



Research paper

Seafarer competency analysis: Data-driven model in restricted waters using Bayesian networks

Kun Shi^{a,b}, Shiqi Fan^{b,*}, Jinxian Weng^{a,**}, Zaili Yang^b

^a College of Transport and Communications, Shanghai Maritime University, Shanghai, China

^b Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, Liverpool, UK



ARTICLE INFO

Keywords:

Maritime safety
Maritime accident
Human factors
Seafarer competency
Bayesian network

ABSTRACT

Despite the efforts of maritime authorities to enhance seafarer competencies through the International Convention on Standards of Training, Certification and Watchkeeping for Seafarers (STCW), human error remains a leading cause of maritime accidents. To thoroughly investigate the impact of various human errors among seafarers on accidents, this paper aims to examine the relationships between seafarer competencies and maritime accidents using a data-driven approach from the perspective of bridge resource management (BRM). Through analysis of historical maritime accident reports, the dataset of seafarer competencies associated with maritime accidents is established. The least absolute shrinkage and selection operator (LASSO) method is employed to identify the critical seafarer competencies for accident prevention. Then, a data-driven Bayesian Network (BN) model, based on a Tree Augmented Naive Bayes (TAN) method, is constructed to reveal the relationship between seafarer competencies and accident types, which are validated by sensitivity analysis and case study. The results indicate that the key seafarer competencies for all maritime accidents are 'Maneuvers', 'Amend/maintain ship course', 'Decision making', 'Cognitive capacity', 'Information', 'Procedure operations', 'Situational awareness' and 'Communication'. Moreover, the study underscores the importance of leveraging lessons learned from past accidents to mitigate risks and ensure safe maritime operations. The findings contribute to a deeper understanding of the dynamics between seafarer competencies and accident types, unveiling the joint impact of different seafarer competencies on maritime accidents. This perspective offers valuable insights for maritime authorities in strengthening maritime safety regulations.

1. Introduction

Maritime transport is one of the most vital global transportation modes, which accounts for approximately 80% of world trade (UNCTAD, 2021). Once a maritime accident occurs, it will cause significant economic losses and casualties. For instance, the Sewol ferry capsized off the southern coast of South Korea in 2014, resulting in the deaths of more than 300 people (Kim, 2023). The vessel Ever Given running aground and blocking the Suez Canal in 2021 disrupted global trade by approximately \$9 billion daily (Talmazan et al., 2021). The investigation of global maritime accidents indicates that restricted waters, such as canals, channels, and straits, are high-risk areas for maritime accidents (Li et al., 2023). Restricted waters are typically located at the confluence of rivers and seas, serving as crucial hubs for trade between ports. Thus, it is necessary to reveal the reasons resulting in

maritime accidents in restricted waters to help maritime authorities make corresponding preventive measures.

Ship maneuvering is a complex human-machine control system where human behavior is vital for the safety of navigation (Han et al., 2021). Previous studies revealed that around 70%–90% of maritime accidents resulted from human factors (Wróbel, 2021). Hence, reducing human errors in ship navigation can effectively enhance maritime transport safety, thereby facilitating the development of international trade. Human reliability has long been a focal point of attention in the maritime sector. The International Maritime Organization (IMO) issued the International Convention on Standards of Training, Certification and Watchkeeping for Seafarers (STCW) in 1978 to enhance the seafarer competency in navigation, which could effectively standardize the watchkeeping practices of seafarers. However, despite the established frameworks and regulations, there remains a significant gap in terms of

* Corresponding author.

** Corresponding author.

E-mail addresses: fanshiqi@whut.edu.cn (S. Fan), jxweng@shmtu.edu.cn (J. Weng).

<https://doi.org/10.1016/j.oceaneng.2024.119001>

Received 4 June 2024; Received in revised form 8 August 2024; Accepted 13 August 2024

Available online 15 August 2024

0029-8018/© 2024 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

comprehensively understanding the full spectrum of competencies required for seafarers in the face of the evolving complexity brought by modern maritime operations. For example, the STCW code lacks in providing adequate standards for assessing the competency of seafarers, thereby failing to capture the true performance of seafarers (Ghosh et al., 2014). The competency of seafarers entails the quality of physical and intellectual proficiency, which is manifested through the utilization of knowledge, skills, mindset, and cognitive patterns, ultimately leading to successful performance (Teodorescu, 2006; Fan and Yang, 2023). Despite obtaining certificates of seafarer competency, seafarers still make significant errors due to their insufficient competency, which leads to maritime accidents during real-world navigation. With the rapid advancement of maritime technology, such as the development of autonomous ships, the maritime sector demands a new analysis method that enables to address the dynamics of human and machine systems onboard ships and to assess the required competency of seafarers in ensuring safe navigation.

Historical accident analysis is an effective method to identify the key risk influencing factors (RIFs) and formulate corresponding measures to prevent maritime accidents. By thoroughly examining various RIFs associated with a dangerous event, the interrelationships between these RIFs and the possibility of accidents could be revealed, enabling the implementation of effective preventive measures. Many researchers utilized historical accident reports to explore the RIFs of maritime accidents. For example, Weng and Yang (2015) utilized the logistics regression model to investigate the injury severity and mortality of the shipping accident. Wu et al. (2021) employed Bayesian networks (BN) to explore safety management issues related to the transportation of electric vehicles on RoPax vessels. These studies provide valuable insights for improving maritime safety management (Li et al., 2024; Ma et al., 2024; Xin et al., 2024). Hence, it is necessary and beneficial to learn lessons from historical accidents to enhance the reliability of seafarers in navigation through the implementation of preventive measures.

This study aims to propose a data-driven method to explore the impact of seafarer competencies on maritime safety in restricted waters, thereby formulating preventive measures to reduce human error. The new contributions of this study consist of (1) utilization of a data-driven method to reveal the relationship between seafarer competencies and maritime accident types; (2) identification of critical seafarer competencies for maritime accidents in restricted waters; (3) the implications of lesson learnt from accidents being applied to enhance human reliability during navigation. The significance of this study lies in its results offering guidance to relevant departments for developing effective measures in future maritime management to prevent potential human errors.

The structure of this study is as follows. The literature review of studies related to human factors in shipping industry is presented in Section 2. Section 3 describes the analytical methods developed to assess seafarer competencies in restricted waters. In Section 4, the analysis results of the model present the impact of various competencies on the probability of different accidents and discuss preventive measures for maritime accidents through the enhancement of seafarer competencies. Section 5 discusses the implications of the BN model for enhancing the navigational safety. The final section summarizes the key findings and contributions of the study.

2. Literature review

2.1. Human factor in maritime operation

In recent years, given that the shipping industry has undergone a paradigm shift from purely human-based navigation to navigation driven by human-machine cooperation, there has been increasing emphasis on exploring the new human factors raised from the change (Ceylan et al., 2021; Li et al., 2021; Liu et al., 2022). Analyzing maritime accidents with a focus on human factors exposes the increasingly

complex role that human elements play in the safety and efficiency of maritime navigation (Fan et al., 2020a,b; Russo et al., 2022; Fang et al., 2024). A full understanding of human factors leading to accidents is one of the most critical aspects of reducing the navigation risk in maritime transportation.

However, there are complex interrelationships among human factors. For example, (Hetherington et al., 2006) categorize human factors into organizational and management issues, personnel issues and design issues. These human factors have been proven to be associated with various unsafe behaviors, actions, and hazardous situations (Antão and Guedes Soares, 2008). The fatigue state, high stress, and anxious emotions of seafarers are significant contributors to unsafe behavior that leads to maritime accidents (Shi et al., 2023; Yang et al., 2023; Fan and Yang, 2024). To clearly reveal the interrelationships of human factors, many researchers have investigated the analysis of human errors in ship accidents from the perspective of human reliability analysis (HRA). In practice, Human Factors Analysis and Classification System (HFACS) is one of the most widely used methods to explore human impacts on maritime accidents. Rothblum (2002) first applied the HFACS method to maritime accidents. Akyuz and Celik (2014) proposed the HFACS-CM framework to evaluate human factors in marine accidents by integrating the Cognitive Map (CM) approach and the HFACS. It indicates the causality of individual and organizational behavior among seafarers in maritime accidents.

Furthermore, several studies emphasize the importance of investigating human errors in maritime accidents to gain a thorough understanding of the risk related to ship navigation through quantitative analysis, thereby gaining valuable insights for preventing the occurrence of accidents. For instance, Li et al. (2021) developed the Association Rule Bayesian Networks (ARBN) method to examine how external factors, such as environmental and ship factors, influence the probability of human errors. Their findings offer specific recommendations for preventing maritime accidents caused by human error across different environments. Similarly, Sheng et al. (2023) explored the probability of human errors occurring under various regional characteristics, considering the spatial heterogeneity of accidents. However, it's essential to note that such studies primarily rely on compiled accident databases for data. Consequently, certain details regarding human factors contributing to accidents may not have been fully considered in these studies (Fan et al., 2020a,b; Li et al., 2021), such as the direct and indirect causes of accidents, as well as an analysis of the actions taken by seafarers before and after the occurrence of accidents. Thus, a more comprehensive dataset of human factors should be incorporated into the analysis of maritime accidents. To address the issues with the dataset, Fan et al. (2020a,b) manually extracted the accident datasets from global historical maritime accident reports, developing a quantitative method to recognize the critical human factors leading to maritime accidents. Some accident prevention measures are provided from the human error perspective (Fan et al., 2020a,b). Maritime accident reports are conducted by various maritime administrations, with the sole purpose of preventing future accidents by identifying the causes and circumstances of accidents, which provide a sufficient data foundation for investigating the influence of human error on accidents.

2.2. Human competency

Human resources management (HRM) is an important concept in modern life and production, as every activity is related to human involvement (Liskova and Tomsik, 2013). HRM represents the effective integration of all human resources, which are widely used to enhance the reliability of teamwork for achieving safe and efficient operations (Fay et al., 2015). Particularly, the competency-based approach in HRM is an effective method for facilitating efficient collaboration among personnel. Koubek (2003) defined human competency as the fundamental characteristics of individuals that lead to their effective or outstanding performance, which manifests as behaviors that yield the

desired outcomes. All successes and failures in organization are linked to the competencies of the participants (Liskova and Tomsik, 2013). Therefore, all issues could be addressed through human competency.

Human competency is relevant only when discussing specific work activities. The necessary human competencies in various industries could be identified by the requirements of the activities, thereby measuring these human competencies to make strategies for enhancing the effectiveness of operations (Liskova and Tomsik, 2013). Based on the HRM theory, crew resource management (CRM) and bridge resource management (BRM) have been developed to enhance the efficiency and safety of air transport and maritime transport, respectively (Authorities, 1998; Hetherington et al., 2006; Weintrit and Neumann, 2011). Regarding CRM, Mansikka et al. (2019) developed a theoretical model of flight deck team performance based on pilot competency, which reveals the interaction between pilot competencies. It evolved a mature aviation safety training approach that reduces human errors in accidents and incidents by training operators in non-technical skills, including cooperation, decision making, and situational awareness (Dowd, 2010; Mansikka et al., 2019). Regarding BRM, O'Connor (2011) pointed that BRM training programs which are not based on current shipping developments are ineffective for managing seafarers. Campanico Cavaleiro et al. (2020) revealed that specific training shall aim at improving the naval competencies to minimize human error and maximize the safety of military teams operating in maritime environments. Hiroaki et al. (2022) also developed a BRM skills training method for remote

ship-handling simulators based on STCW regulations. Additionally, Fan et al. (2023) considered a comprehensive factor including seafarer competencies and navigational factors, proposing a dynamic human-machine system to analyze the interrelationships of seafarer competencies, which could provide valuable insights for reducing human error in maritime industry.

