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Research paper

Risk assessment of maritime autonomous surface ships collisions using an FTA-FBN model

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ABSTRACT

Maritime autonomous surface ships (MASS), presenting the future of maritime transport, are attracting increasing attention from the international maritime community. The collision risk analysis of MASS reveals unsolved challenges, which without appropriate solutions, will result in the error prone development of the relevant risk control measures and policies. Among the challenges, two significant ones in the existing literature are the lack of historical failure data to realise quantitative risk assessment, and 2) the complex causal relationship among the relevant risk factors. This paper aims to develop a new Fault Tree Analysis-Fuzzy Bayesian Network (FTA-FBN) model to conduct the collision risk assessment of MASS with uncertainty in data. First, it establishes a causal relationship among the risk factors through an FTA. Secondly, mapping the obtained FTA diagram into a BN allows fault diagnosis and the identification of the most important factors influencing MASS collisions. In this process, a survey is conducted to collect the primary data for configuring the conditional probabilities of the relevant influential factors and quantifying the developed BN for risk diagnosis and prediction. Finally, the new model is verified by using sensitivity analysis and three axioms and then applied to conduct scenario-based risk prediction and diagnosis to generate insightful findings to guide MASS navigation safety. The results demonstrate that the FTA-FBN model realizes the simplification of the expert scoring process, reduces computational complexity, and addresses the challenge of constructing causal relationships between MASS collisions and their risk factors due to the scarcity of historical accident data. Additionally, the BN backward reasoning identifies key collision risks, including external physical attacks, inadequate training of shore-based operators, insufficient maintenance of ship equipment and systems, and cyber-security threats. The new model when being adapted, can provide a reference for the formulation of safe navigation policies and provide important insights for shipping companies to ensure the safe navigation of their ships and shipbuilders to optimise ship design.

1. Introduction

Conducting MASS risk assessments can help ship owners and operators identify risks that may affect navigational safety and operational efficiency, thereby safeguarding navigational safety, reducing property damage and improving the efficiency of ship operations. Fault Tree Analysis – Fuzzy Bayesian Network (FTA-FBN) is a combination of three methods, FTA (Ruijters and Stoelinga, 2015; Wang et al., 2021), fuzzy logic and BN. Using FTA in conjunction with FBN can improve the accuracy and reliability of risk assessment(Cem Kuzu et al., 2019; Choi and Chang, 2016) in particularly when historical failure data is incomplete, and the risk factors show high interdependency among them. Specifically, FTA can be used to construct fault tree models to identify the root causes and critical events of system failures, while FBN can be used to process probabilistic and uncertainty information in fault tree models to provide accurate and reliable risk assessment results. FTA, fuzzy FTA, FTA-BN have been widely used in previous maritime risk assessment (Sokukcu and Sakar, 2022; Trucco et al., 2008; Wang et al., 2021; Zhang et al., 2018), Table 1 shows the differences between FTA, FFTA, BN, FTA-BN, FTA-FBN and STPA. At present, among the most challenges of MASS risk assessment is the lack of historical data. Within this context, Zhang et al. (Zhang and Zhang, 2023) adopted the entropy-TOPSIS

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Table 1
Differences between FTA, FFTA, BN, FTA-BN, FTA-FBN and STPA.

Method	Description	Advantage	Drawback	Applicable scenario
FTA	Hierarchical top-down deductive reasoning and the application of gate logic symbols to establish the causal chain of events leading to failures.	Comprehensively identifies factors contributing to system failure and is suitable for complex systems. Intuitive, systematic, easy to understand and communicate complex relationships.	Only suitable for static analysis, struggles with complex dependencies and uncertainty.	In industries such as nuclear power, marine, and aviation, employing FTA early in system design can identify potential design flaws and optimize the design.
FFTA	Incorporating fuzzy logic into FTA to address uncertainty.	Enhancing FTA adaptability and practicality through flexible handling of imprecise data.	Model construction and computation are complex, requiring expertise to define fuzzy sets.	Risk assessment where data are imprecise or incomplete.
BN	Representing probabilistic relationships between variables using nodes and edges.	Effectively handles uncertainty and incomplete data, supporting probabilistic reasoning and fault diagnosis.	Complex to build and compute, requiring large amounts of data and expertise.	Diagnosis, prediction, machine learning, and recommender systems for complex systems.
FTA-BN	Combining FTA's systems analysis and BN's probabilistic reasoning	Capable of handling complex dependencies and feedback relationships; can perform fault diagnosis and provide quantitative analysis.	Complex to construct, requiring extensive domain knowledge and data processing capabilities.	Suitable for complex environments that require probabilistic reasoning or involve significant uncertainties.
FTA-FBN	Integrating fault tree analysis with fuzzy Bayesian networks to manage uncertainty and ambiguity in fault data.	Ideal for early design phases, enhancing design safety and handling of system uncertainty; capable of managing complex dependencies; effectively addresses risk assessments without historical data.	Complex modeling requiring significant expertise.	Ideal for scenarios with incomplete or inaccurate data and complex system relationships, as well as for conducting risk assessments without historical data.
STPA	Cybernetics-based safety analysis methods for identifying potential control failures.	Analyzing known failures and exploring interactions and processes that may lead to system failure.	The analysis process is both time-consuming and complex, demanding a high level of expertise from the analyst.	Design and operation of complex and safety-critical systems, such as aerospace and nuclear power.

method for quantitative assessment of MASS navigational risk using traditional ship data. Given the fact that the navigational risks of traditional manned ships and MASS are different, Zhang et al. (D. Zhang et al., 2022) combined traditional ship data and MASS experimental data to conduct new MASS collision risk analysis. Although showing the attractiveness, it is still arguable in terms of the harmony of the historical failure data on manned ships and experimental data on MASS for MASS collision analysis. Hannaford et al. (Hannaford and Hassel, 2021) used scoring scales and structured interviews to obtain expert experience purely with regard to MASS to improve the credibility of the relevant analysis. However, the used methods for processing the data is straightforward, causing the concerns on their ability of handling the uncertainty in the data directly relating to MASS as well as its ability of incorporating the interdependence among the risk factors. This paper aims to apply a holistic method of FTA-BN to evaluate MASS collision risk using primary data from the domain experts for the first time within the context of MASS collision risk. FTA-BN has been used to analyse risk of high uncertainty in the fields of chemical, mineral, nuclear safety, etc. (Goodman, 1988; Iverson et al., n.d.), but yet in the context of MASS.

