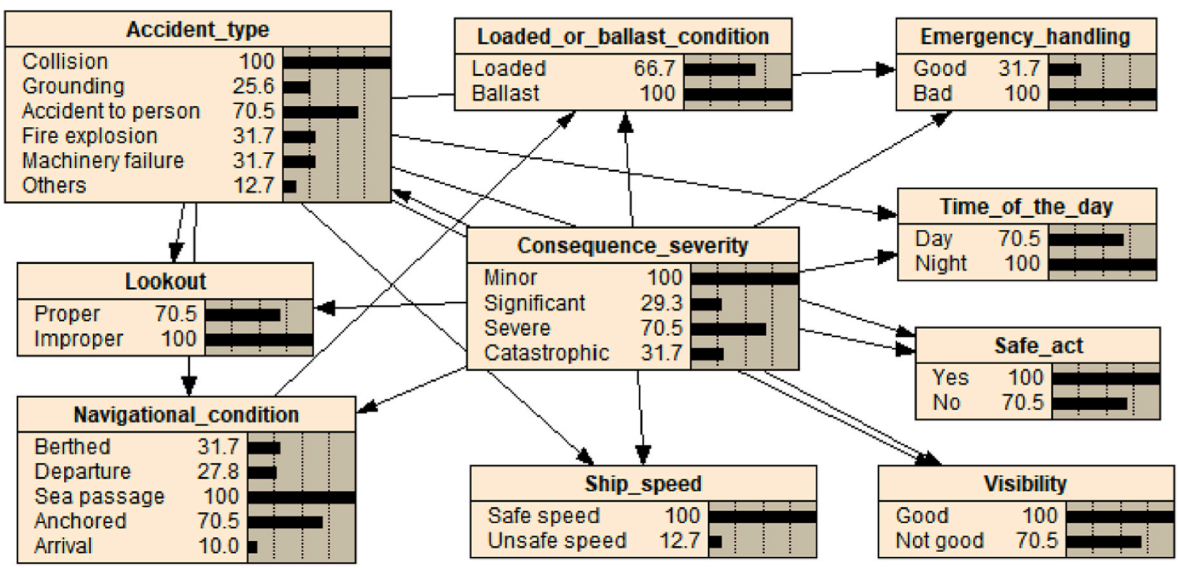

Fig. 8. MP explanation.

that the outcomes from Figs. 6 and 7 both align with reality. The prediction generated from flexible nodes' states remains reasonable in this scenario. This capability allows the proposed model to be utilised effectively in flexible situations. Not all BN model nodes are explicitly mentioned in every accident report; for instance, 'load or ballast condition' is not specified in the accident case (MO-2022-002). Utilising the proposed BN allows for probability explanations of the states of nodes of interest, even when data is incomplete.

Additionally, implications can be inferred from analysing the MP scenario, offering a plausible explanation for a specific level of consequence severity. Fig. 8 depicts the outcome of the MP scenario. Each IF is shown with one state at the 100% level, while others exhibit varying degrees of increase or decrease at lower levels. The bars at 100% represent the MP states of the IFs leading to a specific consequence severity. In contrast, the shorter bars denote the states of the IFs with low probability. In Fig. 8, 'minor' consequence severity is depicted as the MP outcome. All the IFs demonstrate their MP states leading to 'minor' consequence severity. Consequently, a 'minor' consequence severity is likely to occur under the following conditions:

(1) At 'night', with 'sea passage' navigational condition and 'safe speed', while the vessel is in 'ballast' condition.
(2) 'Good' visibility, 'improper' lookout, and 'yes' for safe act.
(3) In the event of a 'collision' for accident type, accompanied by 'bad' emergency handling.

The conditions outlined above disclose that some IFs (i.e. 'improper' lookout, 'unsafe act', 'bad' emergency handling) have significant interrelationships with accident consequences. Dangers can quickly arise through 'unsafe acts' and may go unnoticed due to 'improper' lookout. Moreover, 'bad' emergency handling can deteriorate the situation, significantly increasing the risk of accidents as reaction time is limited and emergency handling skills are lacking in the face of danger. It also aligns with the accident case (MO-2012-006) findings that lookout and emergency handling skills can be developed to help avoid collisions.