However, with the continuous development of maritime technologies, the role of seafarers is changing. For instance, the control of ships will gradually transition from seafarers to machines (Liu et al., 2022). The existing BRM analysis framework struggles to adapt to the assessment of seafarer competency (O'Connor, 2011). Thus, drawing lessons from historical accidents is imperative to reduce human errors and ensure maritime safety. To fulfil this gap, this study will incorporate seafarer competency into maritime accident analysis based on historical accident reports. It aims to identify the key seafarer competency associated with maritime accidents, thereby formulating targeted measures for reducing human errors in navigation. It offers a fresh perspective on preventing various types of maritime accidents by focusing on key human factors.

3. Methodology

In this study, a data-driven method for analyzing seafarer competency is proposed to investigate the influence of various competencies among seafarers on maritime accidents. As depicted in Fig. 1, the

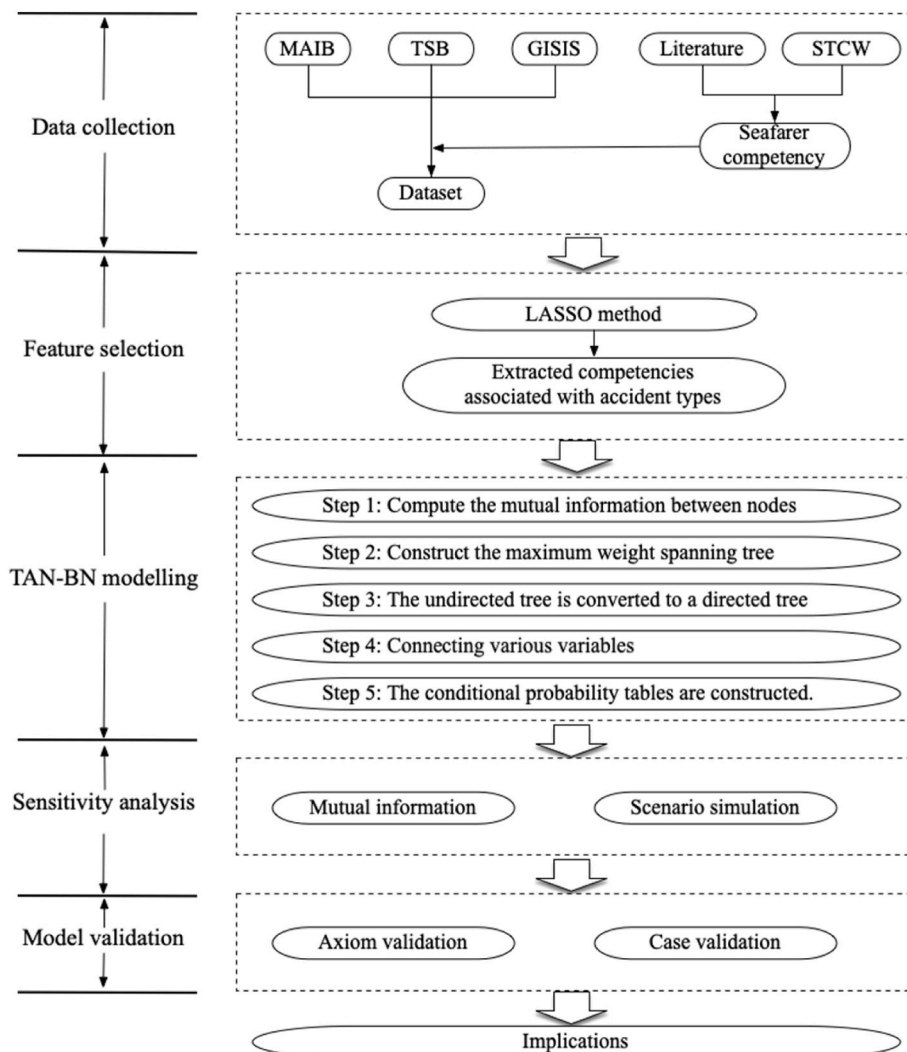


Fig. 1. The analysis framework of seafarer competency in restricted waters.

proposed analysis framework comprises the following main steps: data collection, feature selection, Tree Augmented Naive Bayes (TAN) modelling, BN modelling, sensitivity analysis, and model validation. The modelling and analysis processes will be detailed in the ensuing sections.

3.1. Data collection

A maritime accident report often presents a comprehensive investigation of its occurrence and hence provides insights into preventing future accidents by ascertaining their causes and circumstances. It provides detailed navigational information before and after the accident, which includes a narrative of the accident process and an analysis of causes. This study analyzes seafarer competencies in restricted waters by utilizing data from the three most used maritime accident database sources, including the Marine Accident Investigation Branch (MAIB) and the Transportation Safety Board (TSB) collected from Jan. 2012 to Dec. 2017, as well as the Global Integrated Shipping Information System (GISIS) collected from Jan. 2005 to Apr. 2021. Following the data pre-processing framework established in previous studies (Fan et al., 2020a,b, 2022), 49 maritime accidents are extracted due to their comprehension in terms of the identified risk factors (e.g. Fan et al., 2022), hereby the human competencies, including 18 collision, 15 grounding, 7 contact, and 11 other accidents. Table 1 displays the seafarer competencies employed in this study, derived from the STCW code, the Bridge Team Management code, and previous studies (STCW, 1978; Swift, 2004; Fan and Yang, 2023). By conducting a manual analysis of the text within the reports, this study has compiled a database consisting of 64 vessel accidents in restricted waters. These include 22 vessels from the MAIB, 13 vessels from the TSB, and 29 vessels from the GISIS, all attributed to human errors by seafarers.

To clearly explain this process of data collection, one case, namely *Prospect*, from the MAIB is selected to demonstrate the extracted process of seafarers' competencies. A trawler *Prospect* grounded on Skibby Baas rocks at the north entrance to Lerwick Harbour on August 5, 2013 (MAIB 7/2014). Initially, the skipper's SA was compromised because they had consumed alcohol before returning to the vessel, which significantly impaired their performance. Moreover, the skipper's SA was further reduced by distraction during navigation, which was evident by a prolonged telephone conversation during the voyage (i.e. a lack of SA). Then, the nautical charts were not sufficiently used by the skipper, which primarily relied on visual navigation (i.e. lack of EQM). As a result, the skipper had difficulty obtaining sufficient and effective information to sense and evaluate the navigational environment (i.e. lack of INF). Subsequently, the skipper altered the vessel course to avoid Skibby Baas (i.e. lack of SO). However, the skipper did not adequately consider the potential influence of the predicted tidal stream on the vessel's course toward Skibby Baas, despite being aware of its rate and direction (i.e. a lack of KNO). The Port Control watchkeeper attempted to alter the risk to the vessel *Prospect*, but their efforts were unsuccessful (i.e. a lack of COM). When ending the telephone conversation, the skipper did not check the position of the ship (i.e. a lack of PO). The vessel grounded at the end.

3.2. Feature selection

To obtain comprehensive reports which reveal evidence relating to all the above listed human competency, the established database is still relatively small despite the efforts in the investigation of the aforementioned three main sources recording maritime accidents. Compared to all the competency factors in Table 1, such a size of data will possibly not be able to deliver a reliable result. It is evident that incorporating a large number of variables into a prediction model with a limited number of training data can significantly compromise its robustness and reliability (Dernoncourt et al., 2014). More specifically, in the BN modelling process, when there are numerous nodes with limited data, it diminishes the accuracy of calculating conditional probability tables (CPTs) (Fan

Table 1
Seafarer competencies during navigation.

Seafarer competency	Abbreviation	Description	Source
Knowledge	KNO	A comprehensive grasp of relevant equipment, proficient skills, and a well-grounded sense of precaution, demonstrating the capability to handle routine tasks and respond effectively to emergencies.	STCW (1978)
Cognitive capacity	CC	Seafarers' cognitive capacity is related to their cognitive states and mental workloads, which are influenced by inattention, observation missed and communication failures.	Fan et al. (2020, 2023)
Information	INF	The ability to obtain accurate information from nautical charts, publications, radar, ECDIS, and Automatic Radar Plotting Aid (ARPA).	Fan and Yang (2023)
Task demand	TD	The ability to recognize the existence of a problem that needs to be addressed in a given navigational condition.	Fan and Yang (2023)
Situational awareness	SA	The ability to perceive the surrounding navigation conditions, which is related to factors such as distraction, and the use of recreational drugs, or alcohol.	Swift (2004), and Fan et al. (2020a,b)
Teamwork and leadership	TWL	It involves supervision within the team and providing social and cognitive support to various officers on duty.	Swift (2004)
Communication	COM	Ineffective communication among the crew, such as misunderstanding caused by cultural differences.	STCW (1978)
Decision making	DM	Utilizing information, knowledge, situational awareness, teamwork, and effective communication to arrive at rational choices is at the core of decision-making.	STCW (1978)
Equipment correctly used	EQM	Inadequate EQM competency, such as mispositioning or neglection alarm systems, leads to human error. Moreover, effective use of navigational aids like functional lights is vital for reducing seafarers' cognitive load.	Fan et al. (2020) and STCW (1978)
Maneuvers	SO	An appropriate steering mode is chosen according to the prevailing various navigational environments conditions. Furthermore, collision avoidance actions are implemented in compliance with the International Regulations for Preventing Collisions at Sea (GOLRES).	STCW (1978)
Amend/maintain ship course	SC	The ship's course and speed are adjusted and maintained by utilizing sufficient information, possessing adequate knowledge, and correcting any errors in equipment or systems.	STCW (1978)
Procedure operations	PO	The correct operation includes adherence to	STCW (1978)

(continued on next page)

Table 1 (continued)

Seafarer competency	Abbreviation	Description	Source
		contingency plans, cargo operations, handling of hazardous cargoes, cargo inspection, and pollution prevention measures.	

and Yang, 2024). Therefore, it is crucial to extract the features relevant to accident occurrences to ensure the interpretability and efficiency of the model in predicting maritime accidents.

In this study, the least absolute shrinkage and selection operator (LASSO) method is utilized for feature selection. LASSO is a commonly used regression analysis method for feature selection, aiming to enhance the predictive accuracy and interpretability of the model. It realizes the reduction of the magnitude of model coefficients by adding an L1 regularization term to the traditional linear regression loss function, which shrinks the irrelevant variables. Currently, this method is widely used in maritime transportation fields (Wang et al., 2018). Compared to common feature selection methods such as support vector regression and the random forest method, the prediction model built using features extracted by LASSO demonstrates greater accuracy and stronger interpretability (Zhang et al., 2021; Zhou et al., 2022). The LASSO is feasible to integrate with the BN to analyze maritime accidents with a small sample size (Fan and Yang, 2024).