Bolbot et al. (2023) and Guo et al. (2023) identified and analyzed the risk factors due to the MASS's interaction with other ships by BN. Wróbel et al. (2020) used a Systematic Theory Process Analysis (STPA) approach to model the safety structure of an autonomous merchant vessel from a qualitative perspective firstly, then quantitatively assess it in conjunction with the literature review. In addition, Chaal et al. (2020) and Zhou et al. (Zhou et al., 2020, 2021) also conducted hazard identification and analysis of system safety and crash risk of MASS using STPA. MASS overcomes the risks associated with human negligence in keeping watch, failure to follow a prescribed course and physical and psychological discomfort, and uses communication equipment, machinery and control systems to transmit information and operate the ship remotely. Bucchianico et al. (2016) disclosed that human errors were transferred from the crew to the shore-based operators. While reducing the collisions caused by human negligence lookout (Haugen et al., 2018), it also brings new risks such as cyber security (Chang et al., 2021; Rødseth and Burmeister, 2015; Wróbel et al., 2017), communication failures (Larisa Dobryakova et al., 2016) and mechanical equipment failures (Abaei et al., 2021). Besides, Veitch et al. (Veitch and Alsos, 2022) conducted a detailed review based on 42 studies on MASS navigational safety, which showed that shore-based operators are critical to ship navigational safety and that the commonly used research methods are STPA (W. Li et al., 2023; Ventikos et al., 2020) and BN. A review on MASS risk and reliability analysis road strength planning is well documented in the literature (Z. Li et al., 2023).

Different with the previous studies in the current literature, this paper makes methodological contributions by proposing a new FTA-FBN model and its application for quantitative assessment of collision accident risks of MASS. From an applied research perspective, this paper also makes new contributions including: 1) Identifying the risk factors influencing MASS collisions through the literature review, and purification and verification; 2) Using FTA to establish the logical relationship between MASS collision risk factors; 3) Using the fuzzy theory to convert expert judgements into relevant probabilities to realise the quantitative evaluation of the collision accidents of MASS; 4) Using BN to predict the probability of MASS collisions and the identification of key risk factors influencing MASS collisions by fault diagnosis; 5) Developing a useful tool based on the FTA-FBN model to support quantitative evaluation of MASS at different levels of uncertainty in risk data.

The rest of this paper is organized as follows. Section 2 identifies the collision risk factors for MASS. Section 3 describes the new methodology. Section 4 analyzes the MASS risk using newly collected primary data and the sensitivity analysis is conducted to validate the model before the result discussion. Section 5 draws the conclusions.

2. Identification the risk factors influencing the collisions of MASS

2.1. MASS risk analysis review

Recently, risk assessment for MASS has gradually become a popular topic, and many scholars have conducted risk identification and analysis from the perspectives of human error, ship systems and equipment, and cyber security, respectively (Bolbot et al., 2022; Chang et al., 2021; C. Fan et al., 2020; Fan et al., 2022, 2021). In MASS, Romas et al. (Ramos et al., 2020) argue that the human element is transferred from a ship to the shore-based operators. Fan et al. (Fan and Yang, 2023), Bahoo-Toroody et al. (Bahootoroody et al., 2022) and Yoshida et al. (2021) used machine learning algorithms in conjunction with experiments conducted by experienced captains (D. Zhang et al., 2022) to analyse the relationship between the mental load of the maneuvering crew and the safety of MASS navigation.

Secondly, MASS collision risk is studied from the perspective of collision avoidance systems and path planning. For instance, the design and development of collision avoidance systems (Hwang and Youn, 2022; Kim et al., 2022; Namgung and Kim, 2021; Ni et al., 2022), real-time collision avoidance detection systems (Yoo and Lee, 2021; W. Zhang et al., 2022; Zhang et al., 2021), and collision avoidance-based path planning (Geng et al., 2019; Mou et al., 2021; Namgung, 2021). Collision avoidance systems use artificial intelligence and machine learning to autonomously sense their surroundings, obtain information about the vessel in real time and make decisions with much less reliance on people. However, the test results of the system depend on the number of test scenarios and their coverage, and the number of ship collision scenarios is often limited and only fits specific research interests.

Huang et al. (Huang and van Gelder, 2020) modelled MASS movements from a temporal and spatial perspective. Li et al. (2021) improved on the method using a rule-aware time-varying conflict risk (R-TCR) based ship collision avoidance algorithm, which does not rely on expert judgement and takes into account multi-ship encounters. However, operator preferences cannot be fully taken into account due to different operator qualifications and the uncertainty of the target vessel's movement is ignored.

Overall, through the review studies on MASS, in area of navigation risk and reliability analysis (Z. Li et al., 2023; Thieme et al., 2018), cyber security (Schinas and Metzger, 2023), and the advantages, challenges and future directions of MASS (Chae et al., 2020; Chen et al., 2023; Goerlandt, 2020), it is witnessed that new quantitative risk analysis models for MASS collisions are highly demanded in the current literature. In this work, we conducted a survey to collect expert opinions on collisions in MASS, due to insufficient collision data for assessment. The application of Noisy-OR in calculating the conditional probability of BN simplifies the calculation process, reduces the complexity of expert scoring, and enhances the accuracy of the conditional probability table (CPT). This technique is highly valuable when dealing with noisy and uncertain observational data in practical problems.

2.2. Identification of MASS collision risk factors

The first step of carrying out ship collision risk is to identify the relevant influential factors (S. Fan et al., 2020; H. Li et al., 2023). The factors were manually collected from maritime accident reports (S. Fan et al., 2020) and then filtered based on their frequency of occurrence. In this process, accident reports were sourced from the official website of the China Maritime Safety Administration (MSA , https://www.msa.gov.cn). After thorough review, a total of 330 reports were collected for the period 2015 to 2021. To ensure the study's accuracy and reliability, further screening was conducted. Inland vessel collisions and other irrelevant reports were eliminated through manual review, focusing solely on maritime collisions. Ultimately, 294 marine collision reports were retained. Out of 294 collision reports, we selected factors that occurred more than 15 times (S. Fan et al., 2020). We determined that a frequency limit of 15 adequately covers commonly occurring risk factors, based on our professional judgement and research experience. This choice helps us avoid excessive focus on rare factors and better reflects the common risk factors in collisions. Prior research and industry practice (Wang and Yang, 2018) have shown that this option is a widely accepted and more reasonable and meaningful choice. Next, the literature survey taking into account MASS collision risk factors were conducted to purify the ones identified from accident reports. The purified risk factors are then identified in this paper, are shown in Table 2.

After manual extraction and purification, the most frequently occurred risk factors influencing ship collisions and MASS navigation in the literature, such as natural environmental factors (wind, rain and fog), were further examined by the domain experts of MASS expertise to ensure their fitness in the MASS collision risk analysis. The selected experts and their qualifications are introduced in the methodology section (e.g. Section 3.1). Finally, after filtering and collating, the risk factors are summarized in four aspects: human, ship system equipment, cyber security and environment.

