

Incorporation of human factors into maritime accident analysis using a data-driven Bayesian network

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Abstract: A data-driven Bayesian network (BN) is used to investigate the effect of human factors on maritime safety through maritime accident analysis. Its novelties consist of 1) manual collection and analysis of the primary data representing frequencies of risk factors directly derived from maritime accident reports, 2) incorporation of human factors into causal analysis with respect to different maritime accident types, and 3) modelling by a historical accident data-driven approach, to generate new insights on critical human factors contributing to different types of accidents. The modelling of the interdependency among the risk influencing factors is structured by Tree Augmented Network (TAN), and validated by both sensitivity analysis and past accident records. Our findings reveal that the critical risk factors for all accident types are ship age, ship operation, voyage segment, information, and vessel condition. More importantly, the findings also present the differentiation among the vital human factors against different types of accidents. Most probable explanation (MPE) is used to provide a specific scenario in which the beliefs are upheld, observing the most probable configuration. The work pioneers the analysis of various impacts of human factors on different maritime accident types. It helps provide specific recommendations for the prevention of a particular type of accidents involving human errors.

Keyword: Maritime accident, Maritime safety, Bayesian networks, Data-driven Bayesian, Human reliability analysis, Maritime risk

1. Introduction

Most shipping accidents (e.g. collisions, groundings, crash, fire and explosions) are characterised with a feature of low probability-high consequence. Catastrophic maritime accidents may cause huge loss of human lives, damage to the

30 society and environment (Zhang and Thai, 2016). Analysing maritime accidents becomes one of the effective ways to
31 reduce the risks of maritime transportation. Maritime administrations conduct accident investigation to learn how the
32 systems fail and why accidents happen (Schroder-Hinrichs et al., 2011). It then simulates maritime administrations to
33 review and revise regulations, standards and management. To mitigate the risk and improve the safety of maritime
34 transportation, the International Maritime Organisation (IMO) introduced the Formal Safety Assessment (FSA)
35 methodology for its applications to the rule-making process (IMO, 2002; IMO, 2013). According to the literature, the
36 organisation, working condition, and navigational environment are the major driving forces to maritime accidents
37 (García-Herrero et al., 2012).

38 Although modern ships are highly equipped with advanced technologies (*e.g.* navigation technology, onboard
39 information, bridge resource management systems), human factors present a major contribution to accidents. There is
40 no consensus on the statistical analysis of the causations leading to maritime accidents, due to the different
41 perspectives on the analysis and use of various investigation approaches. However, human errors, technical failures,
42 and mechanical failures are traditionally highlighted as the main root causes of accidents (Celik and Cebi, 2009a). The
43 maritime sector initiated the studies on the contribution of human and organisational factors (HOFs) to maritime
44 accidents from the occurrence of the capsizing of the Herald of Free Enterprise in 1987 (Transport, 1987). Since then,
45 accident investigations pay more attention to human factors in maritime safety. It is widely accepted that the human
46 element, accounting for 75%-96% of maritime casualties, plays an important role in accidents involving modern ships
47 (Trucco et al., 2008a, Fan et al., 2018, Tzannatos, 2010). Human factors are often viewed as causes behind anything
48 that goes improperly at sea.

49 Human factors are usually adopted as a concept that considers other relevant factors, including workplace conditions,
50 physical and natural environment, procedures, technology, training, organisation, management, as well as seafarers
51 (*i.e.* fatigue, task load, mental state, etc.) (Psarros, 2015). Several researchers have studied the contribution of human
52 and organisational factors to ship accidents (Chauvin et al., 2013, Chen et al., 2013, Xi et al., 2017). The majority of
53 accidents occurred due to one of or the combination of the following causes: poor crew competence, fatigue, lack of
54 communication, lack of proper maintenance, lack of application of safety culture and protocols or other procedures,
55 inadequate training, poor situation assessment, and stress (Vinagre-Ríos and Iglesias-Baniela, 2013, Fan et al., 2018).
56 Generally, seafarers often face more accidents than the crews working onshore, as reported by Roberts and Hansen
57 (2002). Also, there is a consideration that a system for the training and assessment of the non-technical skills (NTS) of
58 co-operation, leadership and management skills, situation awareness and decision making, needs to be established in

59 the maritime industry (Saeed et al., 2016). Thus, the effective control of these causes will help reduce the risk and
60 improve safety at sea.

61 Risk analysis is an effective way of devising mitigation measures that prevent accidents. Among the studies on the risk
62 analysis of maritime transportation, historical data analyses have been widely used. A number of papers have used
63 historical accident data for such purposes (Zhang et al., 2013; Zhang et al., 2016). Ronza et al. (2003) investigated 828
64 accidents in port areas using event trees to predict the frequency of accidents. Kujala et al. (2009) included detailed
65 accident statistics over a ten-year period in a collision model, to analyse the safety in the Gulf of Finland. Jin and
66 Thunberg (2005) proposed the logic regression model based on accident data from 1981-2000, to analyse fishing
67 vessel accidents.

68 This study investigates how human factors combined with non-human factors affect maritime transportation using risk
69 analysis. Allowing for the drawbacks arising from traditional studies, this study proposes a novel risk assessment of
70 the human factors contributing to maritime accidents. Since 75-96% of maritime accidents involve human elements, it
71 is worth of clarify the extent to which a maritime accident can be defined as a human-related maritime accident. This
72 study aims at investigating how different risk factors generate, in an individual or combined manner, an impact on
73 different types of human-related maritime accidents. Based on recorded maritime accident reports from the Marine
74 Accident Investigation Branch (MAIB) and the Transportation Safety Board of Canada (TSB) between 2012 and
75 2017, a primary database is developed. Owing to the use of accident data, the Tree Augmented Network (TAN) model
76 is developed to construct a BN and train the data, to propose a data-driven BN-based approach for accident analysis.

77 The rest of the paper is structured as follows. The literature review on human factors research in maritime accidents
78 and data-driven BN-based maritime accident modelling is conducted in Section 2. Section 3 demonstrates the
79 methodology of Risk Influencing Factors (RIFs) identification, BN structure learning, and sensitivity analysis. Section
80 4 analyses the results of the RIFs for different ‘accident types’, illustrates the combined manners generated by RIFs,
81 and highlights the implications through providing a plausible explanation for the observed findings. Finally, Section 5
82 concludes the paper.

83 2. Literature review

84 2.1 Human factors in maritime safety studies

85 Since the United States Coast Guard (USCG) reported in 1993 that human factors had essentially caused
86 approximately 80% of maritime accidents and near misses, there has been an overwhelming understanding that human

factors play a significant role in a considerable number of incidents or catastrophes by triggering chain events. Also Branch et al. (2004) disclosed that watchkeeping manning levels and individual's abilities to discharge duties were essential factors resulting in collisions and groundings.

The preliminary findings of literature review are summarised in Table 1. For organisational factors, Lu and Tsai (2008) studied the influence of the safety culture in ship accidents, concluding that the job safety, management safety practices and safety training were among the top influencers. On the other hand, people surrendered the level of vessel safety standards to a profitable activity, due to commercial affairs (Vinagre-Ríos and Iglesias-Baniela, 2013). It showed that increase and decrease in the level of ship-owners' profits influence the amount of risk tolerated in their ship operation. From this point of view, human factors were also derived from the practices and operating policies established by shipping companies.

Table 1 Strengths and weaknesses of the relevant research

Researchers	Journals	Strengths	Weaknesses
Lu and Tsai, 2008	Accident Analysis & Prevention	Considered the organisational factors, and empirically evaluated the influence of safety climate on vessel accidents from a seafarer's perspective	Factors were limited and it did not illustrate the interaction between organizational factors.
Vinagre-Ríos and Iglesias-Baniela, 2013	The Journal of Navigation	Mentioned the increasing incidence of human errors, and pointed out how commercial affairs of shipping market influences the risk behaviour of shipping business decision-makers.	Not interacted with other risk factors
Antão and Guedes Soares, 2008	Reliability Engineering & System Safety	Identified the difference in the pattern of human factors and other factors associated with high-speed crafts accidents, as compared with the more traditional ocean-going ships	Human factors were limited to human tasks, including set speed, set heading, look out planning, trip maintenance, engine, and others.
Celik and Cebi, 2009	Accident Analysis & Prevention	Improved Human Factors Analysis and Classification System (HFACS) framework to identify the role of human factors in shipping accidents. Improvement of safety precautions in shipping companies	Did not reflect the influences between different factors levels.
Chen et al., 2013	Safety Science	The use of HFACS-MA model with WBA can help ensure the relevant latent conditions and indicate the adverse influences between different factors levels.	It needed a dedicated HOFs framework with detailed items specified for marine accidents and the weights of the HOFs identified.
Yang et al., 2013,	Ocean Engineering	Proposed a modified CREAM to facilitate human reliability quantification in marine engineering; developed a quantitative human reliability analysis method using fuzzy Bayesian; realised real time monitoring of marine engineers' failures under uncertainty	It required appropriate consideration of the influence of the CPCs with neutral effects in the establishment of belief fuzzy rule bases.
Soner et al., 2015	Safety Science	Used Fuzzy Cognitive Mapping (FCM) with HFACS to propose a novel proactive modelling and add value to predicting the root causes revealed in various levels.	Detailed predictions of suggested safety mechanisms need to be studied in order to manage the operational level.
Pristrom et al., 2016	Reliability Engineering & System Safety	Used data collected from the Global Integrated Shipping Information System (GISIS) together with expert judgement	There was no detailed human factors data.
Zhang et al., 2016	Safety Science	A literature review on expert knowledge and BN modelling for shipping accidents in view of risk and uncertainty.	New methods for experts' knowledge elicitation should be developed to improve the model validity.

Chauvin et al., 2013	Accident Analysis & Prevention	Used HFACS to identify contributory factors involved in 39 collisions; used MCA and hierarchical clustering to reveal three patterns of factors	The small number of collisions studied but the high number of variables.
Wang and Yang, 2018	Reliability Engineering & System Safety	Showed the key factors influencing waterway safety including the type and location of the accident and conducted a novel scenario analysis to predict accident severity.	The completeness of the data mined from the text case was arguable. It focused more on objective variables than human factors.