In general, the selection of important seafarer competencies through the LASSO algorithm could be expressed as follows:

$$\text{Min} \left\{ \frac{1}{2n} \sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^p |\beta_j| \right\} \quad (1)$$

where n represents the number of maritime accidents; p represents the number of seafarer competencies; y_i is the i th accident type; x_{ij} is the j th seafarer competency of the i th observation; β_0 is the intercept term and β_j is the coefficient of the j th competency; λ is the regularization parameter, which controls the strength of the L1 regularization term to prevent overfitting and improve the model's generalization capability. As the regularization parameter λ increases, more coefficients are shrunk towards 0. When a coefficient is shrunk to 0, the corresponding competency is excluded from the model. Generally, the optimal value of λ is obtained through cross-validation. Finally, by comparing the mean-square error (MSE) of the model with various λ , an appropriate number of seafarer competencies that significantly influence maritime safety is determined.

3.3. Tree Augmented Naive Bayes modelling

To gain a comprehensive understanding of the role of seafarer competency in ensuring maritime safety, the BN model is employed in this study to analyze the relationship between seafarer competencies and maritime accidents. Within structured BN, each node symbolizes a seafarer competency, and directed edges denote conditional dependencies among these competencies, enabling the representation of complex relationships through a directed acyclic graph (DAG). This BN model facilitates the determination of the joint probability distribution encompassing all competencies, which helps in investigating the specific impact of seafarer competency on maritime accidents. The joint probability distribution of a BN is defined by the following formula:

$$P(X_1, \dots, X_n, C) = P(C) \cdot \prod_{i=1}^n P(X_i | C) \quad (2)$$

where X_n represents the n th feature of seafarer competency, and C represents the type of maritime accidents.

The result accuracy depends on the match of the model and the available data. In other words, a BN model of a large number of nodes could be not driven by small data. Oppositely, when big data is available, the over simplified model could result in reduced accuracy. In this work, TAN and LASSO are used in a hybrid manner to address the balance between the limited data availability and a simple but sufficient model structure. More specifically, the TAN algorithm utilizes a data-driven approach to establishing the BN model for analyzing seafarer competency. The selection of RIFs relies on a LASSO method to improve the relevance of nodes and the robustness of the model. Additionally, the structure and CPTs of the model are trained using historical data. The model is validated through sensitivity analysis and case studies, which aids to further ensure the result accuracy. The following are the key steps for constructing the seafarer competency analysis model:

Step 1: Determine the correlation degree between seafarer competencies and the accident category variable C by computing their conditional mutual information (CMI). A higher value of CMI indicates a stronger relationship between seafarer competencies and accident type C . The calculation expression formula of this correlation is shown below:

$$I(X_i, X_j | C) = \sum_{x_{ik}, x_{jk}, C_l} P(x_{ik}, x_{jk}, C_l) \log \frac{P(x_{ik}, x_{jk} | C_l)}{P(x_{ik} | C_l) P(x_{jk} | C_l)} \quad (3)$$

where I is the CMI; x_{ik} represents the k th state of X_i in seafarer competency; x_{jk} represents the k th state of X_j in seafarer competency; C_l represents the l th type of maritime accidents.

Step 2: By constructing the maximum weight spanning tree, the most prominent relationships between seafarer competencies X_i and accident types C are elucidated. This structured approach facilitates the identification of the most influential competencies X_i contributing to maritime accidents, thereby facilitating subsequent analysis and model development.

Step 3: Based on the calculated mutual information (MI) I , determine the directional connections between accident type C and the nodes representing seafarer competencies within the established undirected tree, elucidating the influence of seafarer competencies on accident types.

Step 4: Incorporate the variable of accident type C into the undirected tree by establishing directed connections from C to all variables of the seafarer competencies X_i , thus constructing the BN structure. This step is crucial for modelling the influence of accident types on seafarer competencies within the TAN-BN framework.

Step 5: After constructing the tree structure of relationship between seafarer competencies and accident types, the CPTs of the model are calculated utilizing the maritime accident data to provide it with the necessary parameters for probabilistic inference and prediction. Based on the collected data, the CPT of each seafarer competency under different accident types or other seafarer competencies is calculated using the following equation:

$$P(X_i | C_l \text{ or } X_j) = \frac{\text{Count}(X_i \cap C_l \text{ or } X_j)}{\text{Count}(C_l \text{ or } X_j)} \quad (4)$$

where $P(X_i | C_l \text{ or } X_j)$ represents the probability of X_i given the probability specific states of maritime accident C_l or seafarer competency X_j that are related on X_i ; $\text{Count}(C_l \text{ or } X_j)$ is the number of the specific maritime accident C_l or seafarer competency X_j in the collected datasets; $\text{Count}(X_i \cap C_l \text{ or } X_j)$ represents the number of seafarer competency X_i under specific maritime accident C_l or seafarer competency X_j . This step completes the construction of the TAN-BN model, which effectively describes the relationships between seafarer competencies and accident types.

3.4. Model validation

3.4.1. Mutual information

To elucidate the relationship between maritime accidents and seafarer competencies for effective safety management and training strategies, this study employs MI to establish the interdependencies between maritime accident types and seafarer competencies. MI is an effective method for quantifying the mutual dependencies among variables, which could be used to determine the importance of various seafarer competencies in maritime accidents in this study. The higher values of MI reflect the greater the significance of the seafarer competency. The calculation process of MI could be represented as follows:

$$I(C, x_i) = - \sum_{C,i} P(C, x_{ik}) \log \frac{P(C, x_{ik})}{P(C)P(x_{ik})} \quad (5)$$

3.4.2. Sensitivity analysis

Sensitivity analysis serves as a crucial method for assessing how variations in a model's inputs or parameters influence its outcomes. It aims to ascertain the effect of input parameter uncertainties on the model's forecasts or conclusions, thereby pinpointing the parameters with the most substantial impact on the findings. This study assesses how seafarer competency affects various maritime accidents by adjusting the occurrence likelihood of different states for each seafarer competency. For instance, by updating one competency while fixing all other competencies, the changes in probabilities of various types of maritime accidents are observed to assess the impact of this seafarer competency on accident types.

In addition, sensitivity analysis could also be utilized to validate the reliability and robustness of the BN model by validating axioms. Previous studies indicated that axiom validation emerges as a prevalent approach in this domain, providing a structured framework to assess model validity (Fan et al., 2020a,b; Cao et al., 2023; Fan and Yang, 2024). Hence, two fundamental axioms must be adhered in the outcome of sensitivity analysis, as follows:

- (1) The first axiom requires that the posterior probability of the accident type C_l will increase or decrease with any corresponding adjustment (increase or decrease) in the prior probability of any seafarer competencies X_i .
- (2) The second axiom stipulates that the cumulative effect of the probability changes across seafarer competencies in set $Y_l = \{X_1, X_2, \dots, X_k\}$ should not be less than that of the probability change across the set of y_l ($y_l \in Y_l$), where Y_l and y_l represent the posterior probability of the specific accident type l .

3.4.3. Case study

Given that the model is derived from data-driven methods, case studies are employed to verify the model's effectiveness and robustness. Real case testing is a commonly used method for validating the model, involving verification using historical accident data that was not previously utilized (Liang et al., 2022). The detailed process is shown in the following steps:

- (1) Firstly, new accident reports that are not included in the database of this study are analyzed and used as the validation set to test and verify the model.
- (2) Secondly, by inputting the seafarer competency data extracted from new accident reports into the model, the output results are compared with the actual accident types to assess the effectiveness of the model.

4. Results and discussions

4.1. Feature selection

In this study, all inputted variables x (i.e., seafarer competency) are divided into two distinct states: '1' and '2'. Specifically, state '1' signifies the presence of the requisite seafarer competency in seafarers when facing the specified type of accident, whereas state '2' denotes the absence of such seafarer competency. Furthermore, the output variable (i.e., accident types) is categorized into four states: state 1 (i.e., collision), state 2 (grounding), state 3 (contact), and state 4 (other accidents), based on the characteristics of restricted waters such as high traffic density and limited navigable areas (Szlapczynski and Szlapczynska, 2017; Fan et al., 2022). To identify seafarer competencies closely related to maritime accidents, it is necessary to first determine the optimal regularization parameter λ . Then, the optimal LASSO algorithm is used to select from all seafarer competencies. The 5-fold cross-validation method is used because it finds the highest λ when the MSE is within the standard error rang, as shown in Fig. 2. The MSE results from the cross-validation of LASSO exhibit a significant decreasing trend with the increase of λ . The minimum MSE occurs at $\lambda = 0.0287$, indicated by the intersection of the green and blue lines in the figure. After determining the optimal λ , the feature coefficients derived from LASSO are utilized to ascertain the critical seafarer competencies. Fig. 3 shows the feature coefficients of various seafarer competencies. It can be observed that the coefficients of KNO, TD, TWL, and EQM are shrunk to 0 and removed from the TAN structure modelling, leaving 8 seafarer competencies selected, including CC, INF, SA, COM, DM, SO, SC, and PO.

4.2. TAN modelling

According to the approach of TAN-BN modelling in Section 3.3, the BN structure is constructed using the seafarer competencies selected through LASSO algorithm. In this study, the Netica software (version 6.09) is utilized to establish the BN model of the TAN structure based on the dataset. This is a commonly used software specialized in building BN, which provides a learning network function based on Eq. (3) for

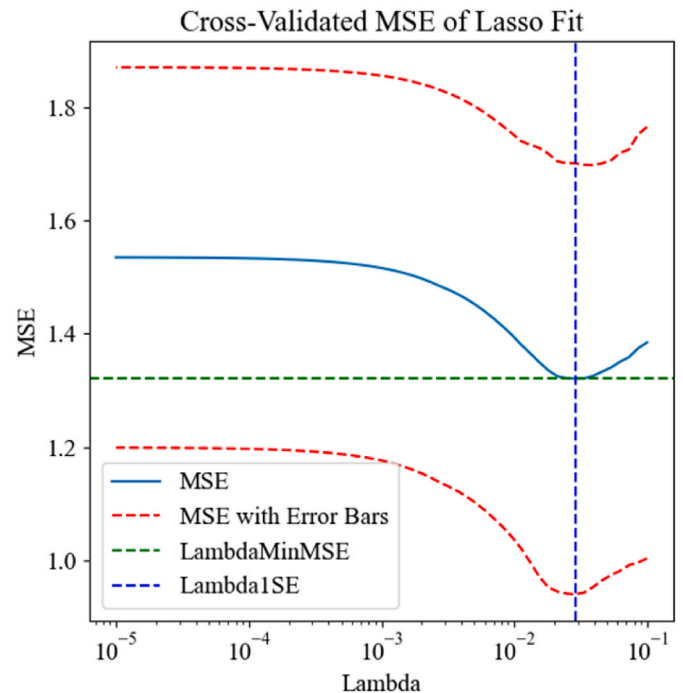


Fig. 2. The cross-validated MSE results from the LASSO model.