Among the collision risk factors for MASS, developer errors are significant. An engineer reported that due to coding logic errors and improper handling of boundary conditions by the algorithm, MASS failed to execute effective collision avoidance during tests, nearly causing an accident. Meanwhile, Romas et al. (Ramos et al., 2018) and Man et al. (Abilio Ramos et al., 2019) also highlighted that coding errors and inadequately designed human-machine interfaces are common during the development and testing phases of MASS, increasing collision risks. Furthermore, in a U.S. self-driving car incident, incorrect coding led the collision detection subsystem to malfunction, erroneously causing the vehicle to pull over and severely injure a pedestrian, underscoring the grave consequences and severity of coding errors.

3. Data and methodology

3.1. Data sources

Expert scoring has been widely used in maritime risk analysis, factor identification, data acquisition (Qiao et al., 2020). However, MASS currently lacks historical data on collisions. This paper therefore uses an expert scoring method (based on fuzzy values, in Section 3.2) to conduct a survey and obtain expert opinion as a data source for MASS collision accidents. The expert's field of work, title, years of experience and education can reflect the expert's experience, cognitive and judgmental abilities, which to a certain extent can affect the accuracy of the results. This study mainly selects experts using the following criteria (Qiao et al., 2020; Ung, 2021; Yazdi et al., 2017).

1) Professional qualifications: The selected experts have profound knowledge in the fields of navigation, automation, ship engineering and human-computer interaction, and they all come from universities, shipping companies, autonomous ship research institutes and shipyards around the world. They have rich theoretical knowledge and practical experience, which can make the questionnaire results more comprehensive and reliable.
2) MASS working experience: having direct or indirect involvement in the research and development, operation or management of MASS, which ensures that they have a practical basis for understanding the human factors in MASS operation.
3) Years of work experience and educational background: this implies to some extent whether the experts are experienced or not, for experienced experts, it can make the calculation more realistic and accurate, and the highest degree obtained can reflect the cognitive ability, knowledge level, etc. of the experts.

A total of 40 questionnaires were distributed and 34 valid (with the answers to all the questions) questionnaires were returned. Although the number of experts is relatively small, the respondents cover a wide range of key areas related to MASS. These areas include engineers involved in MASS design and development, experienced shipmasters, chief mates, and chief engineers, as well as experts and academics in MASS navigational risk research. They have extensive experience in working with MASS and can provide assessments and insights from multiple perspectives. In addition, the respondents are representative of universities, shipping companies, autonomous ship research institutes, and shipyards around the world. Among them, 88.24% had intermediate posts or above, 82.36% had working experience of more than 10 years, and the expert qualification information is shown in Table 3.

According to the risk factors identified in Section 2.1, 19 questionnaire questions are designed for the possibility of collisions caused by each factor, as shown in Table 10 in the appendix. Due to the large content of the questionnaire, linguistic terms can better help domain experts to express their opinions. In the literature, 4–7 linguistics terms

Table 2
Risk factors are derived from accident reports, the literature and expert judgements.

Level 1	Level 2	Level 3	Description	Source	Traditional ships	MASS
Human error	Shore-based manipulation errors	Improper operation of shore-based operators	Due to carelessness or lack of knowledge, operators may make poor decisions, neglect monitoring, perform incorrect maneuvers, and fail to follow collision avoidance rules (including failure to maintain safe speeds)	(Wahlström et al., 2015; Man, 2015; Haugen et al., 2018; Man et al., 2018; Ahvenjärvi, 2016), (Porathe, 2014; Ramos et al., 2020; Chalmers University of Technology, Sweden et al., 2014; Bucchianico et al., 2016)		✓
		Failure to take effective avoidance actions in time	In emergency situations, operators fail to keep a high vigilance, respond slowly, do not comply with collision avoidance rules (such as using safe speeds), and delay taking early avoidance measures like slowing down.		✓	✓
		Failure to perform the obligation to avoid ships	It means that when ships meet, they fail to comply with Article 13 of the collision avoidance rules and fail to fulfill the obligation of surrendering.			✓
		Insufficient training of shore-based operators	Operators have insufficient control skills and emergency response capabilities, and do not have corresponding ship driving qualifications.		✓	✓
		Inconsistent work of ship and shore	It refers to the disharmony of ship-shore work caused by inconvenient communication between ship-shore staff.			✓
	Developer errors	Improper system design	As the system developer is not a senior captain, and the navigation experience is insufficient, there is a certain discrepancy between the designed system and the actual operation process.			✓
		Human coding errors of the system	It refers to coding errors that occur during coding by developers.			✓
	Some of the risk factors for traditional ships	Negligent lookout	The crew did not use visual, auditory and other means to look out.	Ship's collision accident reports	✓	
		Poor communication	Poor crew communication between ships.		✓	
		Operation errors	The captain or crew did not fully estimate the risk of a certain water area, resulting in operational errors.		✓	
		Physiological factors	Seasickness, fatigue, eating disorders, etc.		✓	
		Psychological factors	Negative emotions caused by poor psychological quality and long-term work pressure.		✓	
Ship system equipment failure	Management issues	Failure to regularly inspect and maintain ship equipment	The company fails to regularly inspect and maintain the ship according to relevant regulations.	(Man, 2015; Ahvenjärvi, 2016; Porathe, 2014; Ramos et al., 2020; Chalmers University of Technology, Sweden et al., 2014; Bucchianico et al., 2016; Hogg and Ghosh, 2016; Thieme and Utne, 2017; Lazakis et al., 2016; Rødseth and Burmeister, 2015; Wróbel et al., 2017), (H.-C. Burmeister et al., 2014), (H. Burmeister et al., 2014; Zghyer et al., 2019), (C. Fan et al., 2020)	✓	✓
		Incomplete safety management system	The company has not established a safe management system, and has failed to effectively manage and monitor the navigation dynamics and ship equipment dynamics of its sailing ships.		✓	✓
	Failure of system and equipment	Radar sensing system failure	It refers to the fault caused by the poor contact between the starting contactor of radar or the poor contact between carbon brush and commutator.			✓
		Ship-Shore communication failure	Due to bad weather and its own error code, the communication between ship and shore fails, operators may not be able to adjust the speed in time to respond to changing sea conditions or traffic, thus increasing safety risks.			✓
		Sensor failure	Refers to the sensor failure caused by fixed deviation or drift deviation.			✓
	Structure and performance	Overloading	Refers to the overload of the ship during the shipping process.		✓	✓
		Ship performance	The structure and stability of the ship are poor, and the design and construction of the ship have not been strictly examined and inspected.		✓	✓
		Situational judgement ability	The command and situation judgement ability of the MASS to the shore-based control center.			✓
		Target recognition ability	Refers to the ability of autonomous ships to identify surrounding targets during navigation.			✓