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99 However, human factors have complex casual relations with each other. Lema et al. (2014) applied a K-means
100 clustering method to indicate that human factors coexist with the condition of a ship and other external factors. It was
101 widely accepted that human factors were associated with a variety of unsafe actions, behaviours, omissions and
102 hazardous conditions, and the human element was a key factor in maritime accidents (Antão and Guedes Soares,
103 2008). A lot of attention has been paid to the risk analysis of accidents' causes related to human factors. Celik and
104 Cebi (2009b) proposed a Human Factors Analysis and Classification System (HFACS) approach to identify human
105 factors in shipping accidents. It revealed the hierarchy structure of human factors and the logic relations within the
106 structure. In line with HFACS, Reason's Swiss Cheese Model and Hawkins' SHELL model, Chen et al. (2013)
107 modified the HFACS to make it more applicable to maritime accidents (*i.e.* HFACS-MA model), to comprehensively
108 describe HOFs in maritime sector. In addition, human performance defined by human reliability in accidents was
109 analysed, and the human failure probabilities were estimated to assess the risk level of shipping industry (Yang et al.,
110 2013, Yoshimura et al., 2015, Yang and Wang, 2012). Soner et al. (2015) combined Fuzzy Cognitive Mapping (FCM)
111 with HFACS to generate a proactive model in fire prevention on-board ships, which revealed that human factors were
112 significant, leading to the failures of maritime operations with an enormous and long-term loss.

113 To analyse human factors, the maritime accident database is used as one of the most valuable sources to obtain the
114 primary data, including the global database like Global Integrated Shipping Information System (GISIS) (Pristrom et
115 al., 2016), and the historical accident data collected from national/regional maritime administration (Zhang et al.,
116 2016). However, such databases contain less detailed information than the extractions from maritime accident reports.
117 From this perspective, the investigation reports of maritime accidents provide the navigational circumstance, process
118 of the failure chain, environmental information, direct or indirect causes of the accidents, and the actions taken during
119 the accidents. Even the hidden potential hazards and causal relations between various factors are demonstrated in
120 detail. However, few studies utilised accident reports to conduct accident and human factors analysis due to the time-
121 consuming process of extracting the data from each report. Therefore, even studies utilising accident reports provided
122 limited content of the data sources. For instance, Chauvin et al. (2013) underlined 39 vessels involved in 27 collisions
123 derived from the accident reports, identifying the importance of Bridge Resource Management (BRM) for situations

124 of navigation in restricted waters. Chen et al. (2013) utilised the accident reports of selected cases from MAIB for
125 accidents analysis providing a complement measure. Wang and Yang (2018) analysed all accident investigation
126 reports by China's Maritime Safety Administration (MSA), to conclude the key risk factors influencing waterway
127 accident severity.

128 To determine human factors in maritime, 109 accident reports extracted from 152 reports in MAIB and 52 accident
129 reports obtained from 61 reports in TSB during 2012-2017 have been reviewed, as these two organisation are among
130 the most representative from the literature (Chauvin et al., 2013, Graziano et al., 2015, Kum and Sahin, 2015).

131 According to such reports, human factors are derived.

132 Previous studies relying mainly on the secondary database for RIFs identification were unable to present primary
133 information from accident reports. One of the novelties of this study is to incorporate human factors derived from
134 accident reports into accident analysis, combined with other external factors, considering both subjective and objective
135 factors. New insights brought by the data acquisition through the investigation of accident reports, cannot be achieved
136 by only relying on the secondary or existing databases.

137 2.2 Data-driven BN in maritime accident modelling

138 Quantitative risk and reliability analysis techniques have been widely used to reduce the probability of failure in
139 maritime sectors, including Hazard and Operability Studies (HAZOP), Failure Mode and Effects Analysis (FMEA),
140 Fault Tree Analysis (FTA), Event Tree Analysis (ETA) and Bayesian Network (BN). (Yeo et al., 2016; Zhang and
141 Thai, 2016). BN has become popular for maritime risk modelling during the period of 2004–2013. It has been widely
142 applied to maritime risk analysis, including collision risk assessment (Hanninen and Kujala (2012); Ma et al., 2016),
143 human reliability analysis (Martins and Maturana, 2013), and risk estimation (Montewka et al., 2014). Zhang et al.
144 (2013) and Zhang et al. (2014) estimated the navigational risk through FSA and BN to improve the navigational safety
145 in the Yangtze River, and established the BN for the analysis and prediction of the congestion risk of inland
146 waterways. In addition, BN was constructed to represent the dependencies between the indicators and accident
147 consequences (Zhang et al., 2016), revealing that the accident consequences were the most sensitive to the position
148 where the accidents occurred.

149 Weber et al. (2012) pointed out that the number of publications on BN in risk analysis increased every year, due to its
150 advantages of learning and inference algorithms. Compared with other classical methods used in dependability
151 analysis, BN sustains its advantages by conducting multi-state variable modelling. For example, BN displays similar
152 features as the Fault Tree (FT) which fits for the two-state variables, but has additional ability to model a multi-state

153 variable and several outputs. In addition, FT can also be translated into BN to make it applicable for the system
154 (Khakzad et al., 2011, Mahadevan et al., 2001, Bobbio et al., 2001, Trucco et al., 2008b, Montani et al., 2006).
155 However, the system modelling tends to be complicated with increasing variables, while leading to an apparent
156 increase of parameters and related functions (Weber et al., 2012). For instance, Markov chain (MC) analyses the
157 probability of a failure event with the dependencies among variables and has the ability to represent multi-state
158 variables, which implies sophisticated system when the number of variables increases. However, BN has required a
159 relatively low number of parameters and a small-size conditional probability table.

160 Moreover, BN is a competitive approach for maritime risk modelling owing to its abilities to utilise either expert
161 knowledge and/or data-driven methods. When failure data in the relevant investigations are absent, expert knowledge
162 continues to be an essential data source for shipping accident modelling (Fu et al., 2016; Zhang and Thai, 2016).
163 Experts' knowledge was found to play an essential role in BN structures, regarding the definition of the relative
164 probabilities due to the insufficient historical data (Hänninen and Kujala, 2014; Zhang and Thai, 2016).

165 In light of this characteristic, BN is appropriate for modelling maritime accidents since it enables quantitative risk
166 analysis of HOFs (Trucco et al., 2008b, Akhtar and Utne, 2014, Castaldo et al., 2016) and allows for analysing RIFs to
167 rationalise relevant regulations for risk control practice by a data-driven approach (Yang et al., 2018). However,
168 compared to the studies using expert judgements in BN construction, data-driven BN in maritime risk analysis
169 involves less subjective bias but is scarce, requiring more experimental evidence to be collected before its wide
170 practical applications.

171 To fulfil this gap, the study uses new primary data derived from maritime accident reports to conduct a data-driven
172 BN to generate the structure of RIFs. Consequently, it will provide new insights on the differentiation among critical
173 human factors contributing to each of the different types of maritime accidents.

174 3. Methodology

175 3.1 Identification of RIFs

176 To analyse the maritime accident types under various RIFs, identifying and selecting the RIFs from the accident
177 reports are necessary. The data was obtained from case-by-case analysis of recorded maritime accidents from MAIB,
178 and TSB. These reports are among the most representative from the literature (Chauvin et al., 2013, Graziano et al.,
179 2015, Kum and Sahin, 2015).

180 To generate the RIFs, the procedure consists of four stages: (1) online database searching, (2) reports screening and
 181 selection, (3) refining and analysis, (4) RIFs selection. Through online database searching, the maritime accident
 182 reports from MAIB (<https://www.gov.uk/maib-reports>) and TSB ([http://www.bst-tsb.gc.ca/eng/rapports-](http://www.bst-tsb.gc.ca/eng/rapports-reports/marine/index.html)
 183 [reports/marine/index.html](http://www.bst-tsb.gc.ca/eng/rapports-reports/marine/index.html)) between Jan. 2012 to Dec. 2017 were obtained. In order to ensure the human element
 184 relevance, these accident reports are screened with a focus on human factors-related accidents. For instance, some
 185 accidents disobeying rules of passengers or weather caused accidents in small fishing vessels, are discarded due to that
 186 they are irrelevant to human factors. Therefore, the study generates the database with 161 reports involving 208
 187 vessels. Then, the reports are further refined and analysed, especially according to the illustration of ‘safety issues’
 188 and ‘common factors’. To identify the most relevant factors (i.e. 32 risk factors in Table 2), manual analysis from
 189 original maritime accident reports generates 77 factors first. All the risk factors relating to human performance were
 190 first identified from maritime accident reports. Domain experts were then invited to fine turn them to merge those of
 191 high similarity. The other factors are retained even they have revealed some interdependence, but in the meantime
 192 present significant difference. The quantitative extent to which one factor influences another is calculated through the
 193 TAN modelling.

194 Moreover, it is necessary to set the appropriate criterion to select RIFs. Using a low criterion threshold allows more
 195 human-related RIFs to be selected. However, involving a large number of variables with a low sample size will not be
 196 able to ensure the robustness of the model. Oppositely, using a high criterion threshold offers sufficient samples for
 197 risk analysis, but excludes some important human-related factors, such as factors 27, 13, 30. So the criterion threshold
 198 of 19.35% was calculated from averaging the frequencies of all common factors in Table 2. Therefore, 14 common
 199 factors whose frequencies were higher than the average value, 19.35%, were extracted as RIFs in the study. They are
 200 sea condition, information, management system, weather condition, equipment and device, clear order, supervision
 201 and supports, experienced, communication, vessel condition, risk assessment, safety culture, complacent, regulation.