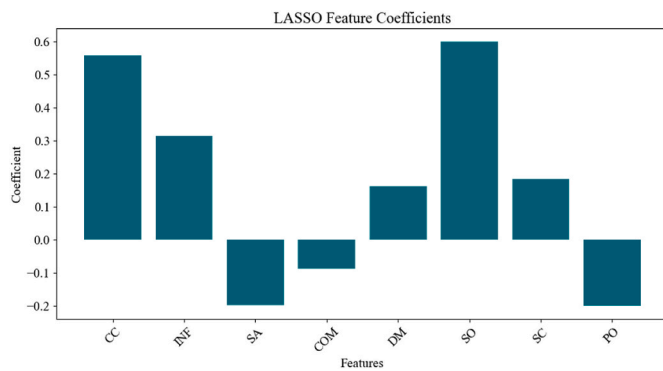


Fig. 3. The LASSO feature coefficients.

building BN structure. Utilizing the maritime accident dataset, the TAN-BN model is constructed to elucidate the relationship between maritime accident types and 8 seafarer competencies. Then, the CPTs for all seafarer competencies are calculated through case-based learning, thereby obtaining the posterior probability of each feature. Table 2 presents the CPTs of INF, and the CPTs of other seafarer competencies can also be calculated from historical data. As a result, the BN model that reflects the relationship between seafarer competency and accident types is illustrated in Fig. 4, which could be used to assess the reliability of navigation safety for seafarers of different competencies. It is indicated that the most frequent accident caused by seafarer competency in restricted waters is the ‘collision’ accident, accounting for 41.7%, followed by ‘grounding’ accidents at 23.5%, ‘other’ accidents at 17.6%, and ‘contact’ accidents at 11.8%. Additionally, the probabilities of seafarers ‘SO’, ‘SA’, ‘COM’, and ‘INF’ competencies being in ‘state 2’ are higher, indicating that the lack of these competencies in seafarers is more likely to lead to maritime accidents.

4.3. Model validation

4.3.1. Mutual information calculation

According to Eq. (5), the MI between seafarer competencies and types of maritime accidents is calculated, as shown in Table 3, which reveals the degree of correlation between them. The results suggest that the competency of ‘SO’ among seafarer competency has the most significant effect on types of accidents, with the MI value of 0.0612, followed by ‘SC’ at 0.0503, ‘DM’ at 0.0469, ‘CC’ at 0.0335, ‘INF’ at 0.0334, ‘PO’ at 0.0327, ‘SA’ at 0.0177, and ‘COM’ at 0.0038. It can be seen that MI values for most seafarer competencies are greater than 0.03. Therefore, the results focus on discussing seafarer competencies with MI values greater than 0.03. Results indicate that the essential factor influencing the accident types is the seafarers’ ship-handling skills, including ‘SO’ and ‘SC’ competencies. This is similar to the study by Kaptan et al. (2021), who highlighted the necessity for seafarers to make the most appropriate operation decisions to mitigate risks and avoid accidents in restricted waters. The insufficient ship-handling skills of seafarers directly contribute to the occurrence of maritime accidents.

Table 2
The CPTs of INF.

Accident type	SA	INF	
		1	2
Collision	1	0.45	0.55
	2	0.29	0.71
Grounding	1	0.67	0.33
	2	0.50	0.50
Contact	1	0.67	0.33
	2	0.25	0.75
Others	1	0.80	0.20
	2	0.50	0.50

Besides, the dynamic human-machine system developed by Fan and Yang (2023) considers the ‘SO’ and ‘SC’ competencies of seafarers as output parameters of human error. This further underscores the significance of seafarers’ ship-handling skills for safe navigation. Hence, it is crucial for maritime authorities to prioritize strengthening supervision and training of seafarer’s ship-handling skills, alongside the advancement of maritime autonomous surface ships (MASS), to effectively prevent maritime accidents.

Following, the ‘DM’ competency of seafarers, as a non-technical skill (Barnett, 2005), also significantly influences the ‘accident types’. As the decision-maker responsible for navigating the vessel, officers of the watch (OOW) must issue navigational commands to respond to potential risks. An incorrect decision could increase the navigation risk, such as delayed decisions, or no action taken in response to dangerous situations. For instance, due to the master’s delayed intervention, the collision incident involving *City of Rotterdam* was inevitable, as reported in MAIB March 2017. Additionally, incorrect decision-making by seafarers is also a significant factor contributing to the absence of ‘SO’ and ‘SC’ competencies (Fan and Yang, 2023). Therefore, some auxiliary decision-making technologies, such as intelligent collision-avoidance decision-making systems (Wang et al., 2024), should be developed and applied in the shipping industry can assist seafarers in making correct decisions, thereby enhancing maritime safety.

Subsequently, attention also needs to be paid to the self-ability of seafarers, including ‘CC’, and ‘INF’ competencies. Mental workload refers to the cognitive demand placed on individuals to accomplish given tasks (Dijksterhuis et al., 2011). Higher mental workload is required to complete more sophisticated tasks. Once the seafarers are under excessive mental workload, their behavior is likely to be affected. A simulation investigation shows that a high workload among seafarers increases the occurrence likelihood of maritime accidents (Orlandi and Brooks, 2018). Therefore, more seafarers should be assigned to the bridge team when dealing with complex tasks to reduce the workload of OOWs. The study also suggests that seafarers’ states (i.e. physical and mental states) should be constantly monitored during voyages to prevent a loss of their ‘CC’ competency. In addition, effective information acquisition is a crucial factor influencing seafarers’ competency to make effective decisions and situational awareness (Han et al., 2021; Fan and Yang, 2023). The influence of seafarers’ PO competency is relatively minor, which may be because the main accidents (e.g., collision, grounding, and contact accidents) in restricted waters are primarily caused by their ship-handling skills.

The above results indicate that the ship-handling skills of seafarers are the most important competency influencing the maritime accident types in restricted waters, followed by their non-technical skills and self-ability.

4.3.2. Sensitivity analysis

To further explore the impact of seafarer competency on accident types, a sensitivity analysis is conducted to analyze the impact of each state of various seafarer competencies on maritime accidents. The occurrence probabilities of different states of seafarer competencies are adjusted to 100% individually to observe the specific impact of each state on maritime accident types, as shown in Table 4. The first row presents the prior occurrence probability of various accidents in this model, which serves as a baseline. The probability in subsequent rows indicates the occurrence probability of accidents under different states of seafarer competencies.

For ‘collision’ accidents, it can be seen that when ‘state 1’ of ‘SO’, ‘state 2’ of ‘SC’, ‘state 2’ of ‘DM’, ‘state 1’ of ‘CC’, ‘state 1’ of ‘INF’, ‘state 2’ of ‘PO’, ‘state 2’ of ‘SA’, and ‘state 1’ of ‘COM’ are set to 100% individually, the probabilities of ‘collision’ accidents decrease. Conversely, when the other states are set to 100%, the probability of collision accidents increases. The results show that a lack of ‘SO’ competency among seafarers is directly related to collision accidents. This implies limitations of navigation areas in restricted waters, incorrect

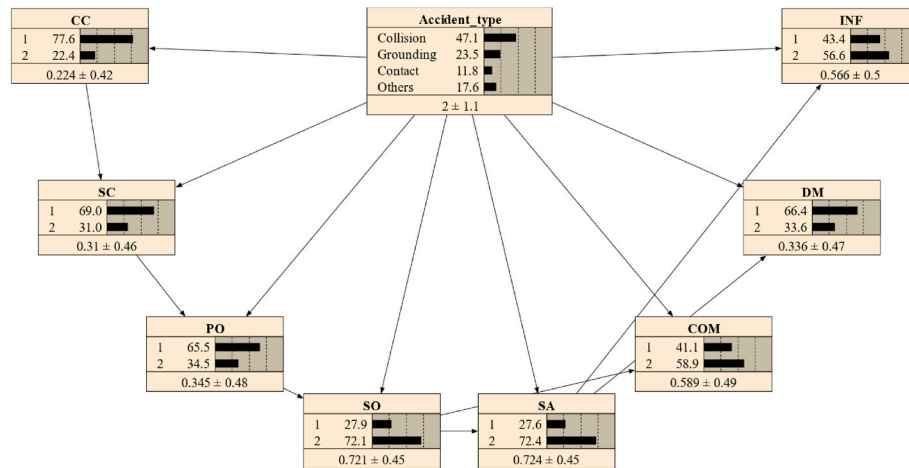


Fig. 4. The analysis model of accident types based on seafarer competencies.

Table 3
MI between seafarer competencies and accident types.

Node	MI	Percent	Variance of Beliefs
SO	0.0612	3.38	0.0075
SC	0.0503	2.78	0.0055
DM	0.0469	2.60	0.0024
CC	0.0335	1.85	0.0052
INF	0.0334	1.85	0.0045
PO	0.0327	1.81	0.0043
SA	0.0177	0.98	0.0016
COM	0.0038	0.21	0.0002

Table 4
The results of sensitivity analysis.

Seafarer competency	State		Occurrence probability			
	1	2	Collision	Grounding	Contact	Other
	/	/	47.1%	23.5%	11.765%	17.6%
SO	100%	0	28.8%	22.2%	15.3%	33.7%
	0	100%	54.1%	24.1%	10.4%	11.4%
SC	100%	0	50.5%	16.1%	12.5%	21.0%
	0	100%	39.5%	40.1%	10.2%	10.3%
DM	100%	0	48.6%	18.7%	9.67%	23.0%
	0	100%	44.0%	33.1%	15.9%	7.0%
CC	100%	0	42.3%	25.0%	11.8%	21.0%
	0	100%	63.7%	18.5%	11.7%	6.06%
INF	100%	0	37.2%	28.5%	9.86%	24.4%
	0	100%	54.6%	19.7%	13.2%	12.5%
PO	100%	0	53.4%	22.7%	11.5%	12.4%
	0	100%	35.0%	25.1%	12.3%	27.5%
SA	100%	0	53.6%	13.5%	11.6%	21.3%
	0	100%	44.6%	27.4%	11.8%	16.2%
COM	100%	0	45.8%	21.1%	13.0%	20.1%
	0	100%	47.9%	25.2%	10.9%	16.0%

maneuvers by seafarers can easily lead to a lack of sufficient space for avoiding collisions, resulting in accidents. A lack of self-ability (i.e., ‘CC’ and ‘INF’ competencies) among seafarers will increase the probability of collision accidents. This could be due to seafarers with inadequate cognitive and information processing abilities being unable to effectively assess potential risks based on the information provided by navigational aids (Lee and Sanquist, 2000), thereby resulting in collision risks.

The probabilities of ‘grounding’ accidents decrease when ‘state 1’ of ‘SO’, ‘state 1’ of ‘SC’, ‘state 1’ of ‘DM’, ‘state 2’ of ‘CC’, ‘state 2’ of ‘INF’, ‘state 1’ of ‘PO’, ‘state 1’ of ‘SA’, and ‘state 1’ of ‘COM’ are each set to 100%, while they increase when other states are individually set to

100%. The results indicate that when seafarers lack ship-handling skills or proper decision-making abilities, grounding accidents are more likely to occur. This could be because seafarers are unable to effectively maintain or timely adjust the course and speed of the vessel, leading to potential deviations from safe navigational routes or stability loss. Moreover, incorrect decisions could also lead to course deviation (Lee and Sanquist, 2000). It should be noted that an absence of correct procedure operations also increases the risk of grounding accidents. This may be due to seafarers taking inappropriate actions as a result of not following the correct procedures.