(continued on next page)

Table 2 (*continued*)

Level 1	Level 2	Level 3	Description	Source	Traditional ships	MASS
		Comprehension of the navigational environment	The ability of an autonomous ship to understand the navigation environment during navigation.			✓
		Failure to provide crew as required	Staffing does not meet the basic requirements to ensure the safety of the ship's navigation.	Ship's collision reports	✓	
		Navigational command	The ship did not follow the correct course, resulting in overtaking with other ships.		✓	
		Emergency rescue	During navigation, the steering gear and other functional faults of the ship were not eliminated and repaired in time.		✓	
Cyber attacks and physical attack	Cyber-attacks	Hacker attacks	Hackers attack the IT system of the control center, resulting in system paralysis, thus achieving the purpose of destroying MASS.	(Hogg and Ghosh, 2016; Lazakis et al., 2016; Rødseth and Burmeister, 2015; Wróbel et al., 2017; Zghyer et al., 2019; Haugen et al., 2018; Chang et al., 2021)		✓
		Remote hijacking	Refers to the signal interference to the communication system, thus hijacking the ship.			✓
		Spread of false information	Sending false information to the control center, causing the operator to misjudge.			✓
	Physical attack	Piracy, terrorist attacks	Pirates or terrorists attack MASS by physical means.		✓	✓
Poor environment	Harsh natural environment	Low visibility	For example, in foggy days, the visibility is less than 200m.	(Chalmers University of Technology, Sweden et al., 2014), (H. Burmeister et al., 2014), (C. Fan et al., 2020; Utne et al., 2020; Rødseth and Burmeister, 2015; Burmeister et al., 2015; Acanfora et al., 2018) and Ship's collision accident reports	✓	✓
		Bad weather	Such as storms, short-term gales, short-term heavy rainfall and severe convective weather.		✓	✓
		Hydrology	Such as ebb tide, the flow rate is 4–5 knots, and the tide is as high as 5 m. In addition, water depth similarly affects a vessel's ability to maneuver and limits steering angles, thereby increasing the risk of collision.		✓	✓
	Poor navigation environment	Heavy traffic on the channel	Ships enter and leave the anchorage frequently, there are many passing ships or the navigation density in the waters is high.		✓	✓
		Navigation aid system failure	Faults caused by abnormal signal display of AIS equipment on ships.		✓	✓
		Existing obstacles	It means that the channel is not cleaned and there are obstacles.		✓	✓

are often used to support experts' subjective evaluation (Z. Yang et al., 2009) such as very small, small, slightly small, medium, slightly large, large and very large. In this study, questionnaires were distributed using the Questionnaire Star survey tool, and experts were only required to select the appropriate options based on their own empirical judgement, and the results were eventually collected for processing and analysis of the data.

3.2. *The methodology*

It is necessary and vital to conduct the risk assessments of MASS for the safe operations of ships, particularly concerning the co-existence of manned and autonomous ships. Scholars have studied the safety of MASS navigation from different perspectives. There are various methods suitable for maritime safety risk assessment. Zhang et al. (2018) used FT and fuzzy theory to evaluate the fire accident of the Nanjing Yangtze River Bridge. This method cannot diagnose faults and handle uncertainty problems. In order to overcome the uncertainty problem, Sakar et al. (Kabir, 2017) combined the FTA with BN for the ship grounding accident. Although the FTA-BN model overcomes the uncertainty problem, the prior probability of BN is determined by collecting reports, so it is inapplicable to research lacking historical data. Notably, Trucco et al. (2008) also used FTA-BN to incorporate human and organizational factors into the maritime risk analysis. Sokukcu et al. (Sokukcu and Sakar, 2022) used the FTA-BN model combined with expert opinions to conduct probabilistic risk analysis on collision risks. This research overcomes the constraints of FTA in terms of conditional dependence and static characteristics, but in the calculation of BN conditional probability, it is directly converted according to the logic gate rule (i.e. the CPT is 0 or 1), and then it is fine-tuned by experts.

To evaluate MASS navigation risk, there is a lack of historical data on accidents, and single methods (such as BN, fuzzy theory, etc.) cannot establish the logical relationship between risk factors (Kabir, 2017). Therefore, in this section, a new methodology of four steps, as shown in Fig. 1 is put forward. First, it uses FTA to identify the risk factors that influence MASS collisions. Then, it establishes the logical relationship

Table 3
Expert qualification information.

Working field	Number	Education level	Number	Job title	Number	Service periods	Number
Captain or mariner	18	Junior college or below	2	Junior title	4	1~5 years	4
Maritime Risk Research Expert	10	Junior college	15	Intermediate title	19	6~10 years	2
shipping company	6	Bachelor	7	Senior title	8	11~15 years	14
\	\	Master	8	High title	3	16~20 years	7
\	\	Doctor	2	\	\	more than 20 years	7

between the relevant risk factors. Thirdly, it conducts a risk assessment by deductive reasoning layer by layer (Sakar et al., 2021). Moreover, the top event of FTA can be either an already occurring accident or a predicted accident, which is very applicable for MASS currently little applied. It is more appropriate to map FTA to BN because the structure is similar. However, it is impossible to diagnose the key factors influencing MASS collisions only by establishing logical relations, so it is necessary to obtain the posterior probability of each node by using reverse inference of BN. Furthermore, FTA does not permit bidirectional reasoning and cannot quantify uncertain accident data (Ding et al., 2021; Kabir, 2017). To overcome this limitation, this paper presents BN, combining FTA with BN (Ding et al., 2021; Feng et al., 2020; Sakar et al., 2021) for the quantification of risk factors at the fourth step. Forward reasoning can help obtain the collision probability, and backward reasoning (fault diagnosis) can identify the key factors influencing MASS collisions. In addition, the fuzzy language of experts is converted into Fuzzy Failure Probability (FFP) (Lin and Wang, 1997; Yuhua and Datao, 2005) through fuzzy theory, which is used as the prior probability of BN nodes. Therefore, this paper establishes the FTA combined with the FBN model, namely the FTA-FBN (Ding et al., 2021; Feng et al., 2020; Sakar et al., 2021). The flowchart of the model is shown in Fig. 1.