202 Table 2 The risk factors contributing to human errors in maritime accidents.

Number	Risk factors	Frequency
1	Poor communication and coordination	30.77%
2	Ineffective supervision and supports (lone watchkeeper or working isolated, improper supervision of loading operation)	32.69%
3	No detailed passage plan or revised passage plan was unsafe	13.46%
4	Swift duty between pilots and seafarers or change of the steering mode	1.44%
5	Over-reliance on devices (AIS, GPS...), or poor lookout	15.38%
6	Fast speed	9.62%

7	No clear order (not accurately interpret and apply the requirements of a safe manning document)	37.50%
8	Limited time to respond	12.50%
9	Lack of situation awareness	14.42%
10	Fatigue/asleep/tiredness and desire to rest	13.46%
11	Emotion (low level of arousal, panic, anger, unhappiness)	1.92%
12	Unfamiliar with/lack of equipment knowledge, inexperienced, ill-prepared	32.69%
13	Complacent about the duties or underestimation of the severity of the condition (low state of alertness)	21.63%
14	Recreation drugs, alcohol	6.73%
15	Cognitively overload	4.81%
16	Physical incapacitation	0.96%
17	Distracted/insufficient attention	16.35%
18	Stress	0.48%
19	Poor condition of the vessel, increasing complexity of propulsion arrangements, and modifications made to vessels, size	28.85%
20	Devices and equipment on board not fully utilized or operated correctly (BNWAS switched off, alarm system not in the recommended position or not noticed)	37.98%
21	Ergonomic impact of innovative bridge design (visual blind sector ahead, motion illusion)	11.06%
22	Insufficient or lack of updated information (poor quality of equipment data, falsified records of information, relies on a single piece of navigational equipment); no automatic means or without indicators for necessary observing (working indicators, light)	45.67%
23	Weather condition: wind, visibility (dense fog)	39.42%
24	Sea condition: falling tide, current, waves	53.37%
25	Noisy and vibrating environment	0.96%
26	Fairway traffic (traffic density, repetitive nature of the route)	16.35%
27	Inappropriate or ambiguous code, endorsement, regulations, procedure, instructions, formal published guidance; operation manual, requirement	19.71%
28	Lack of risk assessment	26.92%
29	Dysfunctional management system (shore management, maintenance management, bridge source management, on board management, safety management systems, port service, qualification examination, inadequate training, practice, emergency drill)	40.87%
30	Lack of safety culture, precautionary thought	24.52%
31	No medical and fitness standards for crews	2.40%
32	Commercial pressure, public pressure or industrial pressure (financial constrains)	4.33%

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However, human factors in maritime accidents are usually combined with other external factors, such as sea condition, weather condition, fairway traffic, and vessel condition, to affect the safety procedure in navigation. From this perspective, it is beneficial to combine human factors with other non-human RIFs to investigate their combined effect on maritime safety. Referring to the previous factors analysis studies (Wang and Yang, 2018; Fan et al., 2020), 16

208 important risk factors are described as important factors contributing to maritime accidents as stated in the literature
209 and accident reports. It contains ship type, hull type, ship age, length, gross tonnage, ship operation, voyage segment,
210 ship speed, vessel condition, equipment/device, ergonomic design, information, weather condition, sea condition, time
211 of day, fairway traffic. It is evident that five overlapped factors exist in both groups (i.e. human and non-human),
212 including vessel condition, equipment/device, information, weather condition, sea condition. These factors not only
213 make significant contributions to maritime accidents but also are connected to human factors in maritime safety. At
214 last, it encompasses a total of 25 RIFs, seen in Table 3.

215 Table 3 25 RIFs defined in maritime accidents

No	RIFs	Notation	Description	Corresponding values
1	Ship type	R_{ST}	Passenger vessel, tug, barge, fishing vessel, container ship, bulk carrier, RORO, tanker or chemical ship, cargo ship, others.	1, 2, 3, 4, 5, 6, 7, 8, 9, 10
2	Hull type	R_{HT}	Steel, wood, aluminium, others	1, 2, 4, 5
3	Ship age (years)	R_{SA}	(0 5], [6 10], [11 15], [16 20], >20, NA	1, 2, 3, 4, 5, 6
4	Length (m)	R_L	≤ 100 , >100 , NA	1, 2, 3
5	Gross tonnage (GT)	R_{GT}	≤ 300 , 300 to 10000, >10000 , NA	1, 2, 3, 4
6	Ship operation	R_{SO}	Towing, Loading/unloading, Pilotage, Manoeuvring, Fishing, At anchor, On passage, others	1, 2, 3, 4, 5, 6, 7, 8
7	Voyage segment	R_{VS}	In port, Departure, Arrival, Mid-water, Transit, others	1, 2, 3, 4, 5, 6
8	Ship speed	R_{SS}	Normal, fast	1(normal), 2(fast)
9	Vessel condition	R_{vc}	The condition of vessel has nothing to do with the accidents; Increasing complexity of propulsion arrangements, modification made to vessels, size contributes to the accidents	1(good), 2(bad)
10	Equipment /device	R_E	Devices and equipment on board operate correctly; Devices and equipment not fully utilised or operated correctly (e.g., BNWAS switched off, alarm system not in the recommended position or not noticed)	1(good), 2(bad)
11	Ergonomic design	R_{ED}	Ergonomic friendly or ergonomic aspects has nothing to do with accidents; Ergonomic impact of innovative bridge design (e.g., visual blind sector ahead, motion illusion)	1(good), 2(bad)
12	Information	R_I	Effective and updated information provided; Insufficient or lack of updated information (e.g., poor quality of equipment data, falsified records of information, relies on a single piece of navigational equipment, without working indicators or light for necessary observing)	1(good), 2(bad)
13	Weather condition	R_{WC}	Good/poor considering rain, wind, fog, visibility	1(good), 2(bad)
14	Sea condition	R_{SC}	Good/poor considering falling/rising tide, current, waves	1(good), 2(bad)
15	Time of day	R_{TD}	07:00 to 19:00, other	1(good), 2(bad)
16	Fairway traffic	R_{FT}	Good or poor considering complex geographic environment, dense traffic, or receptive nature of the route contributing to ignorance	1(good), 2(bad)
17	Communication	$A1$	Good or poor communication and coordination	1(good), 2(bad)
18	Supervision	$A2$	Effective or ineffective supervision and supports (lone watchkeeper or working isolated, improper supervision of loading operation)	1(good), 2(bad)
19	Clear order	$A6$	Good or unclear order from documents (not accurately interpret and apply the requirements of a safe manning document)	1(good), 2(bad)

20	Experienced	A11	Familiar or unfamiliar with/lack of equipment knowledge, experienced or inexperienced, good or ill-prepared;	1(good), 2(bad)
21	Complacent	A12	Properly understand or complacent about the duties/underestimation of the severity of the condition (low state of alertness)	1(good), 2(bad)
22	Regulation	A18	Good or inappropriate/ambiguous code, endorsement, regulations, procedure, instructions, formal published guidance; operation manual, requirement	1(good), 2(bad)
23	Risk assessment	A19	Good or lack of risk assessment	1(good), 2(bad)
24	Management	A20	Good or dysfunctional management system (including shore management, maintenance management, bridge source management, on board management, safety management systems, port service, qualification examination, inadequate training, practice, emergency drill)	1(good), 2(bad)
25	Safety culture	A21	Good or lack of safety culture, precautionary thought	1(good), 2(bad)

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217 Most of the definitions of variables' states can be extracted from accident investigation reports. For example, 'accident
218 type', 'ship type', 'hull type', 'ship operation', and 'voyage segment', are classified into different states according to
219 the classification of MAIB or TSB, which are widely accepted in the industry. In the process of accident reporting
220 analysis, hull type are defined as steel (1), wood (2), glass reinforced plastic (3) (MAIB 8-2017), aluminium (4), foam
221 reinforced plastic (5) (MAIB 7-2017), polyester (6) (MAIB 24-2016). However, the accident statistics reveals that 3,
222 5, and 6 take account a very low proportion in total. Therefore, these three types are combined as one – 'others' and
223 defined as state 5. Finally, in the table, it is presented as state 1,2,4,and 5. The other variables are graded according to
224 the literature (e.g. Wang and Yang, 2018), including 'ship age', 'length', and 'gross tonnage'. In addition, 'vessel
225 condition', 'communication', 'supervision', etcetera, are graded based on whether it is blamed for the faults in
226 accidents, as data characteristic described in the reports.

227 3.2 BN structuring learning- TAN

228 Using the RIFs, there are two approaches for the BN structure learning. One relies on expert knowledge, which takes
229 advantage of subjective causal relationships to build a BN structure. An alternative approach is a data-driven method
230 to reveal the interactive dependencies between RIFs, which relies on the learning algorithm and data correlation in the
231 BN model. This study develops the BN structure by the latter approach. First, the raw data from maritime accident
232 reports is manually analysed to generate a database containing 161 reports involving 208 vessels. The sample size for
233 such database is applicable for the risk analysis using a data-driven approach. As far as data-driven approach is
234 concerned, there are many approaches, e.g. Naïve Bayesian Networks (NBN), Augmented naive Bayesian Networks
235 (ABN), and TAN. Among them, TAN learning constructs qualitative BN representing RIFs' interactive dependencies,
236 which helps generate insights on critical human factors contributing to different types of accidents. In addition,
237 Friedman et al. (1997) pointed out that TAN outperforms naive Bayes, while maintaining the computational simplicity

238 and robustness that characterise naive Bayes. TAN is proved to be more competitive and accurate than other data-
 239 driven network construction approaches (Murphy and Aha, 1996).

240 A BN encodes a joint probability distribution over a set of random variables U , which is an annotated directed acyclic
 241 graph (DAG). Let $U = \{A_1, \dots, A_n, C\}$ where n stands for the number of RIFs, the variables A_1, \dots, A_n are the RIFs and
 242 C is the class variable (accident types). Consider a graph structure where the class variable is the root, that is,

243 $\prod C = \emptyset$ ($\prod C$ denotes the set of parents of C in U), and each RIF has the class variable as its unique parent, *i.e.*

244 $\prod A_i = \{C\}$ for $1 \leq i \leq n$. A BN defines a unique joint probability distribution over U given by

$$245 \quad P(A_1, \dots, A_n, C) = P(C) \cdot \prod_{i=1}^n P(A_i | C). \quad (1)$$

246 The DAG on $\{A_1, \dots, A_n\}$ is a tree if $\prod A_i$ contains only one parent for all A_i , except for one variable without parents
 247 (referred as the root). There is a function π which can define a tree over A_1, \dots, A_n , if there is exactly one i such that

248 $\pi(i) = 0$ (*i.e.* the root of the tree), and there is no sequence i_1, \dots, i_k such that $\pi(i_j) = i_{j+1}$ for $i \leq j < k$ and $\pi(i_k) = i_1$

249 (*i.e.*, no cycles). Such a function defines a tree network where $\prod A_i = \{C, \dots, A_{\pi(i)}\}$ if $\pi(i) > 0$, and $\prod A_i = \{C\}$ if

250 $\pi(i) = 0$.