The probabilities of ‘contact’ accidents decrease when the likelihood of ‘state 2’ of ‘SO’, ‘state 2’ of ‘SC’, ‘state 1’ of ‘DM’, ‘state 2’ of ‘CC’, ‘state 1’ of ‘INF’, ‘state 1’ of ‘PO’, ‘state 1’ of ‘SA’, and ‘state 2’ of ‘COM’ are individually increased to 100%. Conversely, when the likelihood of these states decreases to 0, the probability of ‘contact’ accidents increases. Existing studies indicate that decision-making errors increase the probability of contact accidents (Kaptan et al., 2021), which aligns with the findings of this result. Additionally, a lack of ‘INF’ competency results in seafarers being unable to timely detect risks, while a deficiency in ‘PO’ competency leads to an inability to execute correct emergency procedures to prevent the occurrence of contact accidents.

For the likelihood of ‘other’ accidents, a decreasing trend is observed when ‘state 2’ of ‘SO’, ‘state 2’ of ‘SC’, ‘state 2’ of ‘DM’, ‘state 2’ of ‘CC’, ‘state 2’ of ‘INF’, ‘state 2’ of ‘SA’, ‘state 2’ of ‘COM’, and ‘state 1’ of ‘PO’ are individually set to 100%, while an increasing trend is observed when other states are set to 100%. In summary, it can be seen that the model adheres to axiom 1 by comparing the updated results with the initial values.

Moreover, the result of sensitivity analysis also reveals the impact of specific competency states on the likelihood of accidents. For instance, in collision accidents, when ‘state 1’ of the ‘SO’ competency is set to 100% occurrence likelihood, there is the lowest probability for a ‘collision’ accident (28.8%) to occur compared to other states. It shows that the likelihood of collision accidents is minimized when the seafarer possesses ‘SO’ competency. This can be explained by the seafarers’ ‘SO’ competency directly impacting the movement and response of a vessel. Seafarers with good maneuvering skills can accurately control the speed, course, and position of the vessel, effectively avoiding other ships, especially in emergency encounter situations. This suggests that enhancing training in seafarers’ ‘SO’ competency is crucial for reducing collision accidents. Conversely, when the occurrence likelihood of ‘state 2’ of the ‘CC’ competency is set to 100%, the probability of ‘collision’ accidents occurring is the highest (63.7%), indicating that the greatest likelihood of a collision accident occurs when the ‘CC’ competency is absent. This may be due to the seafarers’ lack of ‘CC’ competency, which can delay their recognition and response to collision risks, lead to

misdjudgment of other vessels' intentions, or result in missing important warning signals and navigational information. Kaptan et al. (2021) pointed out that proficient maneuvering skills and appropriate workload enable the effective avoidance of potential collision situations. Therefore, when the ship sailing in restricted waters, it is necessary to monitor the 'SO' and 'CC' competency of seafarers to avoid potential collision risks. For instance, seafarers' workload and emotions can be monitored using a physiograph (Fan et al., 2018, 2021; Shi et al., 2023), while their ship-handling skills can be monitored via video (Ding et al., 2023).

In terms of 'grounding' accidents, seafarers who possess 'state 2' of the 'SC' competency exhibit the highest likelihood of encountering such accidents, at 40.1%. It could be observed that the absence of 'SC' competency has the greatest impact on grounding accidents, significantly increasing their likelihood. This indicates that ship grounding accidents primarily result from seafarers' insufficient use of information and knowledge to correct and maintain the ship's course and speed. In contrast, those with 'state 1' of the 'SA' competency show a comparatively lower probability of experiencing such accidents, recorded at 13.5%. This highlights the importance of good situational awareness in reducing the likelihood of grounding accidents. When seafarers have a strong understanding of the surrounding navigational conditions, they can effectively avoid errors in the vessel's speed and course. To prevent the potential grounding risk in restricted waters, it is imperative to develop and implement equipment that assists seafarers in situational awareness and monitors the navigational status of the vessel. For example, integrating existing sensor data to identify the navigational environment can be beneficial (Sanfilippo, 2017). Thombre et al. (2022) reviewed the development of sensors and AI techniques for improving the situational awareness of MASS in the future.

Regarding 'contact' accidents, seafarers possessing 'state 2' of the 'DM' competency exhibit the highest probability of experiencing contact accidents at 15.9%, whereas those with 'state 1' of the 'DM' competency demonstrate the lowest probability, at 9.67%. This emphasizes the pivotal role of decision-making in influencing maritime safety outcomes. In restricted navigational environments, incorrect decisions by seafarers will directly lead to accidents (Kaptan et al., 2021). Therefore, seafarers' decision-making abilities should be strengthened through training. The intelligent decision-making systems for vessels should be developed to assist seafarers in making effective decisions.

In addition, it becomes evident that seafarers in 'state 1' of the 'SO' competency are more prone to 'other' accidents (33.7%), whereas those in 'state 2' of the 'CC' competency exhibit a reduced likelihood of such incidents (6.06%). This could be attributed to the effective reduction of collision accidents by 'SO' competency, consequently elevating the proportion of other accidents.

To validate the TAN-BN model developed in this study, the occurrence likelihood of various types of accidents is investigated by minor changing the states of each node to validate the model against Axiom 2. Firstly, based on the findings from Section 3.3.1 regarding the

significance of seafarer competencies in influencing maritime accident types, the most crucial competency (i.e., SO) is selected for sensitivity analysis. Secondly, the occurrence probability of this accident type is recorded by making slight adjustments to this competency. Specifically, the probability of one state is increased by 10%, while the probability of another state is decreased by 10%. Then, the procedure continues with adjustments to the probability of the next competency, successively obtaining the adjusted probabilities for the states of the parent node. Similarly, this adjustment process is also applied to other types of accidents. The results of the sensitivity analysis conducted for axiom 2 verification are shown in Table 5. The results in each row of accident types are calculated independently, where the first column represents the original occurrence probability of accidents, and the other columns show the updated occurrence rates by continuously altering the competencies. Axiom 2 is validated by analyzing the variation trends in updated results compared to the initial values. Specifically, the accident occurrence rates of each accident type gradually increase as the competency varies, confirming that the model conforms to Axiom 2. Hence, the model presented in this study is demonstrated to be reasonable and reliable through the method of axiom validation.

4.3.3. Case study

Furthermore, this study inputs accident report data, which was not part of the training data, into the TAN-BN model for case study validation. Two different accident types of reports are randomly selected from the website of MAIB as the case studies to validate the BN model. Both accidents are required to occur in restricted waters and be caused by human factors. For example, a new maritime accident with a report reference number of MAIB August 2021 is chosen for case studies to validate the effectiveness of the model. In this report, a serious marine casualty occurred on June 25, 2020 when the ro-ro freight ferry *Arrow* grounded in the approach channel of Aberdeen Harbour. According to the description of the report, the seafarer competencies in this study could be extracted as follows:

- (1) The master of *Arrow* and the PEC holder did not effectively communicate for the master/pilot information exchange, which missed the opportunity to discuss the contingencies (i.e. state 2 of COM).
- (2) Due to the confidence displayed by the PEC holder and the PIs on the radar, the captain decided to continue the approach in the thick fog. This is an irrational decision-making (i.e. state 2 of DM).
- (3) *Arrow* was inadequately prepared for pilotage in restricted visibility near Aberdeen Harbour, lacking proper procedures for ensuring navigational safety (i.e. state 2 of PO).
- (4) Despite making all checklist items complete, other actions required by GOLRES were not taken, indicating a lack of SO.

Table 5
Accident rate of a ~10% change in seafarer competencies (units: %).

Seafarer competency	~10% change in seafarer competencies									
SO	/	*	*	*	*	*	*	*	*	*
SC	/		*	*	*	*	*	*	*	*
CC	/			*	*	*	*	*	*	*
INF	/				*	*	*	*	*	*
DM	/					*	*	*	*	*
PO	/						*	*	*	*
SA	/							*	*	*
COM	/									*
Collision	47.1	49.6	50.7	53.1	54.8	55.4	56.7	57.96	57.97	57.97
Grounding	23.5	23.7	26.2	26.8	27.8	29.4	29.5	31.4	31.8	31.8
Contact	11.8	12.25	12.33	12.4	12.8	13.5	13.6	14.0	14.1	14.1
Others	17.6	19.9	21.1	23.0	24.5	26.6	28.4	29.2	30.1	30.1

Note: Each column represents the accident rates with a ~10% change in the respective seafarer competency variable. * indicates the change in this seafarer competency.

- (5) In addition, the PEC holder experienced workload overload (i.e. state 2 of CC) in the fog than other good weather, resulting in a degradation of their cognitive capacity to simultaneously navigate and steer, reaching an unsafe level.
- (6) Due to seafarer’s lack of manual input of danger lines and failure to monitor cross-track error during grounding, the aid navigation equipment was not utilized correctly, resulting in limited assistance provided by the ECS to the bridge team (i.e. state 2 of EQM).
- (7) As an integral aspect of the pilotage planning process, it is imperative for pilots, PEC holders, and bridge teams to comprehend the safe limits of vessel deviation from the base track. Considering the precision of radar navigation, it is improbable that Arrow, in this instance, could have veered more than 10° off the base track of 237° with reliable safety. However, it remains uncertain whether any member of Arrow’s bridge team was aware of this (i.e. state 2 of KNO).
- (8) The remaining members of the bridge team had limited monitoring of the vessel’s progress along the fairway, before the captain noticed and the PEC holder responded. The bridge team’s perception of the surrounding navigation conditions and situational awareness was insufficient (i.e. state 2 of SA).
- (9) Arrow struggled to be kept on track by the PEC holder while navigating in fog. In addition, while the deviation north of the planned track was being corrected, it was over-correct to the south (i.e. state 2 of SC).

Thus, various seafarer competencies of the seafarers involved in this accident are obtained (i.e. set as state 2), while other competencies are set as state 1. It can be seen from Fig. 5 that there is a notable likelihood of 73.3% for the vessel to be involved in a grounding, making it the most likely accident to occur when seafarers lack these seafarer competencies. The MAIB August 2021 investigation results indicate that the vessel experienced a grounding accident, which is consistent with the accident type most likely predicted by this model.

Furthermore, another report (MAIB 5/2023) has also been selected to validate the model. This is a very serious collision casualty that occurred on December 13, 2021, near the Bornholmsgat traffic separation scheme in Sweden. The UK-registered general cargo ship *Scot Carrier* collided with the Denmark-registered split hopper barge *Karin Høj*, leading to the capsizing of the *Karin Høj* and the loss of two crew members. Since the *Karin Høj* not being equipped with a voyage data recorder and the absence of survivors, it is impossible to determine the actions taken by the crew of this vessel. Therefore, this study only investigated the causes of accidents involving *Scot Carrier*. The factors of seafarer competency contributing to this collision could be identified as

follows:

- (1) The 2/O of *Scot Carrier* consumed alcohol before duty and engaged in distracting activities such as using his personal tablet computer while on duty, indicating a lack of SA.
- (2) Due to the customary practice in the Scotline fleet, a singer watchkeeper (i.e. 2/O) navigated during nighttime hours, indicating a lack of TWL.
- (3) In addition, the watchkeeper’s cognitive abilities during the dark lookout environment were impaired due to variations in brightness and distance while viewing the tablet computer (i.e. state 2 of CC).
- (4) The bridge equipment was not properly configured. For instance, alarms of ship intended to alert of hazardous situations were either disabled, silenced, or turned off (i.e. state 2 of EQM).
- (5) The 2/O failed to obtain accurate information from the device due to narrowing the display range of ECDIS, indicating a lack of INF.
- (6) No preventive measures were undertaken by the 2/O during his watch to ensure the vessel’s safe navigation (i.e. state 2 of PO).
- (7) At 0321, the 2/O altered course and adjusted the autopilot to a degree of 270. There would have been no anticipation that *Scot Carrier* would change course toward *Karin Høj* in close proximity, leading to a collision (i.e. state 2 of SO).