3.3. FTA for modelling the relationship of the risk factors influencing MASS collisions

FTA is a top-down deductive failure analysis method (Ruijters and Stoelinga, 2015). This method can make a comprehensive and vivid description of various causes and logical relations, which can be both qualitative and quantitative (Goodman, 1988).

The steps for compiling an FT within the context of MASS collisions are as follows.

Step1: Familiarise the working process of MASS and investigate potential accidents (Ruijters and Stoelinga, 2015; Yang and Wang, 2015)

According to the International Maritime Organization (IMO), MASS is divided into four levels, this paper focuses on MASS level 3 because it is the state where on human intervene exists onboard ships and MASS can entirely distinguish with manned ships from a navigation perspective. The third-level MASS uses sensing technology and sensing information fusion technology to obtain navigation related information, and analyse and process it to provide decision-making advice on speed and route for safe ship navigation. It however still involves remote control from a shore-based control center for emergency and collision avoidance, which should be appropriated addressed in the risk analysis.

Step2: Identify the top event of MASS collision FT

After Step1, the top event is identified as the navigational risk leading to a MASS collision, including: collision between MASS and manned ships.

Step3: Investigate the causes of MASS collisions

In conjunction with the identified risk factors influencing MASS collisions in section 2.1, all causal events of the MASS collision FTA are formulated. They are grouped into four categories: human error, ship

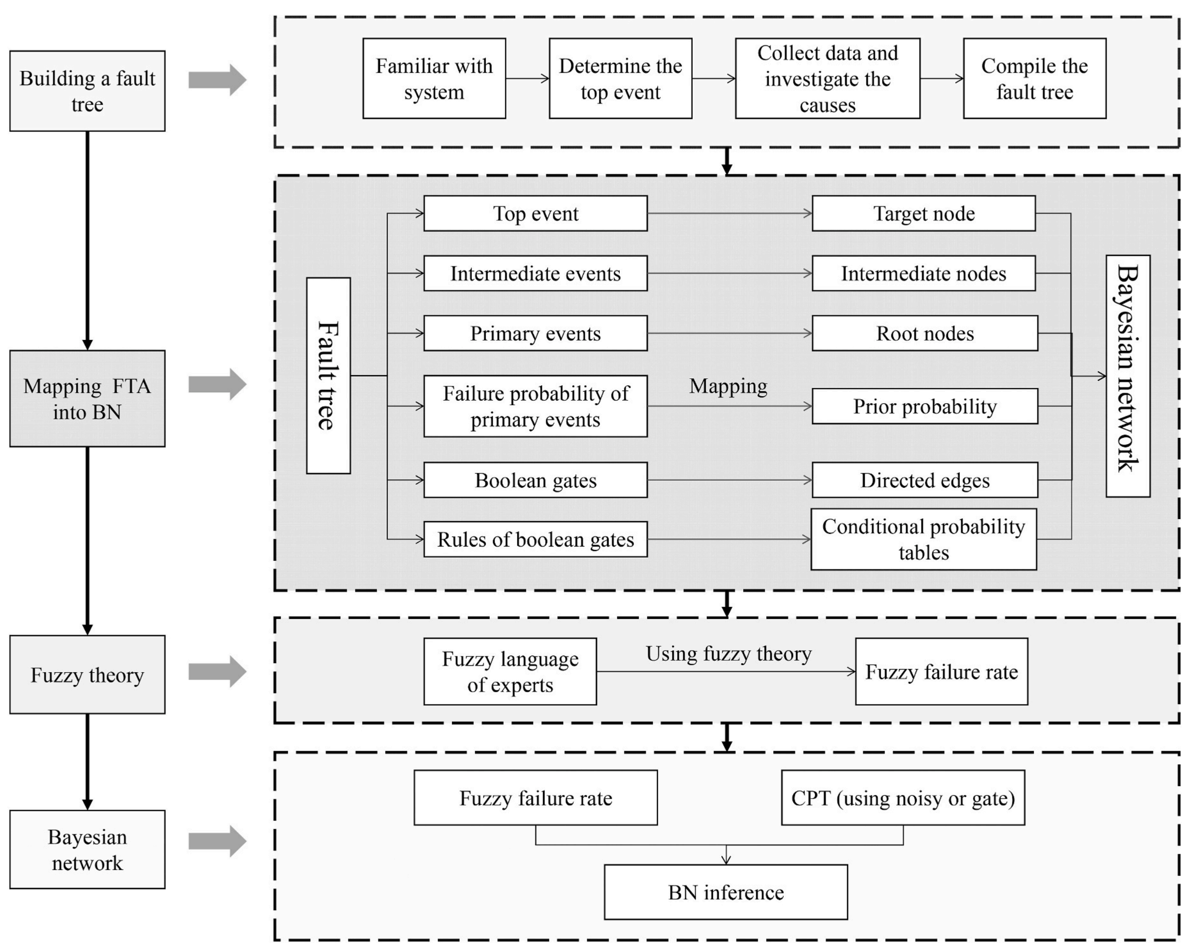

Fig. 1. The flowchart of the model.

equipment failure, cyber security and environmental factors. This includes one top event, 13 intermediate events and 27 basic events, as shown in Table 4.

Step4: Draw the MASS collision FT

A deductive analysis is conducted to configure the relationship among all the events in Step 3 ranging from the MASS collisions, through the intermediate events to basic events. In this process, different gates are used to model that the logical relationship among the events at two neighboring levels to form a qualitative FT.

This study classifies the intermediate events in four categories: human error (A), failure of the ship itself and system equipment (B), external attacks: cyberattacks and pirate/terrorism attacks (C), and harsh environment (D). Combining expert opinion, it is reckoned that in the MASS collision FTA, each of the basic events under a certain intermediate event could lead to the occurrence of that intermediate event independently. Therefore, each basic event is connected via an “OR” gate with its upper-level intermediate event. The simplified result of the FT is shown in Fig. 2, and the detailed development process is described as follows.

For human errors in MASS, this study considers the errors of shore-based operators and system design and developers, and any error of them could lead to a MASS collision. However, improper operation of shore-based operators (X1), failure to take effective avoidance actions in time (X2), failure to perform the obligation to avoid ships (X3), insufficient training of shore-based operators (X4) and inconsistent work of ship and shore (X5) can each lead to shore-based manipulation errors (A1), and therefore they are positioned under A1 with an “OR” gate connection. Similarly, for the system developer, the poor design of the system (X6) and the presence of coding errors (X7) can each lead to a developer error, meaning X6 and X7 are linked with A2 via an “OR” gate.