251 Learning a TAN structure is an optimisation problem. Solving this problem follows the general procedure proposed by
 252 Chow and Liu (1968), who used conditional mutual information between attributes. The function can be defined as

$$253 \quad I_p(A_i, A_j | C) = \sum_{a_{ii}, a_{ji}, c_i} P(a_{ii}, a_{ji}, c_i) \log \frac{P(a_{ii}, a_{ji} | c_i)}{P(a_{ii} | c_i)P(a_{ji} | c_i)} \quad (2)$$

254 where I_p represents the conditional mutual information, a_{ii} is the i^{th} state of RIF A_i , a_{ji} is the i^{th} state of RIF A_j , c_i is the
 255 i^{th} state of ‘accident type’. The optimisation problem, *i.e.* learning a TAN structure, is to find a tree defining function π
 256 over A_1, \dots, A_n such that the log likelihood is maximised.

257 3.3 Sensitivity analysis and model validation

258 3.3.1 Mutual information

259 The mutual information represents the dependence between two variables in the probabilistic theory (Yang et al.,
 260 2018). Deriving from the entropy theory, mutual information is described as an indicator showing the uncertainty of

261 the dataset and interpreted as entropy reduction. The mutual information explains how strong the relationship between
262 the RIF and ‘accident type’.

263 One objective of this study is to identify the relationship between the relevant RIFs and a particular ‘accident type’.
264 ‘Accident type’ is first determined as the fixed variable in mutual information. In this way, the mutual information
265 between the ‘accident type’ and the RIFs can be defined as follows:

$$266 \quad I(s, \alpha_i) = \sum_{s,i} P(s, \alpha_{ij}) \log_b \frac{P(s, \alpha_{ij})}{P(s)P(\alpha_{ij})} \quad (1)$$

267 where S is ‘accident type’, α_i represents the i th RIF, α_{ij} represents the j th state of the i th RIF, $I(S, \alpha_i)$ is the mutual
268 information between ‘accident type’ and the i th RIF. The larger the value of mutual information is, the stronger the
269 relationship between α_i and ‘accident type’. In this way, calculating the value of mutual information can eliminate
270 the RIFs that are relatively less relevant to the ‘accident type’. Then the remaining RIFs are extracted as significant
271 variables with regards to a selected accident type in the model.

272 3.3.2 Sensitivity analysis

273 3.3.2.1 Joint probability

274 Another form of sensitivity analysis is based on a calculation of the network joint probability, which determines how
275 the RIF influences ‘accident type’. The value of the target node (*e.g.* ‘accident type’) is calculated when the state of
276 RIFs is assigned with different values, and the states of the other variables are locked. The calculation of joint
277 probability can be seen in (Wang and Yang, 2018; Trucco et al., 2008b).

278 For example, there are only two variables ‘ship type’ and ‘ship operation’, and ‘ship type’ is the parent node of ‘ship
279 operation’, Set ‘ship type’ as M , ‘ship operation’ as N , ‘ $M=M_i$ ’ means the vessel is at its i th ‘ship type’ state, and the
280 same goes to ‘ $N=N_j$ ’. According to Baye’s rules, the joint probability can be calculated as:

281 $P(M = M_i, N = N_j) = P(M = M_i) \times P(N = N_j | M = M_i)$, where $P(M = M_i, N = N_j)$ refers to the joint probability that
282 events ‘ $M=M_i$ ’ and ‘ $N=N_j$ ’ both occur, $P(M = M_i)$ is the prior probability of the i th ‘ship type’, $P(N = N_j | M = M_i)$
283 denotes the conditional probability of the occurrence of i th ‘ship type’ state given that j th ‘ship operation’ state occurs.

284 3.3.2.2 True Risk Influence (TRI)

285 Once the RIFs are extracted from the mutual information calculation, there is another form of sensitivity analysis to
286 determine the effects of different RIFs in a combined way, *e.g.* scenario simulation. The traditional way sets the

287 scenario with all the other nodes (apart from the investigated ones) locked. Then the states of target node are updated
288 gradually. It is applicable for variables with two states, but does not suit for variables with more than two states
289 Alyami et al. 2019). In this case, the multi-state RIFs make the traditional scenario simulation inappropriate.

290 To overcome the disadvantage of the traditional scenario simulation, a new method was proposed by Alyami et al.
291 (2019). This method aids to obtain the High Risk Inference (HRI) of a type of accidents (*e.g.* collision), by increasing
292 the probability of the state producing the highest influence on collision to 100%. Then it helps calculate the Low Risk
293 Inference (LRI) of collision by increasing the probability of the state generating the lowest influence on the collision
294 to 100%. Then, calculating the average value of HRI and LRI concludes the True Risk Influence (TRI) of each RIF in
295 the case of a particular accident type.

296 Subsequently, the similar analysis procedure is applied to other accident types, 'grounding' and 'flooding', etc., to
297 obtain the variable influence on 'accident type'. Therefore, the sensitivity analysis calculates the TRI values of
298 variables in different accident types, which illustrates the RIFs' influences on accident types. In this way, the average
299 TRI values of all accident types ranks the variables' effects on the 'accident type'. The higher a TRI value is, the
300 higher its corresponding RIF's effect on 'accident type'.

301 3.3.3 Model validation

302 Two axioms to be satisfied in the sensitivity analysis (Yang et al., 2009, Zhang et al., 2013) are expressed as below:

303 Axiom 1: A slight increase or decrease in the prior probabilities of each RIF, should contribute to the correspondence
304 increase or decrease in the posterior probability of the target node (*i.e.* accident type).

305 Axiom 2: The total influence of the integration of the probability variations of x parameters should be no smaller than
306 the one from the set of y ($y \in x$) RIFs.

307 Moreover, the validity of the proposed BN model is also conducted by simulating the past maritime accidents with the
308 associated parameter settings to test if the model can deliver the result reflecting the reality.

309 3.4 Scenario analysis

310 BN modelling can also explain the most probable scenario with reference to a particular accident type. Providing a
311 plausible explanation for the observed findings is called the most probable explanation (MPE). It is a special case of
312 the maximum a-posteriori probability. In case that results of regular belief updating are questionable, the MPE can be
313 used to identify the states of RIFs to provide a scenario for which the beliefs are upheld. It finds a completely

314 specified scenario easier to understand. Then the study gains insights by putting the BN in an MPE mode, entering the
315 evidence, and observing the most probable configuration for the investigated maritime accident type.

316 4. Results and discussion

317 4.1 Description of accident types

318 To generate the RIFs in maritime accidents according to the procedure in Section 3.1, a case-by-case analysis is
319 conducted. In this way, 25 RIFs are defined as the variables in Table 3 for the BN construction. In the quantitative
320 analysis of BN modelling, the accident type is defined as a dependent variable, classified into collision, grounding,
321 flooding fire/explosion, capsized, contact/crush, sinking, overboard, and others, as presented in Table 4. These accident
322 types are defined with respect to the classification of MAIB's maritime accident reports.

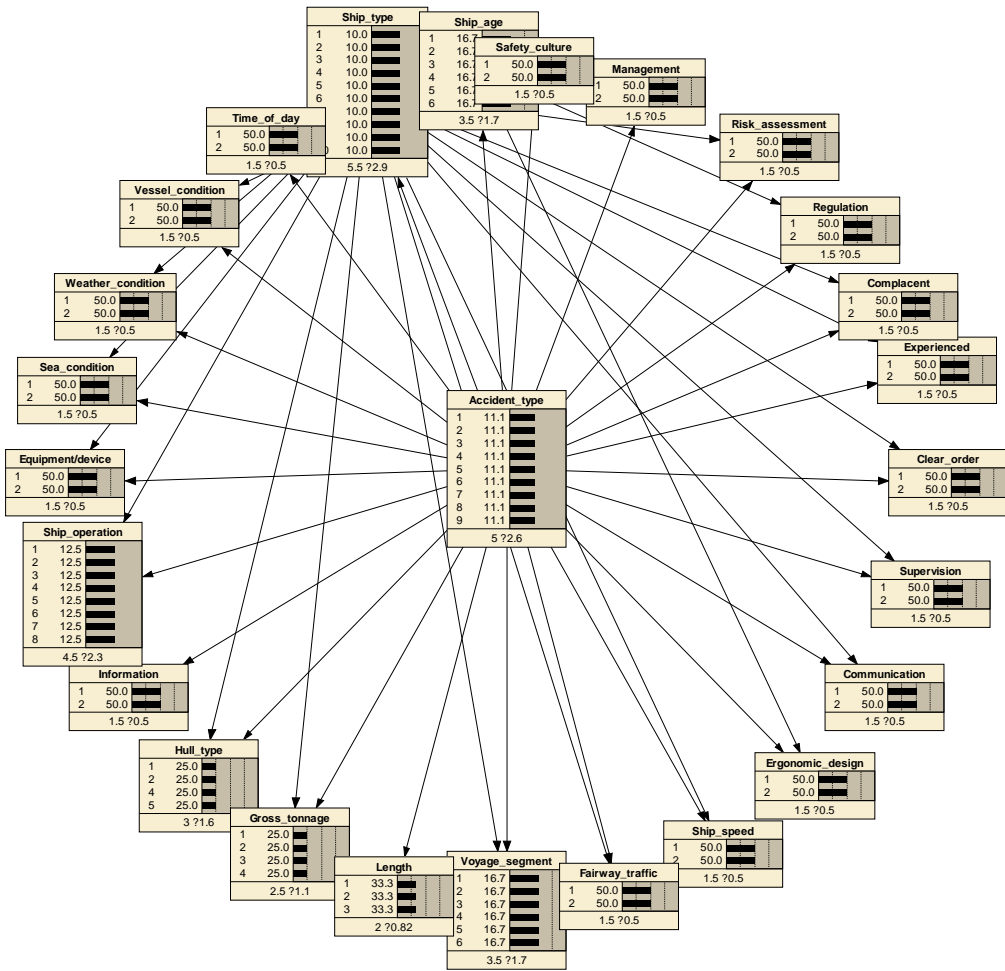
323 Table 4 Accident type

No.	Accident type
<i>S1</i>	Collision
<i>S2</i>	Grounding
<i>S3</i>	Flooding
<i>S4</i>	Fire/explosion
<i>S5</i>	Capsized
<i>S6</i>	Contact/crush
<i>S7</i>	Sinking
<i>S8</i>	Overboard
<i>S9</i>	Others

324

325 4.2 TAN modelling

326 To generate the BN model, 25 RIFs are involved to demonstrate their relationships with the dependent variable (*i.e.*
327 accident type). The Netica software package (Norsys, <http://www.norsys.com>) is applied to assist the calculation. It
328 has a 'learning network' function that develops the TAN network based on Eq. (2). The structure of BN is presented in
329 Fig. 1. After the BN qualitative structure is trained by the data, it is carefully checked by domain experts to ensure all
330 the links between the nodes are meaningful. In this study, no changes are made in the fine-tune process since all the
331 interrelationship suggested by the data reflect the reality.