Therefore, the status parameters of relevant seafarer competencies were set according to the extracted data, as shown in Fig. 6. The results indicate that the probability of a collision accident is 87.4%, making it the most likely predicted accident type. The model results align with the actual types of accidents (MAIB 5/2023) that occurred, further illustrating the robustness of the model.

4.4. MPE analysis

To delve deeper into the distinctions among critical seafarer competencies in various accident types, the most likely explanation (MPE) function of the TAN-BN model is utilized to simulate the most likely scenario associated with a particular accident type. This approach simulates the most likely types of accidents, providing more comprehensive and reliable insights into the seafarer competencies that contribute to these accidents. By predicting the causes of accidents, it helps prevent the occurrence of maritime accidents.

Fig. 7 illustrates the BN model under the MPE mode. In this representation, each node is accompanied by at least one confidence level set at 100%, and typically has several lower-level confidence levels. These lower-level confidence levels could be manually adjusted to 100% to

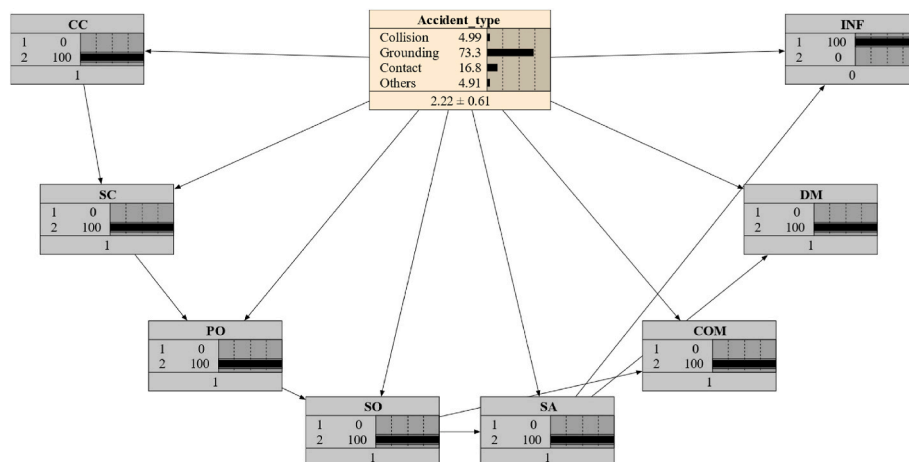


Fig. 5. Case study based on the report (MAIB 8/2021).

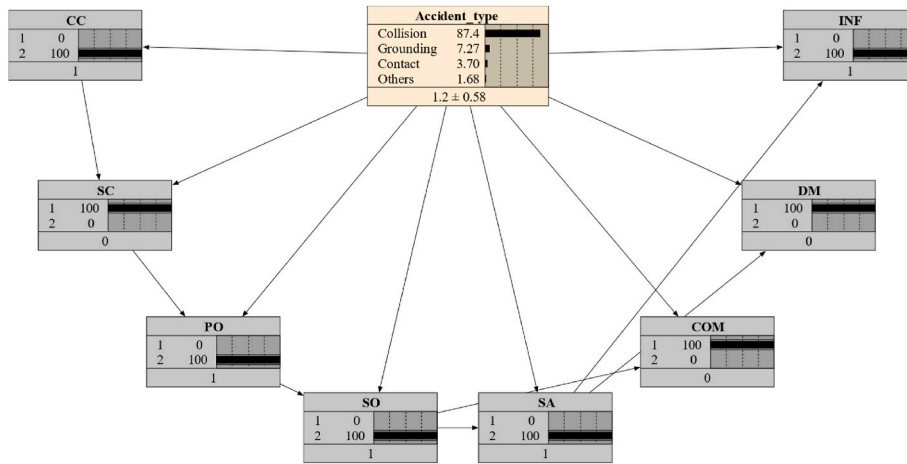


Fig. 6. Case study based on the report (MAIB 5/2023).

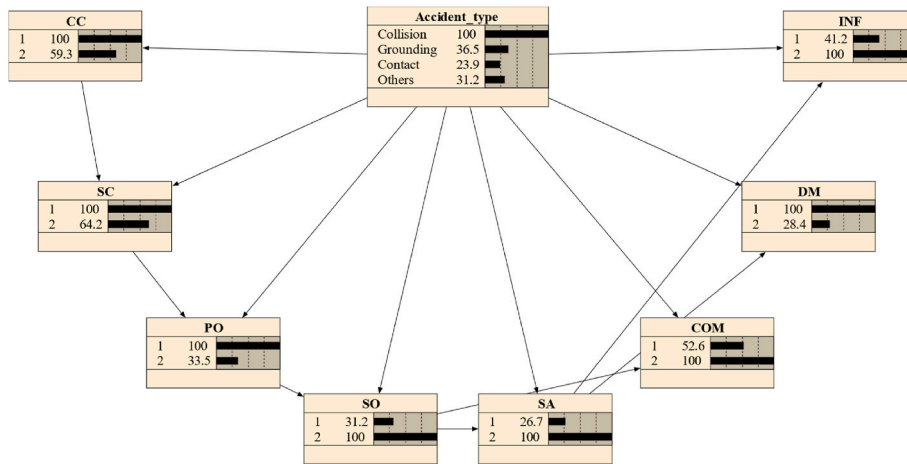


Fig. 7. MPE mode.

obtain the most probable alternative configuration information for each node. Shorter bars indicate a relatively lower probability of alternative states, as other variables are in their most probable configurations. It can be seen from Fig. 7 that the 'collision' accidents are the most likely occurrence accident types based on the highest probability, and the relevant competency nodes identify the most likely states leading to this

accident. Namely, the 'collision' accidents caused by seafarers are more likely to occur under the following conditions:

The seafarers lack access to accurate navigational information, exhibit deficient situational awareness, fail to effectively monitor other vessels, engage in ineffective communication with other seafarers, and perform incorrect navigational operations.

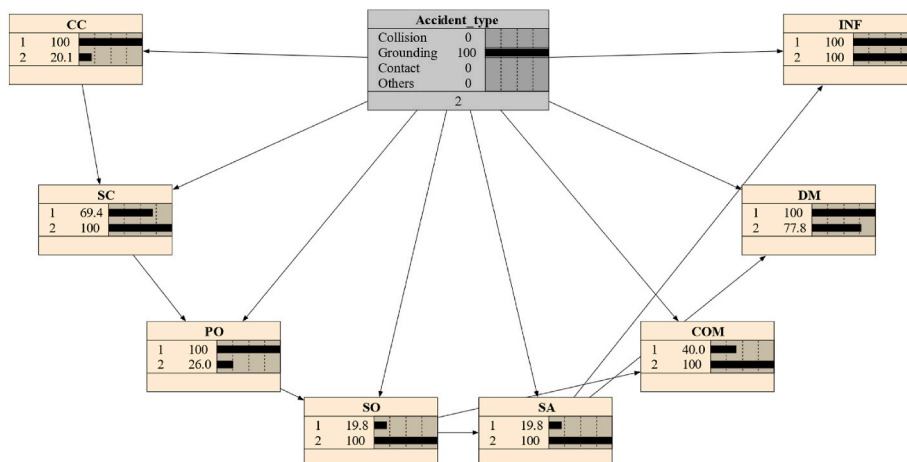


Fig. 8. MPE for 'grounding' accident.

Based on the above configuration, the causality among different seafarer competencies could be found. It could be observed that a lack of information processing ability among seafarers partially affects their situational awareness. A lack of situational awareness and insufficient communication among crew members will lead to maneuvering errors. Hence, reducing deficiencies in seafarers' information processing and communication is an effective way to improve their maneuvering abilities.

Similarly, Figs. 8–10 depict the MPE results of other accident types as 'grounding', 'contact' and 'other', respectively, which also represent the most common occurrence conditions for different accidents. When the 'accident type' is set to 'grounding', the probabilities of 'state 2' for competencies such as 'SC', 'SO', 'SA', 'COM', and 'INF', as well as the probabilities of 'state 1' for competencies such as 'CC', 'SC', 'PO', 'DM', and 'INF', are all observed at 100% level, as shown in Fig. 8. It can be found that both states of 'INF' competency have the same highest probability, which indicate that there may be more than one configuration leading in 'grounding' accident. Compared to the seafarer competency most likely to cause 'collision' accident, the primary reason for 'grounding' accident is the failure of seafarers to effectively control the vessel's speed and direction.

Fig. 9 presents the most probable state of various competencies during 'contact' accidents, encompassing scenarios where seafarers lack 'SO', 'SA', 'COM', 'DM', and 'INF' competencies. It can be found that there may be more than one configuration about 'DM' competency leading in 'contact' accident. While seafarers with the 'DM' competency can effectively mitigate potential 'contact' accidents, the absence of other competencies can still result in such accidents. Through the analysis presented above, it is evident that in the occurrence of maritime accidents, the lack of competencies, including 'SO', 'SA', 'INF', and 'COM', among seafarers exhibits significantly high probabilities. Therefore, managers' timely detection of deficiencies in these seafarer competencies can effectively prevent potential maritime accidents. Additionally, according to Fig. 10, 'other' accidents are predominantly attributable to the lack of 'PO', 'SA', and 'INF' competencies. Compared to other accidents, the absence of 'PO' competency is the main cause of these accidents.

5. Implications

The findings of this study have significant implications for enhancing maritime safety in restricted waters, which makes two insightful contributions. Regarding the theoretical implications, this study provides a new perspective for analyzing human factors in maritime accidents. Utilizing a TAN-BN method, the reliability of seafarer competencies is analyzed to determine the factors contributing to maritime accidents.

Since most maritime accidents are caused by human errors (Wróbel, 2021), the perspective provided by this study is generality applicable in analyzing maritime accidents.

Secondly, for practical implications, the lessons from human errors are learnt from accidents to provide a reference for developing strategies to enhance navigational safety in restricted waters. Undoubtedly, this study is beneficial for professionals involved in maritime safety. For training seafarer competency, maritime authorities can utilize the factors identified by this model, which have a significant impact on accidents, to provide corresponding competency training for seafarers, thereby reducing the likelihood of potential deficiencies in their competency. For instance, training resources from maritime authorities should be prioritized to improve seafarers' ship-handling skills to reduce the occurrence likelihood of maritime accidents. Accidents could be prevented when training is sufficient to ensure that captains can effectively control their vessels and fully comply with collision avoidance regulations. For managing shipboard operations, managers could strategically focus on specific aspects of seafarers' competency performance to minimize the likelihood of human errors. For example, when a ship is navigating in restricted waters, managers can appropriately increase the number of OOWs on the bridge. The cooperation of multiple OOWs can reduce the probability of individual seafarers' cognitive capacity deficiencies or decision-making errors. Additionally, the developers of MASS can gain useful insights on how to prioritize the development of intelligent navigation technologies to assist future human-machine collaboration on MASS (Liu et al., 2022). For example, the development of intelligent collision avoidance systems should be prioritized by developers to reduce the navigation reliance of ships on seafarers' ship-handling skills, which could significantly decrease the likelihood of human error leading to accidents.