For system equipment failure in MASS, the main considerations are management issues (B1), system equipment failure (B2) and poor ship performance (B3), with any one event from B1–B3 leading to B event, connected by an “OR” gate. A failure to regularly overhaul and maintain ship equipment (X8) or an inadequate safety management system or inadequate training occurs (X9) can results in the occurrence of B1. Similarly, if any of X8, X10, X11 and X12 occurs it will cause B2 to occur; X13-X17 are the events associated with MASS structural performance, MASS is strongly dependent on sensing devices, if any of X10 and X13-X17 occurs, B3 happens.

For the MASS external attacks from cyber-attacks and piracy, terrorism (C), the cyber attacks (C1) and physical attacks (X21) are defined as the sub-events. X18-X20 are all relating to cyber attacks. if any of them occurs, it will lead to C1, and therefore they are connected with C1 by an “OR” gate. X21 means external physical attacks.

In terms of harsh environment (D), two intermediate events are considered as poor natural environment (D1) and poor navigable environment (D2). Any of the basic events X22-X24 will lead to D1, while any of the events X25-X27 will contribute to the occurrence of D2. All the names of the events are shown in Table 4.Where, $\boxed{\text{T}}$ represents the top event , $\boxed{\text{A1}}$ … $\boxed{\text{D2}}$ represent middle events , X1 … X27represent basic events , $\oplus$ represents the “OR” gate.

3.4. Calculation of FFP

The fuzzy theory is used to model the linguistic terms used by the domain experts to express their judgements on the prior probabilities (both unconditional and conditional) of the events in the FT and aids to convert such judgements into probabilities. In this study, 7 linguistics terms are used (Lin and Wang, 1997; Yazdi and Kabir, 2017; Yuhua and Datao, 2005) including very small, small, slightly small, medium, slightly large, large, very large, and their fuzzy numbers are defined and shown in Table 5. According to the survey, triangular fuzzy/trapezoidal fuzzy has been widely used in recent years to represent expert linguistic terms(Miri Lavasani et al., 2011; Yazdi and Kabir, 2017). This study uses triangular/trapezoidal fuzzy to describe the expert linguistic terms, as shown in Table 5 and Fig. 3.

The following three steps outline the transformation from fuzzy linguistic terms into fuzzy failure probabilities.

Step 1: Opinions aggregation

According to Eq. (1), aggregating expert opinions (Lin and Wang, 1997; Yazdi and Kabir, 2017) to get the average fuzzy number, and then convert the average fuzzy number into FFP.

$$f = \left(\frac{1}{n}\right)\cdot[z_1 \cdot B_{\lambda 1} + z_2 \cdot B_{\lambda 2} + \cdots + z_n \cdot B_{\lambda n}] \tag{1}$$

Where, f is the average fuzzy number, n is the number of experts, z_i is the number of votes of the i th level, and $B_{\lambda i}$ is the fuzzy set of the i th linguistic terms (i = 1, 2, …7) (Lin and Wang, 1997; Yazdi and Kabir, 2017; Yuhua and Datao, 2005).

Table 4
Symbols and names of events.

Symbol	Name of event	Symbol	Name of event
T	Top event(Collision accident)	X8	Failure to regularly overhaul and maintain ship equipment
A	Human error	X9	Incomplete safety management system
B	Ship system equipment failure	X10	Radar sensing system failure
C	Cyber-attacks and piracy, terrorism	X11	Ship-Shore communication failure
D	Poor environment	X12	Sensor failure
A1	Shore-based manipulation errors	X13	Overloading
A2	Developer errors	X14	Ship performance
B1	Management issues	X15	Target recognition ability
B2	Failure of system and equipment	X16	Situational judgement ability
B3	Structure and performance	X17	Comprehension of the navigational environment
C1	Cyber-attacks	X18	Hacker attacks
D1	Harsh natural environment	X19	Remote hijacking
D2	Poor navigation environment	X20	Spread of false information
X1	Improper operation of shore-based operators	X21	External physical attacks
X2	Failure to take effective avoidance actions in time	X22	Low visibility
X3	Failure to perform the obligation to avoid ships	X23	Bad weather
X4	Insufficient training of shore-based operators	X24	Hydrology (large swells)
X5	Inconsistent work of ship and shore	X25	Heavy traffic on the channel
X6	Improper system design	X26	Navigation aid system failure
X7	Human coding errors of the system	X27	Existing obstacles

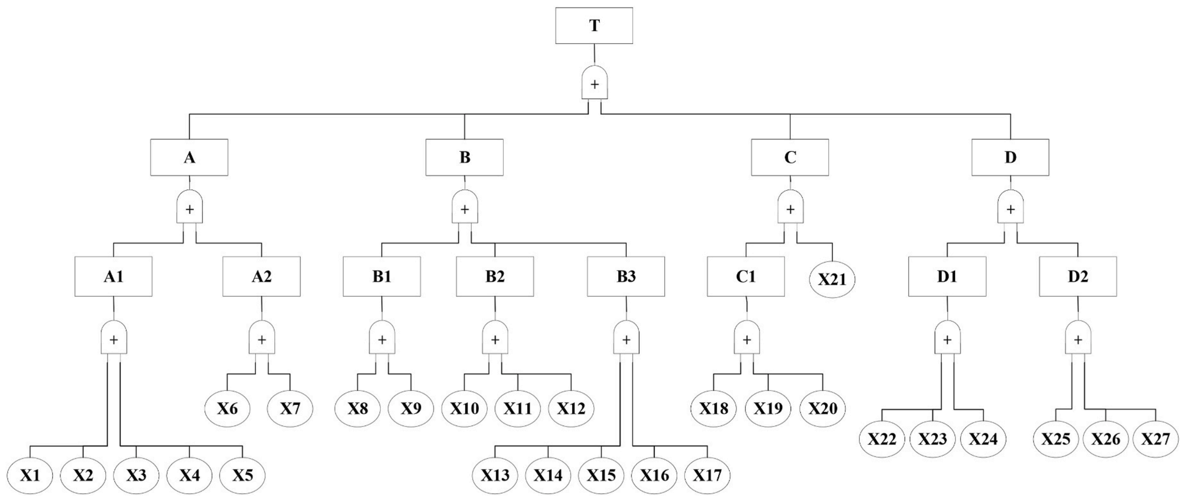

Fig. 2. Simplified FT logic diagram.

Table 5
Triangular/trapezoidal fuzzy numbers for seven linguistic terms (Liu et al., 2005; Miri Lavasani et al., 2011; Yang and Wang, 2015; Guo et al., 2021).