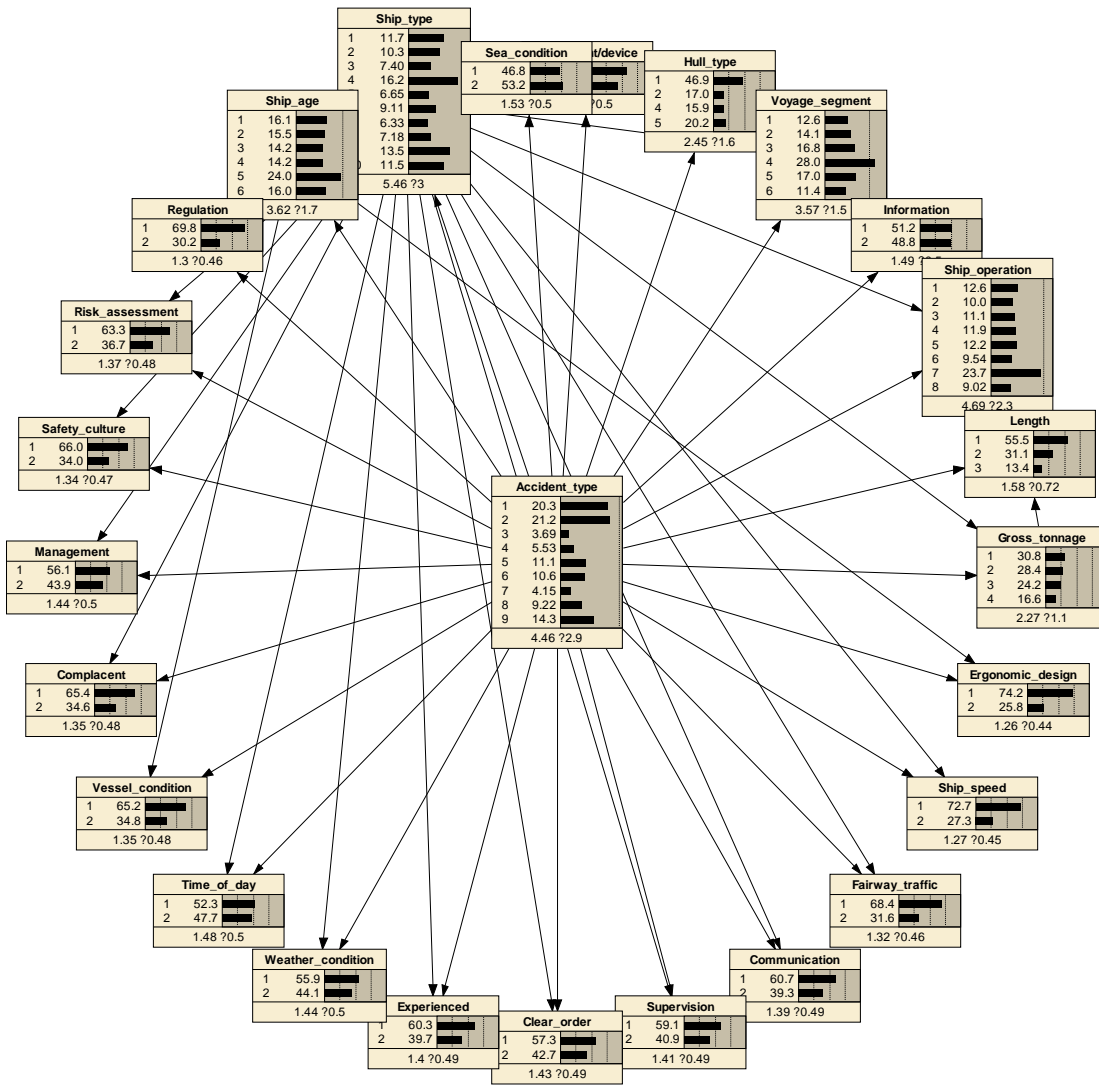


332

333 Fig. 1. Proposed BN for analysis of accident types probability

334 Based on the TAN model, the parameter learning of CPTs from the cases is conducted by Netica Software using the
 335 counting-learning algorithm (https://www.norsys.com/WebHelp/NETICA/X_Counting_Learning_Algorithm.htm).

336 Once the CPTs are constructed and obtained, the posterior probabilities of each variable can be calculated. The
 337 statistical analysis of the probability of variables, reveals interesting initial findings for useful insights regarding safety
 338 caution and accident prevention as follows.



339

340 Fig. 2. Results of TAN

341 Fig. 2 presents the results of TAN involving all the retained 25 RIFs. Among the accidents, grounding and collision
 342 are among the most frequent accident types, accounting for 20.3% and 21.2%, respectively.

343 4.3 Sensitivity analysis

344 4.3.1 Mutual information

345 The mutual information between “accident type” and RIFs is demonstrated in Table 5. From this point of view, the
 346 variables with higher $I(s,R_k)$ reflects essential impacts on “accident type”. When “accident type” is the parent node,
 347 “ship age” with the corresponding mutual information value of 0.05422, has the largest effect on the accident type.
 348 Meanwhile, it can be seen that many mutual information values are less than 0.03 in Table 5. 0.03 is selected in this
 349 study as the threshold for the selection of such factors for further discussion. Variables ‘ship age’, ‘ship operation’,
 350 ‘voyage segment’, ‘vessel condition’, ‘information’, are selected to be calculated for the factor analysis in the next
 351 step. However, it does not rule out the possibility of using a smaller value to take into account more factors in the

352 discussion when and where appropriate. From a methodological perspective, the method of using mutual information
 353 can provide an effective way to analyse the influential individual RIFs in a prioritised list.

354 Table 5 Mutual information shared with ‘Accident type’

Node	Variance Reduction	Percentage (%)	Mutual Info	Percentage (%)	Variance of Belief
Ship_age	0.02399	0.284	0.05422	1.84	0.0015433
Ship_operation	0.3115	3.69	0.05132	1.74	0.0030026
Voyage_segment	0.11	1.3	0.03595	1.22	0.0013546
Vessel_condition	0.07391	0.874	0.03171	1.07	0.0006767
Information	0.06113	0.723	0.03042	1.03	0.0010573
Ship_type	0.03119	0.369	0.02891	0.98	0.0011112
Safety_culture	0.01585	0.188	0.02871	0.973	0.000501
Hull_type	0.1171	1.39	0.02838	0.962	0.0008351
Gross_tonnage	0.0414	0.49	0.02482	0.841	0.0010064
Regulation	0.01091	0.129	0.02306	0.782	0.0005812
Length	0.02874	0.34	0.02151	0.729	0.0003882
Ergonomic_design	0.07421	0.878	0.0194	0.657	0.0006816
Sea_condition	0.0168	0.199	0.01774	0.601	0.0006831
Risk_assessment	0.06751	0.799	0.01466	0.497	0.0004953
Experienced	0.000957	0.0113	0.01271	0.431	0.0003126
Ship_speed	0.006733	0.0797	0.01172	0.397	0.0003134
Weather_condition	0.004131	0.0489	0.00889	0.301	0.0004858
Management	0.02553	0.302	0.00851	0.288	0.0001854
Clear_order	0.01196	0.142	0.00707	0.24	0.0002377
Fairway_traffic	0.03498	0.414	0.00704	0.238	0.0001619
Time_of_day	0.04428	0.524	0.00671	0.227	0.0002614
Complacent	0.003327	0.0394	0.006	0.203	0.000211
Communication	5.57E-05	0.000659	0.00547	0.185	0.0000786
Equipment/device	0.003186	0.0377	0.00541	0.183	0.0001612
Supervision	0.01893	0.224	0.00399	0.135	0.0001467

355

356 4.3.2 Sensitivity analysis

357 With regard to the most important variables influencing each of the investigated accident types, the next step is to
 358 figure out how these variables (the states of variables) affect the target accident type. To do so, the calculation of a
 359 joint probability of each variable and ‘accident type’ is presented in Table 6.

360 Table 6 The joint probability of the TAN model

	Ship age								
	S1	S2	S3	S4	S5	S6	S7	S8	S9
1	23.6	19.8	3.69	3.88	12	13.9	2.56	7.7	12.9
2	22.4	21.1	2.2	4.99	8.81	8.73	3.8	8.21	19.7
3	14.8	23.5	7.24	8.87	8.93	11.2	7.74	8.92	8.82
4	15.8	22.5	2.69	3.72	13.7	12.6	3.33	12.9	12.8
5	16.8	27.7	4.27	5.58	11.7	7.02	4.11	7.15	15.7
6	29.3	6.95	2.07	6.52	10.6	14.3	4.13	13.2	13

Ship operation									
	S1	S2	S3	S4	S5	S6	S7	S8	S9
1	12.8	25.3	3.3	4.74	15.2	9.75	4.48	7.9	16.5
2	15.9	16.3	4.1	6.5	10.3	11.1	4.57	9.81	21.4
3	14.4	28.4	4.08	5.32	9.28	11.9	4.14	8.9	13.6
4	16.5	21.6	3.51	5.05	12.5	12.2	3.92	9.36	15.4
5	16.9	14.2	4.45	5.12	15.4	9.69	3.98	15.9	14.3
6	16.6	20	4.26	6.75	10.7	11.6	5.26	9.27	15.7
7	35.7	22.8	2.64	5.19	6.51	8.71	3.14	6.08	9.23
8	17.5	18	4.51	6.48	12.7	12.2	5.03	9.82	13.7
Voyage segment									
	S1	S2	S3	S4	S5	S6	S7	S8	S9
1	15.3	15.6	4.24	6.03	13.5	11	4.72	9.95	19.6
2	20.3	23.5	3.73	5.31	12.6	10.6	4.16	7.96	11.8
3	11.5	28.5	3.2	5.44	7.72	15.9	4.29	7.54	15.9
4	25.4	22.1	3.17	5.34	11.3	5.86	2.99	10.6	13.3
5	27.5	17.7	3.89	5.02	10.9	9.84	4.67	7.51	13
6	16.5	16.9	4.6	6.53	11.1	14.2	5.12	11.8	13.3
Vessel condition									
	S1	S2	S3	S4	S5	S6	S7	S8	S9
1	24.3	21.191	3.63	4.46	9.56	11.5	2.22	10.1	13.1
2	12.8	21.212	3.8	7.53	13.9	8.99	7.76	7.52	16.5
Information									
	S1	S2	S3	S4	S5	S6	S7	S8	S9
1	21.8	15.8	3.33	6.17	13.2	7.28	4.28	10.6	17.6
2	18.7	26.8	4.06	4.86	8.86	14.1	4.01	7.82	10.8