Furthermore, Fig. 9 demonstrates the types of vessels colliding with bulk carriers. Most bulk carrier collisions involve fishing vessels (61%) and recreational vessels (17%), while cargo ships account for only 6%. One possible explanation for this trend is that fishing vessels and

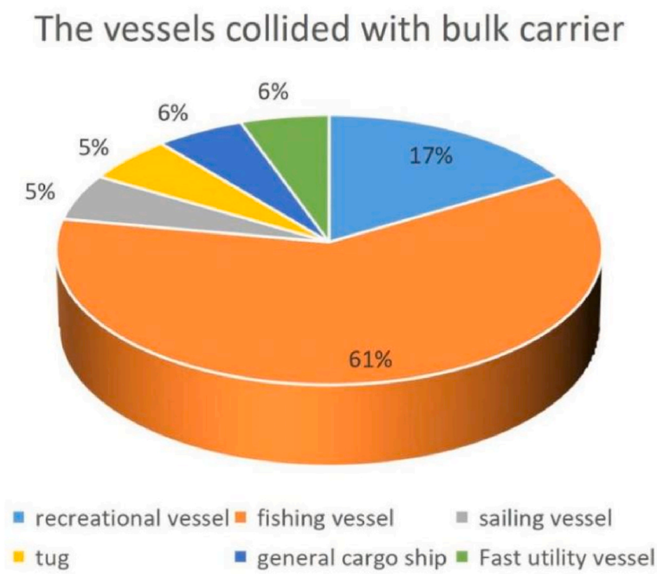

Fig. 9. The vessels collided with a bulk carrier.

Table 9
Most probable scenarios for all consequence severity.

IFs	Minor	Significant	Severe	Catastrophic
Accident type	Collision	Accident to person	Accident to person	Fire/ explosion
Navigational condition	Sea passage	Berthed	Anchored	Anchored
Lookout	Improper	Proper	Proper	Proper
Time of the day	Night	Day	Day	Day
Emergency handling	Bad	Bad	Bad	Bad
Ship speed	Safe speed	Safe speed	Safe speed	Safe speed
Loaded or ballast condition	Ballast	Loaded	Ballast	Loaded
Visibility	Good	Not good	Not good	Good
Safe act	Yes	Yes	No	No

recreational vessels are typically smaller, more challenging to detect, and may have limited manoeuvrability as reported in section 3.1, nearly all collision accidents share common IFs: improper lookout and poor emergency handling.

Furthermore, Table 9 demonstrates the most probable scenarios for each level of consequence severity. 'Significant' consequences are more likely to occur when an 'accident to person' occurs, mainly when the ship is 'berthed' and in a 'loaded' condition. These implications can assist port authorities in enhancing their safety management systems, particularly concerning emergency handling capabilities. They can also take measures to ensure the implementation of safe working practices.

'Severe' consequences often occur when 'accident to person' occurs, mainly when the ship is 'anchored' and in a 'ballast' condition. In such situations, the vessel is probably awaiting a berthing schedule. Certain high-risk deck operations (e.g., working aloft, working in an enclosed space) are typically conducted as routine tasks during this period. These tasks inherently pose a high risk of unsafe actions, potentially resulting in injuries or fatalities. Therefore, when crew members engage in these activities without adhering to safety protocols and with limited emergency handling capabilities, the likelihood of personal accidents significantly increases. Given the limited window for effective rescue, these incidents often have severe consequences. Such cases are illustrated in accident reports (e.g., MAIR 197_001, MAIR 201_001). Hence, deck work must strictly adhere to safe working practices, particularly for tasks with a high risk. A team leader should be designated for each operation, and a permit for dangerous work must be obtained. If feasible, constant supervision should be maintained to ensure safety.