6. Conclusions

This study aims to learn lessons from human errors in historical maritime accident reports by investigating the impact of different seafarer competencies on accidents. A novel data-driven analysis method is developed to explore the influence of seafarer competencies on accident types from both methodological and empirical perspectives. First, seafarer competencies are identified from the literature and STCW codes, which are utilized to extract the corresponding features from accident reports. Second, the LASSO algorithm is employed to further select seafarer competencies relevant to accident types, enhancing the reliability and robustness of the final model. Finally, a data-driven TAN-BN model is constructed to analyze the maritime accidents resulting from seafarer competencies. The sensitivity analysis is conducted to explore the impact of each seafarer competency on various types of

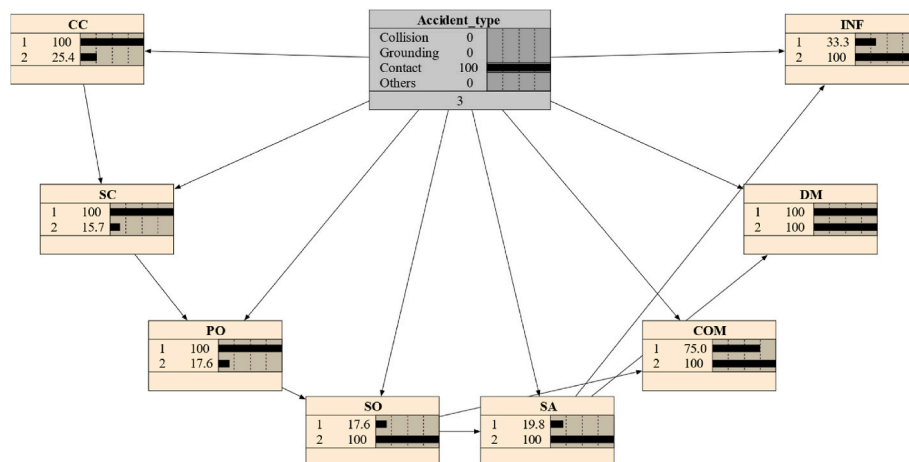


Fig. 9. MPE for 'contact' accident.

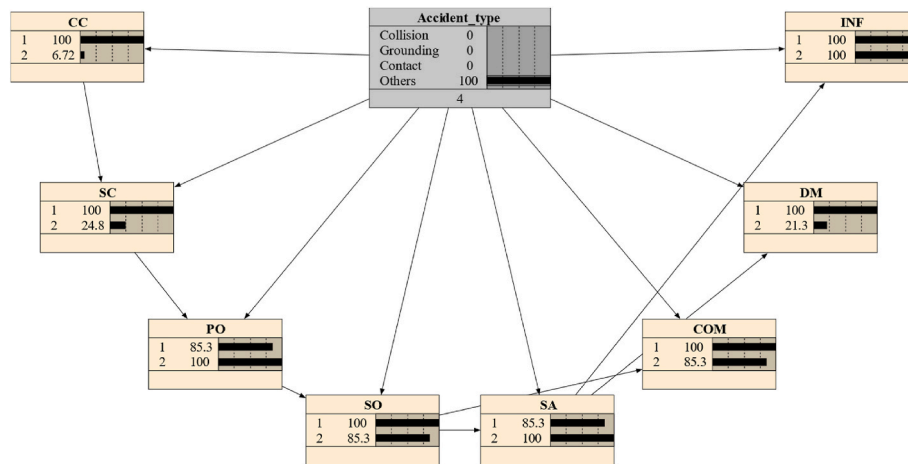


Fig. 10. MPE for 'other' accident.

accidents. Axiom and case validation methods are utilized to ensure the effectiveness of the model.

Results show that seafarer competencies such as 'CC', 'SC', 'PO', 'SO', 'SA', 'COM', 'DM' and 'INF' significantly influence the types of maritime accidents, which are selected by the LASSO algorithm from original features. The most influential seafarer competencies, ranked in terms of their importance, are 'SO', 'SC', 'DM', 'CC', 'INF', 'PO', 'SA', and 'COM' in decreasing order. Furthermore, this study also reveals the impact of various states of different seafarer competencies on accident types. The results indicate that addressing deficiencies in the 'SO' competency among seafarers could reduce the occurrence of maritime accidents. The proposed seafarer competency analysis method provides new insights into maritime safety management. It assists stakeholders in maritime safety by facilitating effective safety management through measures such as monitoring seafarers' duty states and providing competency training.

However, this study has some limitations that can be further addressed. This study collected data associated with seafarers from 64 vessels. Although this study effectively explains the relationship between various states of seafarer competencies and maritime accident types, the inclusion of additional data would contribute to enhancing the generality of the findings, which could provide more detailed suggestions for seafarer management. Secondly, this study primarily focuses on ship accident data in restricted waters. Broader regions of accidents should be incorporated into the study to identify crucial factors affecting navigational safety.

CRedit authorship contribution statement

Kun Shi: Writing – original draft, Visualization, Investigation, Data curation, Formal analysis, Methodology, Validation, Writing – review & editing. **Shiqi Fan:** Writing – review & editing, Software, Methodology, Conceptualization, Project administration, Supervision, Writing – original draft. **Jinxian Weng:** Writing – review & editing, Validation, Supervision. **Zaili Yang:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization, Resources, Writing – original draft.

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. Zaili Yang reports financial support was provided by EU Framework Programme for Research and Innovation Marie Curie.

Acknowledgements

This project has received funding from the European Research Council (ERC) (Grant Agreement No. 864724) and Marie Curie RISE ENHANCE (Grant Agreement No. 823904) under the European Union's Horizon 2020 research and innovation programme.

References

- Akyuz, E., Celik, M., 2014. Utilisation of cognitive map in modelling human error in marine accident analysis and prevention. *Saf. Sci.* 70, 19–28. <https://doi.org/10.1016/j.ssci.2014.05.004>.
- Antão, P., Guedes Soares, C., 2008. Causal factors in accidents of high-speed craft and conventional ocean-going vessels. *Reliab. Eng. Syst. Saf.* 93 (9), 1292–1304. <https://doi.org/10.1016/j.res.2007.07.010>.
- Authorities, J.A., 1998. Crew resource management-flight crew. In: *Temporary Guidance Leaflet 5 (JAR-OPS)*. Joint Aviation Authorities, Hoofddorp, Netherlands.
- Barnett, M.L., 2005. Searching for the root causes of maritime casualties. *WMU Journal of Maritime Affairs* 4 (2), 131–145. <https://doi.org/10.1007/BF03195070>.
- Cao, Y., Wang, X., Wang, Y., Fan, S., Wang, H., Yang, Z., Liu, Z., Wang, J., Shi, R., 2023. Analysis of factors affecting the severity of marine accidents using a data-driven Bayesian network. *Ocean. Eng.* 269, 113563 <https://doi.org/10.1016/j.oceaneng.2022.113563>.
- Cavaleiro, S.C., Gomes, C., Lopes, M.P., 2020. Bridge resource management: training for the minimisation of human error in the military naval context. *J. Navig.* 73 (5), 1146–1158. <https://doi.org/10.1017/S0373463320000235>.
- Ceylan, B.O., Akyuz, E., Arslan, O., 2021. Systems-Theoretic Accident Model and Processes (STAMP) approach to analyse socio-technical systems of ship collision in narrow waters. *Ocean. Eng.* 239, 109804 <https://doi.org/10.1016/j.oceaneng.2021.109804>.
- Dernoncourt, D., Hanczar, B., Zucker, J.-D., 2014. Analysis of feature selection stability on high dimension and small sample data. *Comput. Stat. Data Anal.* 71, 681–693. <https://doi.org/10.1016/j.csda.2013.07.012>.
- Dijksterhuis, C., Brookhuis, K.A., De Waard, D., 2011. Effects of steering demand on lane keeping behaviour, self-reports, and physiology. A simulator study. *Accid. Anal. Prev.* 43 (3), 1074–1081. <https://doi.org/10.1016/j.aap.2010.12.014>.
- Ding, H., Weng, J., Han, B., 2023. A novel deep learning framework for detecting seafarer's unsafe behavior. *J. Transport. Saf. Secur.* 1–26. <https://doi.org/10.1080/19439962.2023.2169801>.
- Dowd, N., 2010. Integrating CRM into an airline's culture: the air Canada process. In: *Crew Resource Management*. Elsevier, pp. 379–398. <https://www.sciencedirect.com/science/article/pii/B9780123749468100159>.
- Fan, S., Blanco-Davis, E., Fairclough, S., Zhang, J., Yan, X., Wang, J., Yang, Z., 2023. Incorporation of seafarer psychological factors into maritime safety assessment. *Ocean Coast Manag.* 237, 106515 <https://doi.org/10.1016/j.ocecoaman.2023.106515>.
- Fan, S., Blanco-Davis, E., Yang, Z., Zhang, J., Yan, X., 2020a. Incorporation of human factors into maritime accident analysis using a data-driven Bayesian network. *Reliab. Eng. Syst. Saf.* 203, 107070 <https://doi.org/10.1016/j.res.2020.107070>.
- Fan, S., Blanco-Davis, E., Zhang, J., Bury, A., Warren, J., Yang, Z., Yan, X., Wang, J., Fairclough, S., 2021. The role of the prefrontal cortex and functional connectivity during maritime operations: an fNIRS study. *Brain and Behavior* 11 (1), e01910. <https://doi.org/10.1002/brb3.1910>.
- Fan, S., Yang, Z., 2023. Analysing seafarer competencies in a dynamic human-machine system. *Ocean Coast Manag.* 240, 106662 <https://doi.org/10.1016/j.ocecoaman.2023.106662>.