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According to Table 6, the state of each variable that poses the highest influence on an accident type is shown (in bold value), as well as the state of each variable that poses the lowest influence on an accident type (in bold value). For example, when a ship is in the state of ‘on passage’, there is the highest probability for the accident to be ‘collision’ (35.7%); when ‘ship operation’ is the state of ‘towing’, there is the lowest probability to be ‘collision’ (12.8%). However, when a ship is in ‘pilotage’, there is the highest probability to be ‘grounding’ (28.4%); in ‘fishing’ operation, there is the lowest probability to be ‘grounding’ (14.2%). For the voyage segment, when in the state of ‘transit’, a ship has the highest probability to be in ‘collision’ (27.5%); when in ‘arrival’ segment, it has the lowest probability to be in ‘collision’ (11.5%), but has the highest probability to be in ‘grounding’ (28.5%). As far as the ship age is concerned, a ship with ages from 11 to 15 has the lowest probability to be involved in ‘collision’ (14.8%), whereas a more than 20-year-old ship has the highest probability to be involved in ‘grounding’(27.7%). Despite good vessel condition and the condition of good information, a ship can still highly associate with ‘collision’, whereas the situation of poor information on-board ship exposes the highest risk of ‘grounding’.

374 In this way, it demonstrates the influence of certain state of a single variable on an accident type. Moreover, it
 375 illustrates how different states of single variable contributes to the probability of a particular accident type. Generally,
 376 more attention should be paid to the red highlighted with the state of the single variable under an accident type, as
 377 these situations show high probabilities of accidents.

378 In terms of TRI sensitivity analysis, Table 7 demonstrates the TRI value of ‘ship age’ against collision. Table 8
 379 indicates the values of all RIFs for all accidents. Moreover, by comparing the updated value of the target node, it is
 380 claimed that the model is in line with Axiom 1.

381 Table 7 TRI of a risk variable (ship operation) for collision

Ship age									
1	2	3	4	5	6	Collision	HRI	LRI	TRI
/	/	/	/	/	/	20.3	9.0	5.5	7.25
100%	0	0	0	0	0	23.6			
0	100%	0	0	0	0	22.4			
0	0	100%	0	0	0	14.8			
0	0	0	100%	0	0	15.8			
0	0	0	0	100%	0	16.8			
0	0	0	0	0	100%	29.3			

382

383 Table 8 TRI of risk variables for all accident types

Node	TRI									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	Average
Ship age	7.25	10.38	2.59	2.58	2.45	3.64	2.59	3.03	5.44	4.44
Ship operation	11.45	7.10	0.94	0.88	4.45	1.75	1.06	4.91	6.09	4.29
Voyage segment	8.00	6.45	0.72	0.76	2.89	5.02	1.07	2.15	3.30	3.37
Vessel condition	5.75	0.01	0.09	1.54	2.17	1.26	2.77	1.29	1.70	1.84
Information	1.55	5.50	0.37	0.66	2.17	3.41	0.14	1.39	3.40	2.06

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385 Specifically, in Table 7, the first row denotes the base-case scenario, and the following rows represent the different
 386 scenarios when each state of the variable reaches 100%. To obtain impact levels of such RIFs in accident types, TRIs
 387 are compared and ranked. Generally, the most important variables for ‘accident types’ are as follows:

388 **Ship age > Ship operation > Voyage segment > Information > Vessel condition**

389 In detail, the most important variables list for different accident types are demonstrated in Table 9.

390 Table 9 The most important variables

Accident type	Ship age	Ship operation	Voyage segment	Vessel condition	Information
S1 Collision	3	1	2	4	5
S2 Grounding	1	2	3	5	4
S3 Flooding	1	2	3	5	4
S4 Fire/explosion	1	3	4	2	5
S5 Capsize	3	1	2	4	4
S6 Contact/crush	2	4	1	5	3
S7 Sinking	2	4	3	1	5
S8 Overboard	2	1	3	5	4
S9 Others	2	1	3	5	4

391

392 From this point of view, different accident types are correlated with different variable priorities. For example, ‘vessel
393 condition’ is the most important RIF for ‘sinking’, but the least important RIF for ‘contact/crush’. ‘Ship operation’
394 contributes more to the accidents like ‘collision’, ‘capsize’, and ‘overboard’, than the accidents of ‘sinking’ and
395 ‘contact/crush’.

396 4.3.3 Model validation

397 To validate the model, it is examined by testing the combined effect of multiple RIFs to the accident types.
398 Accounting for different states of the parent nodes, this study calculates the changed value of each state. The
399 ‘information’ is selected as the first node, the state generating the highest changed value of state 1 (*i.e.* collision) in
400 ‘accident type’ is increased by 10%, while the state generating the lowest changed value of state 1 in ‘accident type’ is
401 decreased by 10%. This procedure is written as ‘~10%’ in Table 10. Then, the same approach is applied to the next
402 RIF, and the integrated changed value is obtained and updated. The updating procedure would continue until all RIF
403 nodes are included. Similarly, the same updating procedure is applied into the state 2, 3... 9 in ‘accident type’
404 respectively, until all states are included.

405 The first column of the data in Table 10 shows the original values in TAN, and other columns state the updated
406 changed values of results. However, each state of ‘accident type’ is calculated separately from each other, *i.e.* each
407 row is computed through the change of states of RIFs in each accident type. From Table 10, the updated values of the
408 target node are gradually increasing or decreasing along with the continuously changing RIFs, so that Axiom 2 is
409 examined.

410 Table 10 Accident rate of minor change in variables

Information	/	~10%	~10%	~10%	~10%	~10%
Vessel condition	/	/	~10%	~10%	~10%	~10%
Voyage segment	/	/	/	~10%	~10%	~10%
Ship operation	/	/	/	/	~10%	~10%
Ship age	/	/	/	/	/	~10%

S1	20.3	20.4	21.2	21.5	22	22.2
S2	21.2	21.761	21.765	22	22.2	22.6
S3	3.69	3.72	3.74	3.76	3.79	3.8
S4	5.53	5.6	5.8	5.82	5.85	5.91
S5	11.1	11.3	11.6	11.7	11.8	11.9
S6	10.6	10.9	11.1	11.371	11.426	11.6
S7	4.15	4.16	4.52	4.57	4.61	4.68
S8	9.22	9.36	9.53	9.61	9.79	9.91
S9	14.3	14.6	14.86	14.945	15.1	15.3

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412

Furthermore, the past maritime accidents (which were not included in the database used for the BN construction) are

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simulated in the proposed BN model to show the validation of proposed BN model. For instance, from the MAIB 5-

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2020, there was a collision between the bulk carrier Gülnak and the moored bulk carrier Cape Mathilde River Tees, in

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England on 18 April 2019. All the parameter settings for the proposed BN model can be obtained based on the

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descriptions, including

417

1) 'Steel' for hull type, 'bulk carrier' for ship type, '2011' for the year of build, '179.88m' for length, '23397' for

418

gross tonnage, 'on passage' for ship operation, '18 April 2019 0324 UTC+1' for the time of day.

419

2) Vessel condition was good because 'vessel had no deficiencies' and 'no evidence was found to indicate that Gülnak

420

or any sister vessels had previously experienced unexpected difficulties when manoeuvring'.

421

3) Experience was good because of the qualified bridge team. Communication was good due to 'the pilot and

422

Gülnak's master discussed the passage plan, ..., advised that the vessel had no deficiencies and that its anchors were

423

cleared away and ready for use'.

424

4) Sea condition and weather condition were both fine because of 'the negligible tidal stream and the light winds'.

425

5) Equipment was not fully utilised. Although no direct cause was identified for the equipment malfunction, a

426

recommendation had been made to ensure that the bridge equipment on the vessel is fully operational.