Rank	Linguistic terms	Meaning (general interpretation)	Failure rate (1/year)	Fuzzy memberships
1	Very Small (VS)	Failure is unlikely but possible during lifetime	$< 10^{-6}$	(0,0,0.1,0.2)
2	Small (S)	Likely to happen once during lifetime	0.25×10^{-5}	(0.1,0.2,0.3)
3	Relatively Small (RS)	Between low and average	0.25×10^{-4}	(0.2,0.3,0.4,0.5)
4	Medium (M)	Occasional failure	10^{-3}	(0.4,0.5,0.6)
5	Relatively Large (RL)	Likely to occur from time to time	0.25×10^{-2}	(0.5,0.6,0.7,0.8)
6	Large (L)	Repeated failure	0.25×10^{-1}	(0.7,0.8,0.9)
7	Very Large (VL)	Failure is almost inevitable or likely to happen repeatedly	$>0.25 \times 10^{-1}$	(0.8,0.9,1,1)

Step 2: Defuzzification

Defuzzification is the process of converting the fuzzy numbers from aggregated expert opinion into clear values. The expert-based fuzzy numbers are first aggregated into membership form using fuzzy addition operator and then defuzzified using Eq. (2) and Eq. (3). There are many methods of defuzzification, such as the center of gravity method, weighted average method, mean area method, and maximum membership degree (Xing et al., 2022), Table 6 demonstrates the difference between the four defuzzification methods.

The center of gravity algorithm is extensively adopted for its high accuracy and robust adaptability to complex fuzzy sets (Guo et al., 2021). It captures detailed information from fuzzy sets, producing smooth and precise outputs. Particularly valuable in scenarios of limited data or intricate fuzzy set configurations, the center of gravity algorithm significantly enhances decision-making quality and reliability through its defuzzification process (Masalegooyan et al., 2022; Xing et al., 2022). Consequently, it is the preferred method for safety-critical applications and complex decision-making scenarios, extensively utilized in risk assessment and decision-making processes for autopilot ships and other advanced control systems (Miri Lavasani et al., 2011; Z. L. Yang et al., 2009).

$$X^{*} = \frac{\int f(x)xdx}{\int f(x)dx} \tag{2}$$

Where X^{*} is the clear value of the trapezoidal fuzzy number output, the

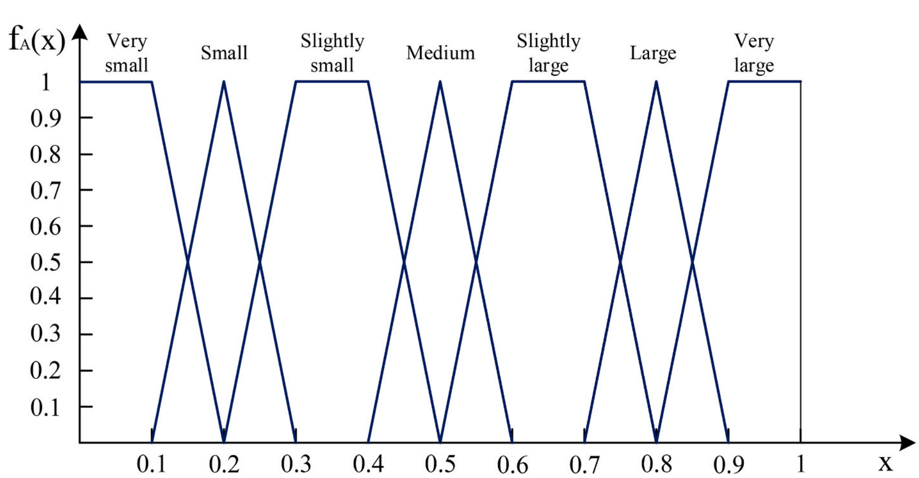

Fig. 3. Fuzzy number of fuzzy linguistic terms.

Table 6
Differences between Center of gravity method and Weighted average method, Mean area method, Maximum membership degree.

Method	Description	Advantage	Drawback	Applicable scenario
Center of gravity method	**Calculate the centroid of the fuzzy set, i.e., the membership-weighted average position.**	**It reflects the entire fuzzy set's information, producing smooth and detailed output.**	**Computation becomes more complex, especially when the membership function has a complex shape.**	**Suitable for handling fuzzy systems with continuous or discrete outputs.**
Weighted average method	Calculate the weighted average using the product of membership degrees and custom weights.	Simpler calculations, suitable for discrete data.	Accuracy depends on the selection of data points, and it is not as smooth as the center of gravity method.	Scenarios where elements in a fuzzy set vary in importance and require distinct handling.
Mean area method	Identify all points where the membership function reaches its maximum, and calculate their average.	Intuitive, easy to understand and implement.	Critical information might be disregarded, particularly when the maximum value appears at the edge of the membership function.	Fuzzy sets exhibit one or more distinct regions of maximum membership.
Maximum membership degree	Choose the single point or the midpoint among multiple points with the highest membership degree.	Fastest calculations, easy to implement.	Outputs are coarse, lacking smooth transitions between values, and often overlook other crucial fuzzy information.	Swift decision-making, real-time systems, and applications with less stringent precision requirements.

trapezoidal fuzzy number after aggregating expert opinions is noted as $\widetilde{R} = (a, b, c, d)$, then the clear value after defuzzification is Fuzzy Possibility Score (FPS), and the calculation process is shown in Eq. (3).

$$FPS = \frac{\int_a^b \frac{x-a}{b-a} x dx + \int_b^c x dx + \int_c^d \frac{d-x}{d-c} x dx}{\int_a^b \frac{x-a}{b-a} dx + \int_b^c dx + \int_c^d \frac{d-x}{d-c} dx} = \frac{1}{3} \times \frac{(c+d)^2 - cd - (a+b)^2 + ab}{(c+d-a-b)} \tag{3}$$

Step 3: Fuzzy Failure Probability (FFP)

Then the FFP can be calculated as follows (Lin and Wang, 1997; Yazdi and Kabir, 2017):

$$FFP = \begin{cases} \frac{1}{10^K} \ (FPS \neq 0) \\ 0 \ (FPS = 0) \end{cases} \text{ where , } \left(K = \left(\frac{1 - FPS}{FPS} \right)^{\frac{1}{3}} \times 2.301 \right) \tag{4}$$

Where K is an intermediate variable being only dependent on FPS.

3.5. Collision risk analysis

3.5.1. BN based MASS collision risk analysis

BN, based on the Bayesian probabilistic theory, uses a directed graph to describe probability relations, and is often called a directed acyclic graph (DAG) (Jianxing et al., 2021). Nodes represent variables, while directed arcs represent the relationships between nodes, using probabilities to represent their interdependencies. The relationship between FTA and BN is illustrated in Fig. 1: the top event corresponds to the target node, intermediate events correspond to intermediate nodes, basic events correspond to root nodes, and the failure probability of basic events corresponds to the prior probability of the BN. The logic gates in FTA, such as the “AND” gate and “OR” gate, correspond to probability gates in BN. Dependencies between events can be represented by combining these logic gates. Therefore, the mapped BN is shown in Fig. 4.