- Fan, S., Yang, Z., 2024. Accident data-driven human fatigue analysis in maritime transport using machine learning. *Reliab. Eng. Syst. Saf.* 241, 109675 <https://doi.org/10.1016/j.res.2023.109675>.
- Fan, S., Yang, Z., Wang, J., Marsland, J., 2022. Shipping accident analysis in restricted waters: lesson from the Suez Canal blockage in 2021. *Ocean. Eng.* 266, 113119 <https://doi.org/10.1016/j.oceaneng.2022.113119>.
- Fan, S., Zhang, J., Blanco-Davis, E., Yang, Z., Wang, J., Yan, X., 2018. Effects of seafarers' emotion on human performance using bridge simulation. *Ocean. Eng.* 170, 111–119. <https://doi.org/10.1016/j.oceaneng.2018.10.021>.
- Fan, S., Zhang, J., Blanco-Davis, E., Yang, Z., Yan, X., 2020b. Maritime accident prevention strategy formulation from a human factor perspective using Bayesian Networks and TOPSIS. *Ocean. Eng.* 210 (May), 107544 <https://doi.org/10.1016/j.oceaneng.2020.107544>.
- Fang, S., Liu, Z., Wang, X., Cao, Y., Yang, Z., 2024. Dynamic analysis of emergency evacuation in a rolling passenger ship using a two-layer social force model. *Expert Syst. Appl.* 247, 123310 <https://doi.org/10.1016/j.eswa.2024.123310>.
- Fay, D., Shipton, H., West, M.A., Patterson, M., 2015. Teamwork and organizational innovation: the moderating role of the HRM context. *Creativ. Innovat. Manag.* 24 (2), 261–277. <https://doi.org/10.1111/caim.12100>.
- Ghosh, S., Bowles, M., Ramnuthugala, D., Brooks, B., 2014. Reviewing seafarer assessment methods to determine the need for authentic assessment. *Australian Journal of Maritime & Ocean Affairs* 6 (1), 49–63. <https://doi.org/10.1080/18366503.2014.888133>.
- Han, S., Wang, T., Chen, J., Wang, Y., Zhu, B., Zhou, Y., 2021. Towards the human-machine interaction: strategies, design, and human reliability assessment of crews' response to daily cargo ship navigation tasks. *Sustainability* 13 (15). <https://doi.org/10.3390/su13158173>. Article 15.
- Hetherington, C., Flin, R., Mearns, K., 2006. Safety in shipping: the human element. *J. Saf. Res.* 37 (4), 401–411. <https://doi.org/10.1016/J.JSR.2006.04.007>.
- Hiroaki, S., Shingo, Y., Kyoko, T., Teppei, U., 2022. Remote use of shiphandling simulator: BRM skill acquisition. *J. Navig.* 75 (4), 813–831. <https://doi.org/10.1017/S037346322000352>.
- Kaplan, M., Uğurlu, Ö., Wang, J., 2021. The effect of nonconformities encountered in the use of technology on the occurrence of collision, contact and grounding accidents. *Reliab. Eng. Syst. Saf.* 215, 107886 <https://doi.org/10.1016/j.res.2021.107886>.
- Kim, S., 2023. [Korean History] 2014 ferry disaster left scars that never healed. <http://www.koreaherald.com/view.php?ud=20231229000426>.
- Koubek, J., 2003. *Anglicko-český Východový Slovník Personalistiky*. Management Press.
- Lee, J.D., Sanquist, T.F., 2000. Augmenting the operator function model with cognitive operations: assessing the cognitive demands of technological innovation in ship navigation. *IEEE Trans. Syst. Man Cybern. Syst. Hum.* 30 (3), 273–285. <https://doi.org/10.1109/3468.844353>. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*.
- Li, G., Weng, J., Hou, Z., 2021. Impact analysis of external factors on human errors using the ARBN method based on small-sample ship collision records. *Ocean. Eng.* 236, 109533 <https://doi.org/10.1016/j.oceaneng.2021.109533>.
- Li, H., Çelik, C., Bashir, M., Zou, L., Yang, Z., 2024. Incorporation of a global perspective into data-driven analysis of maritime collision accident risk. *Reliab. Eng. Syst. Saf.* 249, 110187 <https://doi.org/10.1016/j.res.2024.110187>.
- Li, H., Ren, X., Yang, Z., 2023. Data-driven Bayesian network for risk analysis of global maritime accidents. *Reliab. Eng. Syst. Saf.* 230 (October 2022), 108938 <https://doi.org/10.1016/j.res.2022.108938>.
- Liang, X., Fan, S., Lucy, J., Yang, Z., 2022. Risk analysis of cargo theft from freight supply chains using a data-driven Bayesian network. *Reliab. Eng. Syst. Saf.* 226, 108702 <https://doi.org/10.1016/j.res.2022.108702>.
- Liskova, S., Tomsik, P., 2013. Competency-based approach to human resources management. *AGRICULTURAL ECONOMICS-ZEMEDĚLSKA EKONOMIKA* 59 (11), 496–504. <https://doi.org/10.17221/68/2013-AGRICECON>.
- Liu, C., Chu, X., Wu, W., Li, S., He, Z., Zheng, M., Zhou, H., Li, Z., 2022. Human-machine cooperation research for navigation of maritime autonomous surface ships: a review and consideration. *Ocean. Eng.* 246, 110555 <https://doi.org/10.1016/j.oceaneng.2022.110555>.
- Ma, X., Fan, S., Blanco-Davis, E., Shi, G., Yang, Z., 2024. Bulk carrier accident severity analysis in Australian waters using a data-driven Bayesian network. *Ocean. Eng.* 310, 118605 <https://doi.org/10.1016/j.oceaneng.2024.118605>.
- Mansikka, H., Harris, D., Virtanen, K., 2019. Pilot competencies as components of a dynamic human-machine system. *Human Factors and Ergonomics in Manufacturing & Service Industries* 29 (6), 466–477. <https://doi.org/10.1002/hfm.20809>.
- O'Connor, P., 2011. Assessing the effectiveness of bridge resource management training. *Int. J. Aviat. Psychol.* 21 (4), 357–374. [doi: 10.1080/10508414.2011.606755](https://doi.org/10.1080/10508414.2011.606755).
- Orlandi, L., Brooks, B., 2018. Measuring mental workload and physiological reactions in marine pilots: building bridges towards redlines of performance. *Appl. Ergon.* 69 (December 2017), 74–92. <https://doi.org/10.1016/j.apergo.2018.01.005>.
- Rothblum, A.M., 2002. Keys to successful incident inquiry. In: *Human Factors in Incident Investigation and Analysis, 2nd International Workshop on Human Factors in Offshore Operations (HFW2002)*, Houston, TX. <http://www.mtpinnacle.com/pdfs/KEYS-TO-SUCCESSFUL-INCIDENT-ENQUIRY.pdf>.
- Russo, A., Vojković, L., Bojic, F., Mulić, R., 2022. The conditional probability for human error caused by fatigue, stress and anxiety in seafaring. *J. Mar. Sci. Eng.* 10 (11), 1576. <https://doi.org/10.3390/jmse10111576>.
- Sanfilippo, F., 2017. A multi-sensor fusion framework for improving situational awareness in demanding maritime training. *Reliab. Eng. Syst. Saf.* 161, 12–24. <https://doi.org/10.1016/j.res.2016.12.015>.
- Sheng, T., Weng, J., Shi, K., Han, B., 2023. Analysis of human errors in maritime accidents: a Bayesian spatial multinomial logistic model. *J. Transport. Saf. Secur.* 1–17. <https://doi.org/10.1080/19439962.2023.2235323>.
- Shi, K., Weng, J., Fan, S., Yang, Z., Ding, H., 2023. Exploring seafarers' emotional responses to emergencies: an empirical study using a shiphandling simulator. *Ocean Coast Manag.* 243, 106736 <https://doi.org/10.1016/j.ocecoaman.2023.106736>.
- STCW, 1978. International convention on standards of training, certification and watchkeeping for seafarers (STCW). <https://www.imo.org/en/OurWork/HumanElement/Pages/STCW-Conv-LINK.aspx>.
- Swift, A.J., 2004. *Bridge Team Management*, second ed. The Nautical Institute <https://www.nautinst.org/shop/bridge-team-management-2nd-ed.html>.
- Szlapczynski, R., Szlapczynska, J., 2017. A method of determining and visualizing safe motion parameters of a ship navigating in restricted waters. *Ocean. Eng.* 129, 363–373. <https://doi.org/10.1016/j.oceaneng.2016.11.044>.
- Talmazan, Y., Gubash, C., Yamamoto, A., 2021. Dislodged Suez Canal cargo ship Ever Given held amid \$916 million claim. <https://www.nbcnews.com/news/world/dislodged-suez-canal-cargo-ship-ever-given-held-amid-916-n1264017>.
- Teodorescu, T., 2006. Competence versus competency: what is the difference? *Perform. Improv.* 45 (10), 27–30. <https://doi.org/10.1002/pfi.4930451027>.
- Thombre, S., Zhao, Z., Ramm-Schmidt, H., Vallet García, J.M., Malkamäki, T., Nikolskiy, S., Hammarberg, T., Nuortie, H., H. Bhuiyan, M.Z., Särkkä, S., Lehtola, V. V., 2022. Sensors and AI techniques for situational awareness in autonomous ships: a review. *IEEE Trans. Intell. Transport. Syst.* 23 (1), 64–83. <https://doi.org/10.1109/TITS.2020.3023957>. *IEEE Transactions on Intelligent Transportation Systems*.
- UNCTAD, 2021. Review of maritime transport 2021. UN. https://unctad.org/system/files/official-document/rmt2021_en_0.pdf.
- Wang, C., Zhang, X., Gao, H., Bashir, M., Li, H., Yang, Z., 2024. Optimizing anti-collision strategy for MASS: a safe reinforcement learning approach to improve maritime traffic safety. *Ocean Coast Manag.* 253, 107161 <https://doi.org/10.1016/j.ocecoaman.2024.107161>.
- Wang, S., Ji, B., Zhao, J., Liu, W., Xu, T., 2018. Predicting ship fuel consumption based on LASSO regression. *Transport. Res. Transport Environ.* 65, 817–824. <https://doi.org/10.1016/j.trd.2017.09.014>.
- Weintraub, A., Neumann, T., 2011. *Crew resource management: the role of human factors and bridge resource management in reducing maritime casualties*. In: *Human Resources and Crew Resource Management*. CRC Press.
- Weng, J., Yang, D., 2015. Investigation of shipping accident injury severity and mortality. *Accid. Anal. Prev.* 76, 92–101. <https://doi.org/10.1016/j.aap.2015.01.002>.
- Wróbel, K., 2021. Searching for the origins of the myth: 80% human error impact on maritime safety. *Reliab. Eng. Syst. Saf.* 216, 107942 <https://doi.org/10.1016/j.res.2021.107942>.
- Wu, B., Tang, Y., Yan, X., Guedes Soares, C., 2021. Bayesian Network modelling for safety management of electric vehicles transported in RoPax ships. *Reliab. Eng. Syst. Saf.* 209, 107466 <https://doi.org/10.1016/j.res.2021.107466>.
- Xin, X., Liu, K., Li, H., Yang, Z., 2024. Maritime traffic partitioning: an adaptive semi-supervised spectral regularization approach for leveraging multi-graph evolutionary traffic interactions. *Transport. Res. C Emerg. Technol.* 164, 104670 <https://doi.org/10.1016/j.trc.2024.104670>.
- Yang, L., Li, L., Liu, Q., Ma, Y., Liao, J., 2023. Influence of physiological, psychological and environmental factors on passenger ship seafarer fatigue in real navigation environment. *Saf. Sci.* 168, 106293 <https://doi.org/10.1016/j.ssci.2023.106293>.
- Zhang, S., Wu, J., Jia, Y., Wang, Y.-G., Zhang, Y., Duan, Q., 2021. A temporal LASSO regression model for the emergency forecasting of the suspended sediment concentrations in coastal oceans: accuracy and interpretability. *Eng. Appl. Artif. Intell.* 100, 104206 <https://doi.org/10.1016/j.engappai.2021.104206>.
- Zhou, T., Hu, Q., Hu, Z., Zhen, R., 2022. An adaptive hyper parameter tuning model for ship fuel consumption prediction under complex maritime environments. *J. Ocean Eng. Sci.* 7 (3), 255–263. <https://doi.org/10.1016/j.joes.2021.08.007>.