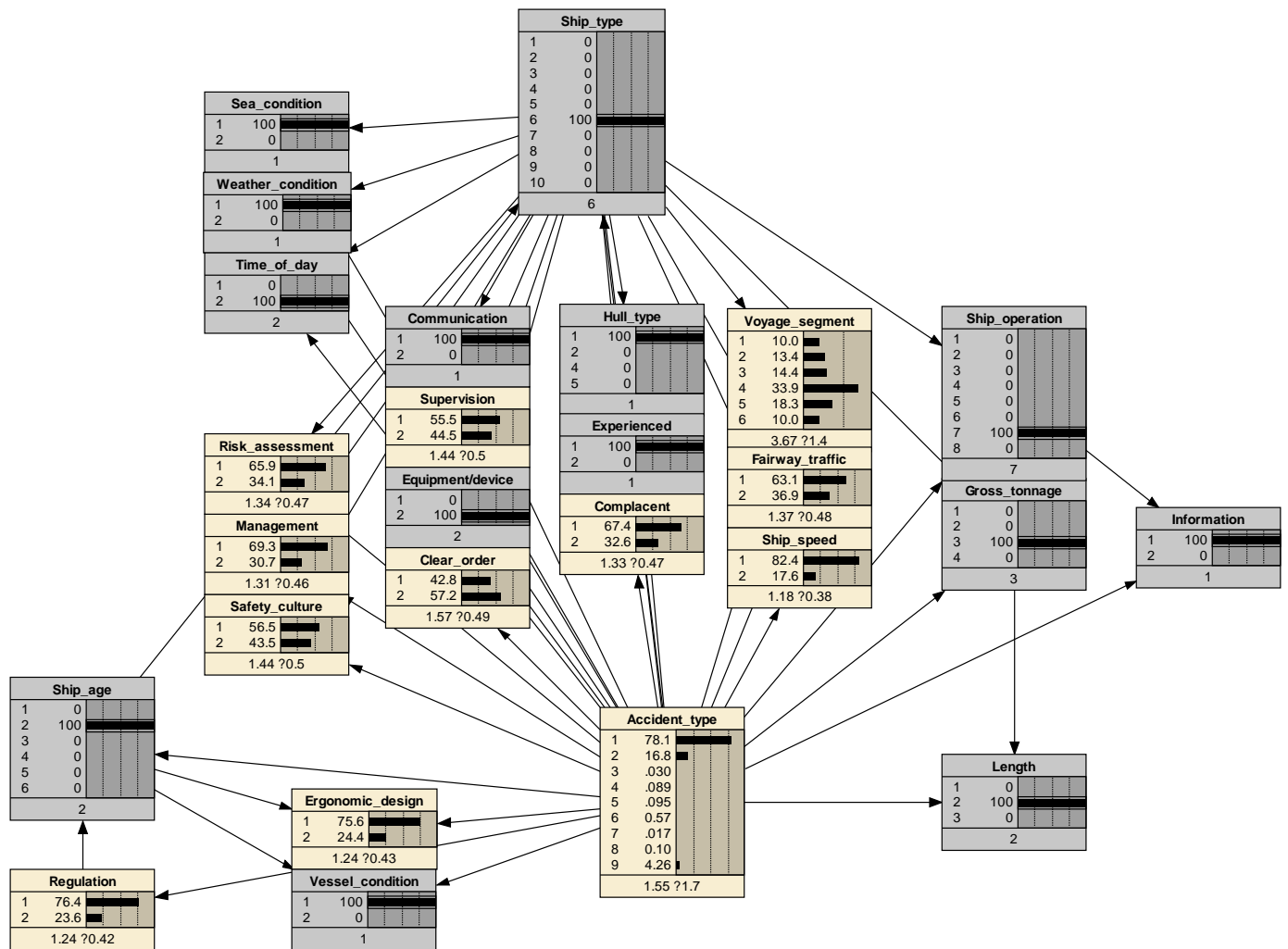


Fig.3 Model validation based on a past maritime accident

The accident report stated that the factors contributing to the inability to fully arrest Gülnak's turn were not apparent, and some information were not recorded. Therefore, the other nodes keep their generic original probabilities given no updated evidence is collected from the accident report. Based on the above parameter settings, it reveals a very high probability of 78.1% for the vessel to be involved in a collision, which further validates the proposed model, as shown in Figure 3.

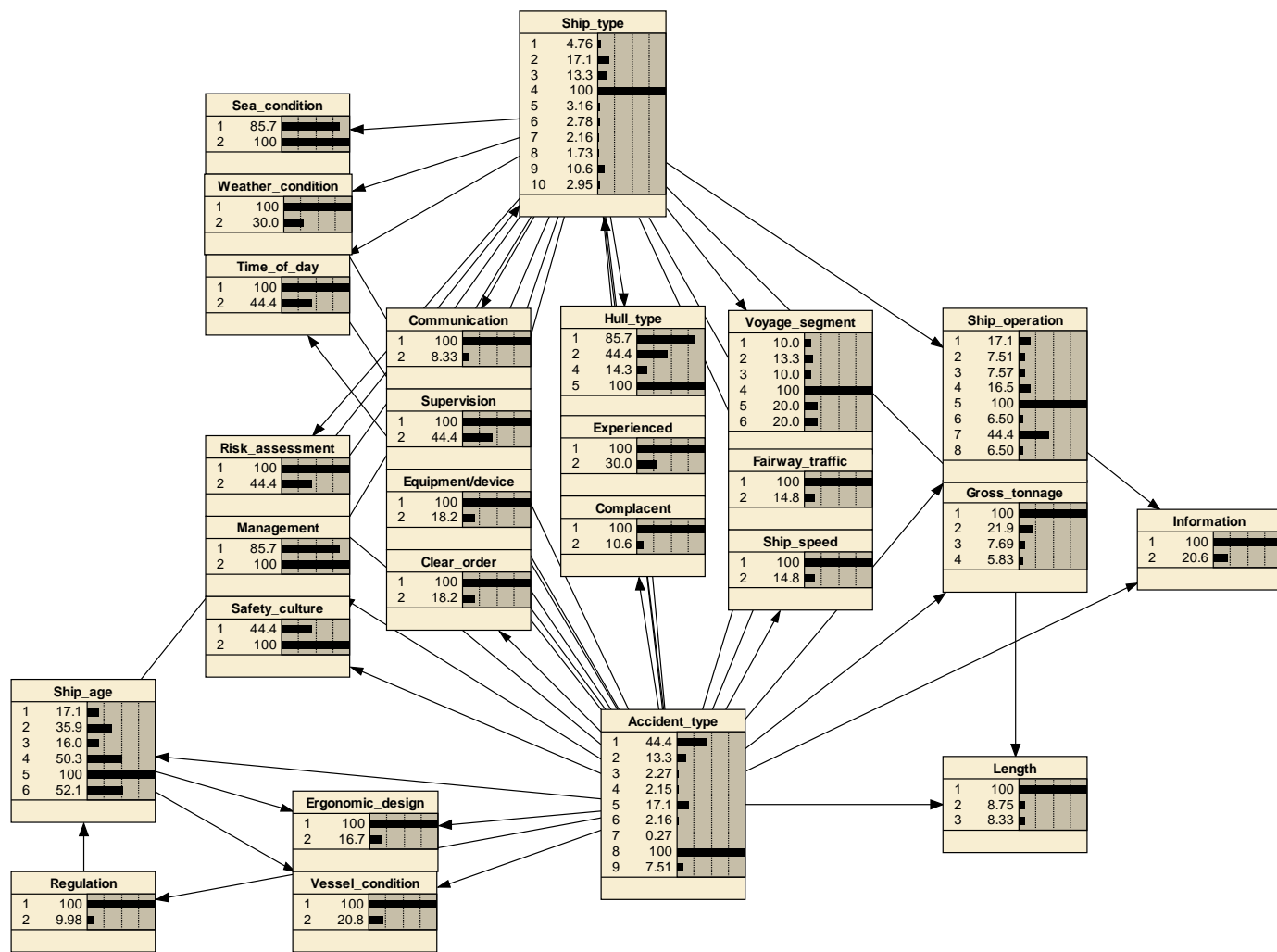
4.4 Implications

The study enables the understanding of differences among critical factors, contributing to different types of accidents by incorporating human factors into the maritime accident analysis. The BN modelling can also help explain the most probable scenario with reference to a particular accident type.

To enable the MPE function, each variable will have a belief-bar at the 100% level, and usually some bars in RIFs are at lower levels, as seen in Fig. 4. It reveals the most probable configuration by assuming the state with the bar at the 100% level for each variable. The shorter bars indicate the relative low probabilities of the other states, given that the

441 other variables are in the most probable configuration. In addition, they are scaled by the same factor used to bring the
 442 longest bar to 100%.

443



444

445 Fig. 4 Most Probable Explanation for BN model

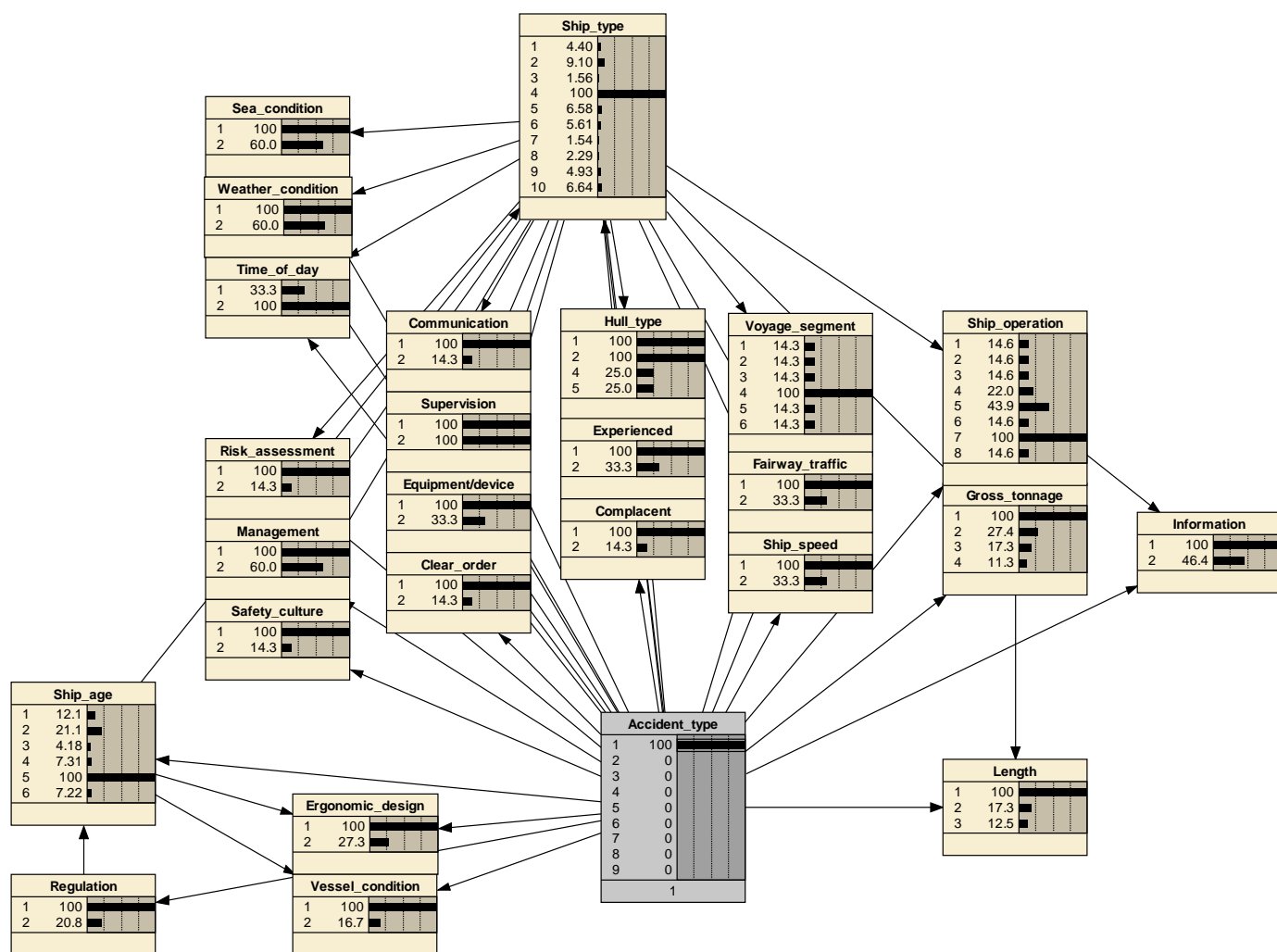
446 From Fig. 4, 'overboard' is the most probable accident type, as its high occurrence frequency, and other RIFs reveal
 447 the corresponding most probable states. That is to say, a 'fishing vessel' tends to be 'overboard' within the following
 448 conditions:

- 449 1) Ship age 'more than 20', ship length '100m or less', gross tonnage '300GT or less', in 'finishing' operation and
 450 'mid-water' voyage segment with 'normal' speed, in 'good condition', with friendly ergonomic design and correctly
 451 operating device, and with effective navigational information;
- 452 2) Bad sea condition, during the time from 7:00 to 19:00;
- 453 3) Dysfunctional management system, lack of safety culture.