'Catastrophic' consequences are commonly associated with 'fire/ explosion' accidents. A typical case is detailed in the accident report (MAIR174_001). The deck work team conducted painting operations in the No.1 port top ballast tank. However, the team did not follow the enclosed space entry permit requirements, e.g., the explosive vapour in the tank was not correctly measured, the ventilation was insufficient, and the blower used for ventilation was not explosion-proof. These unsafe events collectively contributed to the occurrence of the explosion. Such explosions typically resulted in catastrophic consequences, mainly when they occurred onboard. While catastrophic consequences may not occur frequently, they can be devastating when they do. To prevent the worst-case scenarios, it is recommended to implement a two-stage safety measure. The first stage involves taking preventative measures to ensure the safety management system and safe working practices are appropriately executed. The second stage consists of implementing relief and protection measures to mitigate the consequences of an accident. Crew members must be well-trained in emergency handling to implement these measures effectively should an accident occur.

Moreover, the model can be a predictive tool for bulk carriers navigating Australian waters. Stakeholders can adjust the IFs' states to reflect their operational conditions, yielding the corresponding accident types and consequence severity predictive results. By updating the states of one or more IFs, the predicted rate of consequence severity can be adjusted accordingly. This allows them to identify the most significant states of the IFs related to a particular consequence severity. Subsequently, appropriate measures can be implemented to mitigate the severity of the consequences effectively.

4.4. Comparison with similar studies

It is imperative to note that other researchers have conducted similar studies. Hence, conducting a comparative analysis to highlight the contributions of this study is rational and essential. Table 10 shows the details of the comparison. Notably, concerning the identified five most important IFs, Wu et al. (2019b) find that 'number of people in distress', 'ship tonnage', 'emergency resources used', 'wind', and 'time of day' are the critical IFs contributing to collision accident consequences. In comparison, Wang et al. (Wang and Yang, 2018) and Fan et al. (2020a) emphasise ship-related factors (e.g. ship type, ship age). 'Accident type' is highlighted in Wang et al. (Wang and Yang, 2018) and the present research. Besides that, this research complements 'emergency handling' as a significant factor, which is absent in the other studies. From the perspective of good seamanship, contingency plans are required in all the dangerous work and emergencies on board. Emergency handling is compulsory for crew competence and safety management systems. Therefore, it is necessary to include 'emergency handling' as an important IF.

Regarding results and findings, Fan et al. (2020a) highlight the human-related IFs, focusing on maritime accident analysis. While Wu et al. (2019b) primarily focus on the consequences of collision accidents, the 'emergency management' is emphasised. In comparison, Wang et al. (Wang and Yang, 2018) and this study concentrate on consequence

Table 10
Study comparison.

Literature	Important IFs	Results and findings
Wu et al. (Wu et al., 2019b)	1. Number of people in distress; 2. Ship tonnage; 3. Emergency resources used; 4. Wind; 5. Time of day	1. Highlight the role of emergency management; 2. Focus on collision accident consequences; 3. Specific study for the Yangtze River.
Wang et al. (Wang and Yang, 2018)	1. Accident type; 2. Location; 3. Ship type; 4. Ship age; 5. Ship flag	1. Natural, environmental and managerial factors are highlighted; 2. The highest consequence severity tends to occur in a 'sink' accident, 'inland or coastal water' location, with a fishing vessel involved, and a larger ship age; 3. Specific study for China's coastal waters.
Fan et al. (Fan et al., 2020a)	1. Ship age; 2. Ship operation; 3. Voyage segment; 4. Information; 5. Vessel condition	1. Human-related factors are highlighted; 2. Focus on maritime accident analysis; 3. General study for all ship types in undefined waters.
Present research	1. Accident type; 2. Emergency handling; 3. Navigational condition; 4. Ship speed; 5. Visibility	1. Emergency handling is highlighted; 2. Focus on bulk carrier accident consequences; 3. The highest consequence severity tends to occur in a 'fire/explosion' accident; 4. Specific study for Australian waters.

Table 11
The comparison of accident severity analysis.