454 With regards to this explanation, it emphasises the important causal relation between dysfunctional management
 455 system and overboard. The management system refers to shore management, maintenance management, bridge source
 456 management, on board management, port service, inadequate training, emergency drill, etc., which is a complex
 457 system as a significant variable influencing human factors for overboard. From the investigation of MAIB 24-2014, it
 458 is evident that the onboard management of Ovit (of which overboard of the fishing ship occurred), was dysfunctional,
 459 as well as the safety culture developed on the bridge was provided by the insufficient leadership of the master.

460 In addition, a lack of safety culture and precautionary thought are seen as the critical factors for human errors from
 461 Figure 4, which explains some dangerous behaviours of passengers or crews. Lu and Tsai (2008) conducted the factor
 462 analysis revealed six safety climate dimensions, and used logistic regression analysis to evaluate the effects of safety
 463 climate on vessel accidents. The results suggested the job safety has the most critical impact on vessel accidents,
 464 followed by management safety practices and safety training dimensions.

465 Similarly, when ‘accident type’ is selected as state 1 (collision), the MPE is displayed in Fig. 5.



466

467 Fig. 5 Most Probable Explanation for ‘collision’

468 From Fig. 5, there are multiple 100% bars for 'hull type'. Normally, when two or more states of the same variable
469 have bars that are at the 100% level, it indicates that there is more than one configuration with the highest probability
470 (*i.e.* the configurations have equal probability). Then one of the states is to be entered with an artificial finding that
471 the variable is in that state, to see how it changes the multiple 100% bars of other variables. When accident type is
472 selected in Fig. 5, there is a high probability for the 'fishing vessel' to collide under these circumstances:

473 1) Ship age 'more than 20', ship length '100m or less', gross tonnage '300GT or less', 'on passage' operation and
474 'mid-water' voyage segment with 'normal' speed, in 'good vessel condition', with friendly ergonomic design and
475 correctly operating device, and effective navigational information;

476 2) During the time before 7:00 or after 19:00;

477 3) Ineffective supervision or supports of operation.

478 Under this circumstance, ineffective supervision or supports of operation is strongly related to the collision in view of
479 human factors. Ineffective supervision and supports, and improper supervision of loading operation are frequent
480 during the navigation. Lone watchkeeper or working isolated makes the procedures onboard vulnerable to the hazards
481 due to the workload pressure or onboard culture. From MAIB 17-2016 report, although required by the Arco Avon's
482 SMS, the third engineer did not inform the chief engineer or the bridge officer of the leaking problem of fuel or his
483 intention to fix it. The reason for him not doing so is probably to have been influenced by the onboard culture of
484 routine working isolated and the absence of adequate and frequent communication. Also, Arco Avon's chief
485 engineer's standing orders requiring the duty engineer to progress routine duties and conduct planned maintenance
486 while on watch, effectively condoned working alone and disobeyed the guidance provided in the relevant safety
487 regulations (e.g. the Code of Safe Working Practices for Merchant Seafarers 2015 edition). It all contributed to the
488 mistakes the third engineer made. Moreover, from the MAIB 8-2014 report, the mater and chief officer kept lone
489 watchkeeper on the bridge with the functional Bridge Navigational Watch Alarm System (BNWAS) switched off.
490 According to this accident, and several similar others in the past, MAIB demonstrated that it was not safe for only two
491 bridge watchkeepers to operate vessels because of the workloads placed on watchkeeping officers. Branch et al.
492 (2004) reported that at least three of the fifteen ships which failed to keep a proper lookout at night to collision had
493 lone watchkeepers on the bridge. Working isolated or improper supervision increases the risk of human errors in
494 navigation compared to the situations where operations are under supervision.

495 By trying each of the possibilities, all the configurations that are at the highest probability level are revealed. Table 11
496 illustrates the MPE for all accident types. Although there are influences between different RIFs, poor vessel condition

497 such as increasing complexity of propulsion arrangements or modification made to vessels size has a strong relation to
 498 sinking. Insufficient or lack of updated information, such as falsified records of information, relies on a single piece of
 499 navigational equipment, or without working indicators for necessary observing, contributes to grounding, contact, and
 500 other incidents. Ergonomic impact of innovative bridge design (e.g., visual blind sector ahead, motion illusion) is
 501 strongly related to fire and sinking. Also, it emphasises several human factor related variables under different accident
 502 types. For example, there is a high probability for collision to happen under the case of lone watchkeeper or working
 503 isolated. Grounding becomes probable under the circumstance with inadequate risk assessment, dysfunctional
 504 management system, unclear order from documents, and ineffective supervision. The most probable explanation given
 505 human factors for flooding is the lack of safety culture and precautionary thought. Human factors for capsizing are
 506 related to lack of risk assessment, unclear order, and ineffective supervision. The situations with poor safety culture,
 507 dysfunctional management, and unclear order are strongly associated with sinking.

508 Table 11 Most Probable Explanation for all accident types

Variable	S1	S2	S3	S4	S5	S6	S7	S8	S9
Ship age	5	5	5	5	1	6	5	5	2
Ship operation	7	1	5	7	1	7	1	5	2
Voyage segment	4	2	4	4	5	3	5	4	1
Vessel condition	1	1	1	1	1	1	2	1	1
Information	1	2	1	1	1	2	1	1	2
Ship type	4	3	4	4	2	7	2	4	9
Safety culture	1	1	2	1	1	1	2	2	1
Hull type	2	1	2	2	1	1	1	5	1
Gross tonnage	1	2	1	1	1	3	1	1	2
Regulation	1	1	1	1	1	1	1	1	1
Length	1	1	1	1	1	2	1	1	1
Ergonomic design	1	1	1	2	1	1	2	1	1
Sea condition	1	2	1	2	2	1	2	2	1
Risk assessment	1	2	1	1	2	1	1	1	2
Ship speed	1	1	1	1	1	2	1	1	1
Weather condition	1	2	2	2	1	1	1	1	1
Management	1	2	1	2	1	1	2	2	1
Clear order	1	2	1	2	2	2	2	1	2
Fairway traffic	1	1	1	1	1	1	1	1	1
Time of day	2	1	1	1	1	2	1	1	1
Complacent	1	1	1	1	1	1	1	1	1
Supervision	2	2	1	1	2	1	1	1	1

509 5. Conclusions

510 Compared to previous studies focusing on causal factors related to the severity and the probability of maritime
 511 accidents, this study uses a data-driven TAN approach, to investigate how different risk factors generate an impact on

512 different types of maritime accidents with a focus on human factors. To identify RIFs, maritime accident reports from
513 MAIB and TSB within a five-year period of 2012-2017, are extracted and reviewed to develop a primary database on
514 maritime accidents. Then the risk-based TAN model is constructed to analyse RIFs incorporating human factors in
515 maritime accidents. Lastly, the sensitivity analysis is conducted, as well as scenario analysis and MPE to implicate
516 research contributions.

517 According to the calculations of the mutual information, crucial RIFs are ranked against different accident types. The
518 results reveal that critical RIFs for maritime accident types are 'ship age', 'ship operation', 'voyage segment',
519 'information', and 'vessel condition'. Meanwhile, it is evident that:

520 (1) The management system including shore management, maintenance management, bridge source management, on
521 board management, port service, inadequate training, emergency drill, etc., is a significant variable influencing human
522 factors for overboard. Besides, the lack of safety culture explains dangerous behaviours onboard, so as to cause
523 overboard.

524 (2) Ineffective supervision is strongly related to collision. Working isolated or improper supervision increases the risk
525 of human errors in navigation compared to operating under supervision.

526 (3) Collision tends to happen under the case of lone watchkeeper or working isolated. Grounding is probable under the
527 circumstance with inadequate risk assessment, dysfunctional management system, unclear order from documents, and
528 ineffective supervision. The most probable explanation on human factors for flooding is the lack of safety culture and
529 precautionary thought. Human factors for capsizing are related to lack of risk assessment, unclear order, and ineffective
530 supervision. The situation with poor safety culture, dysfunctional management, and unclear order is strongly
531 associated with sinking.

532 The scenario analysis provides a plausible explanation for the observed findings, revealing the most probable scenario
533 concerning a particular accident type. Therefore, it can help identify the potential hazards and effectively assist
534 maritime authorities in developing countermeasures for accident prevention.

535 Generally, the results from the TAN model present differentiation among the vital human factors contributing to
536 different types of accidents, which helps provide useful insights for accident investigation and prevention. However,
537 there is a drawback in the MPE method for implications. For instance, its results can change with the introduction of
538 irrelevant variables, and be deceptive in the situations where even the most probable explanation is improbable.

539 Furthermore, there is a limitation on data representation. There were 161 reports involving 208 vessels (cases) in the
540 study. The state 3 (flooding) of accident type accounts for 3.69% of all accidents, i.e. 7 cases of flooding. To present
541 more representative results, more data to be continuously collected to support the model development. In future work,
542 more attention will be paid to the variables, which are hard to measure in accident reports, *i.e.* mental workload, and
543 situational awareness factors, to explore the risk analysis of individual factors on maritime accidents.

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