Literature	Findings of accident severity analysis
Wang et al. (Wang et al., 2021a)	1. Very serious accidents tend to occur in fishing vessels; 2. Serious accidents tend to occur in passenger ships; 3. Less serious accidents tend to occur in bulk carriers; 4. Oil/chemical tankers tend to have less serious accidents or incidents.
Cakir et al. (Cakir et al., 2021)	1. The worst oil spill consequences tend to occur in general dry cargo ships; 2. The least oil spill consequences tend to happen in recreational vessels; 3. Fishing vessels tend to have oil spill consequences.
Sevgili et al. (Sevgili et al., 2022)	1. The least oil spill consequences tend to happen in gas carriers; 2. The worst oil spill consequences tend to occur in petroleum oil tankers.
Cao et al. (Cao et al., 2023)	1. Very serious accidents tend to happen in fishing vessels; 2. Less serious casualties tend to occur in bulk carriers.
Present research	Bulk carrier accidents tend to have minor consequences.

severity analysis. The 'catastrophic' consequences often occur in 'sink' accidents (Wang et al. (Wang and Yang, 2018)) and 'fire/explosion' accidents (the present research, which aligns with the findings from Tuncel et al. (Tunç et al., 2023)). Regarding the selected geographical areas, Fan et al. (2020a) investigate undefined waters, and the others focus on regional waters.

Besides that, Table 11 compares the findings of accident severity analysis between different articles. Although the previous papers use different accident severity classifications, they also share similarities. According to Wang et al. (2021a) and Cao et al. (2023), the highest accident severity tends to occur in fishing vessels, and the least accident severity tends to happen in bulk carriers (which is in line with present research). Cakir et al. (2021) and Sevgili et al. (2022) show different results because they focus on the consequences of oil spills. Wang et al. (2021a) find that serious accidents tend to occur in passenger ships, oil/chemical tankers tend to have less severe accidents.

5. Conclusion

This study presents a model for analysing the risk and consequences of bulk carrier accidents in Australian waters. A quantitative research method is developed to uncover the correlations and interrelationships between IFs and consequence severity from the perspective of consequence control. The IFs are identified based on a combined analysis of ATSB accident reports and previous research. Subsequently, a database was constructed as a data source by collecting, screening, and extracting information from the ATSB accident investigation reports. Then, a data-driven BN model is developed using the TAN learning method and gradient descent algorithm. This model can aid in conducting both forward and backward diagnoses of consequence severity. The BN modelling is relatively new for maritime consequence severity analysis. Various methods validate the model, including sensitivity analysis, the kappa statistic test, and scenario analysis. The IFs contributing to the severity of the consequences are evaluated and ranked, providing valuable insights for stakeholders when selecting mitigated measures. Following that, significant implications are generated as the primary managerial findings of this study:

(1) The proposed BN offers flexible applications and can empower stakeholders to enhance their safety management system, optimise their decision-making for mitigation, and allocate limited resources effectively.
(2) The insights derived from this study are based on a database compiled from accident reports without the influence of expert judgment. This objectivity enhances the reliability of the findings.
(3) The aggregate effect generated from multiple IFs has yielded valuable insights. A two-stage safety measure encompassing accident prevention and mitigation measures is recommended.
(4) Consequence severity, a topic largely overlooked in this field, has been systemically investigated. Its associated IFs have been identified and ranked in order of importance as accident type, emergency handling, navigational condition, ship speed, visibility, safe act, time of day, loaded or ballast condition, and lookout, all from the perspective of Australian accident reports.

Besides that, the research reveals a few limitations. When more data becomes available, the model could be expanded, and new findings can be drawn, with the results in this study serving as a baseline benchmark. At the same time, certain human and organisational factors, such as safety culture, are challenging to measure and ascertain from investigation reports. Therefore, future research could be conducted to investigate how such factors could be integrated into the developed model in this paper from complementary sources of information for a comprehensive analysis.

CRediT authorship contribution statement

Xiaofei Ma: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Shiqi Fan:** Writing – review & editing, Visualization, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization, Validation. **Eduardo Blanco-Davis:** Writing – review & editing, Supervision, Formal analysis, Conceptualization, Validation. **Guoyou Shi:** Visualization, Supervision, Resources, Formal analysis, Conceptualization. **Zaili Yang:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Zaili Yang reports financial support was provided by European Research Council.

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Appendix

NO.	IFs	Descriptions	Reference
1.	Complacent	Complacent about the duties or underestimation of the severity of the condition (low state of alertness)	Fan et al. (Fan et al., 2022), Mair167-001
2.	Time of day	Day (07:00/18:59), night (19:00/06:59)	Li et al. (Li et al., 2023), Mair163-001
3.	Communication	Good/poor communication and coordination	Fan et al. (Fan et al., 2020b), Mair178-001
4.	Task supervision	Effective/ineffective supervision and support	Fan et al. (Fan et al., 2020b), Mair157-001
5.	Safe act	Comply with or not comply with the safe working practices	Mair179-001
6.	Lookout	Proper/improper lookout affecting the safe operation of the ship	Guo et al. (Guo et al., 2023), Mair167-001
7.	Equipment	Proper/improper use of equipment/devices	Mair167-001, Fan et al. (Fan et al., 2022)
8.	Proper wear PPE	Proper/improper use of PPE	Ozaydin et al. (Özaydı et al., 2022)
9.	Distracted	Distracted/insufficient attention	Fan et al. (Fan et al., 2022)
10.	Ship speed	Safe speed helps avoid accidents, and unsafe speed leads to accidents	Fan et al. (Fan et al., 2020b)
11.	Gross tonnage	(0,3000], (3000,10,000], (10,000,20,000], >20,000	Li et al. (Li et al., 2023)
12.	Ship length	(0,100], (100,200], >200	Li et al. (Li et al., 2023)
13.	Ship age	(0,5], (Editor, 2021; Montewka et al., 2022), (Jon et al., 2021; Kum and Sahin, 2015), (Wang et al., 2021a; Zhang et al., 2021a), >20, NA	Li et al. (Li et al., 2023)
14.	Ergonomic design	Ergonomic friendly or ergonomic aspects have nothing to do with accidents; Ergonomic impact of innovative bridge design (e.g., visual blind sector ahead, motion illusion)	Fan et al. (Fan et al., 2020b)
15.	Weather condition	Good or bad, considering wind, rain, fog, visibility, and extreme weather	Li et al. (Li et al., 2023)
16.	Sea condition	falling or rising tide, current, waves, and sea state	Li et al. (Li et al., 2023)
17.	Visibility	Good or bad visibility	Cao et al. (Cao et al., 2023) Aydin et al. (Aydin et al., 2021)
18.	Regulation	Comply with or not comply with regulations	Cao et al. (Cao et al., 2023)
19.	Risk assessment	Good or lack of risk assessment	Fan et al. (Fan et al., 2020b), Mair179-001
20.	Emergency handling	Effective/ineffective emergency handling	Zhang et al. (Zhang et al., 2021b)
21.	Traffic density	Heavy or Normal traffic	Jon et al. (Jon et al., 2021)
22.	Clear order	Clear/unclear order from documents	Fan et al. (Fan et al., 2020b)
23.	Limited time	Not enough time to take action	Fan et al. (Fan et al., 2022)
24.	Situation awareness	Effective/ineffective situation awareness	Maya et al. (Maya and Kurt, 2020)
25.	Emotional effect	Positive or negative emotional effects (ambition, angry, panic, unhappiness)	Shi et al. (Shi et al., 2023)
26.	Alcohol, drugs	Affected/not affected by alcohol/drugs	Kaptan et al. (Kaptan et al., 2021), Mair182-001
27.	Experience	Familiar/unfamiliar with/lack of equipment knowledge, experienced or inexperienced, good or ill-prepared;	Fan et al. (Fan et al., 2020b)
28.	Information	Providing updated and effective information; Lake of updated and effective information	Li et al. (Li et al., 2023)
29.	Safety culture	Have or lack of safety culture, precautionary thought	Fan et al. (Fan et al., 2022)
30.	Environment disturbance	Affected/not affected by noise and vibration	Hu et al. (Hu et al., 2022)
31.	Management	Good or dysfunctional management system	Fan et al. (Fan et al., 2020b)
32.	Navigational condition	Berthed, departure, sea passage, arrival, at anchor, or in other condition	Li et al. (Li et al., 2023) Cao et al. (Cao et al., 2023)
33.	Loaded or ballast condition	The ship is loaded with cargo or in ballast without cargo when an accident happens	Sangmin Lee (Lee, 2023)

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