BN has been widely used in maritime safety risk assessment. Li and Yang (H. Li et al., 2023) utilized historical collision data from the IMO, identified 23 risk factors, and applied a data-driven BN model to perform risk analysis. Their study successfully revealed the risks associated with various scenarios. Wang et al. (2013) combined BN with evidential reasoning to assess collisions of ships, and the model can effectively assess the risk of ship navigation, but it requires a large amount of historical data, structure learning, and parameter learning, otherwise it cannot establish logical relationships between risk factors. Similarly, Goerlandt et al. (Goerlandt and Montewka, 2014) and Zhao et al. (2021) used BN structural learning to establish logical relationships between risk factors for tanker collision risk during shipping, and inland vessel navigation safety, respectively. Hence, if historical accident data are missing, logical relationships cannot be established by structures learning. To solve the problem, Yu et al. (2021) proposed a rule-based

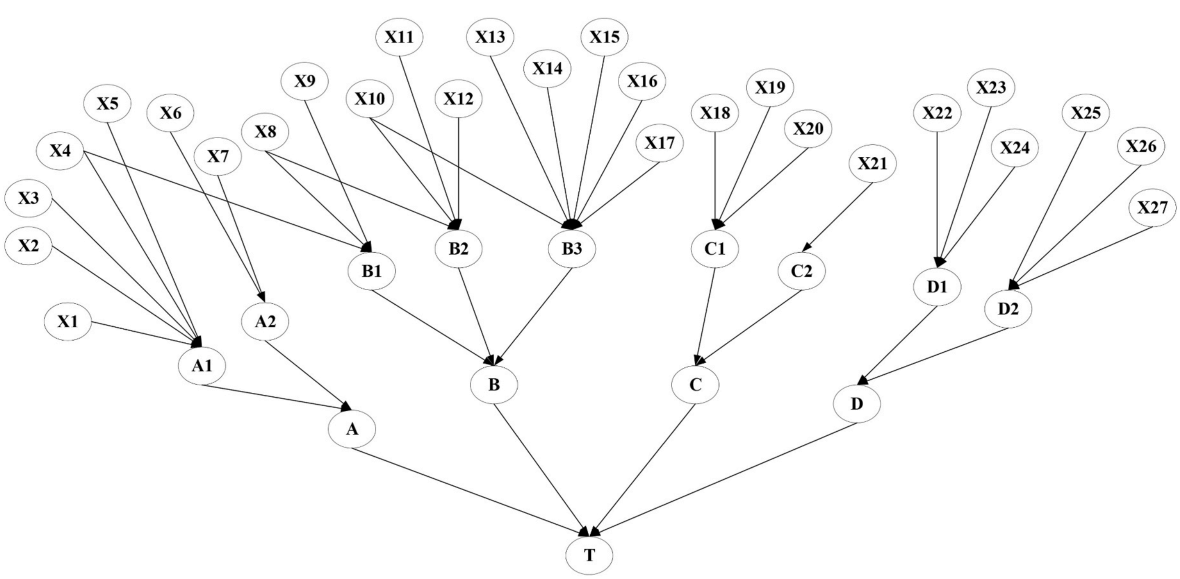

Fig. 4. BN structure of MASS.

BN model to assess the collision risk of ships, and the BN structure was established by defining the logical relationships between risk factor nodes through the formulated causality rules. In addition, Afenyo et al. (2017) established a BN structure for the risk of ship collisions in Arctic shipping, combined with expert experience, and identified collision risk factors by sensitivity analysis, but the conditional probability of this BN model was too conservative.

Since there is no historical failure data on MASS navigation in the real world, it is not possible to conduct a data-driven BN structure and calculate the conditional probability of BN by structure learning and parameter learning. Therefore, introducing the FTA-BN model and mapping FTA to BN allows establishing logical relationships between risk factors and using the Noisy-OR gate (Feng et al., 2020; Jianxing et al., 2021) to determine the CPT for BN, as described in Section 3.5.2.

3.5.2. Calculation of BN conditional probability in MASS

When using BN to assess the risk of MASS, it is a very critical step to determine the CPT of BN. As aforementioned, it is necessary to determine the CPT of BN through expert experience because of lacking historical data. However, the conditional probability of a network involving multiple nodes brings great difficulty for expert scoring. In order to simplify the difficulty, this study introduces a Noisy-OR gate model (Feng et al., 2020; Ji et al., 2022; Jianxing et al., 2021), and combines the fuzzy theory to convert the fuzzy language into conditional probability. Using the Noisy-OR model requires two conditions to be met (Feng et al., 2020; Jianxing et al., 2021): 1) each event is independent of each other, and each event has only two states; 2) assuming that the state of one of the variables x_i is occurrence and other variables is not occurrence, then the probability of its child node Y is $P_i = P(Y = 1|\overline{x_1},\overline{x_2},\cdots,x_i,\overline{x_{i+1}},\cdots,\overline{x_n})$, then the probability P_i is called the connection probability (Feng et al., 2020; Ji et al., 2022; Jianxing et al., 2021) as shown in Eq. (5), The connection probability is obtained by expert judgement, then the conditional probability can be calculated as Eq. (6).

$$P_i = P(Y=1|X_1=0,\cdots,X_i=1,\cdots,X_n=0) \tag{5}$$

$$P(Y|X_p) = 1 - \prod_{i:x_i\in x_p}(1-P_i) \tag{6}$$

It can be known from the above Eq. (6) that when the P_i is 0, the conditional probability is also 0. Therefore, the probability of occurrence can be defined as 0.

3.6. Model validation

3.6.1. Face validity

Face validity refers to whether a test appears to measure the concept or phenomenon being measured. In layman's terms, this means whether the test is intuitive (Pitchforth and Mengersen, 2013; Yu et al., 2020). Face validity can be assessed in a number of ways. One common method is to compare the results of a test with other known measurements to determine their correlation. Another method is to use expert assessment, where an expert assesses whether the items on the test are related to the concept or phenomenon being measured. These methods can help assess the facial validity of the test and determine whether the test accurately reflects the concept or phenomenon being measured.

3.6.2. Validation through sensitivity analysis

Using a new model for risk assessment requires validation of the reliability of the model (Pristrom et al., 2016; Zaili Yang et al., 2008). Firstly, the rationality of the model is judged by experts, and then verified by sensitivity analysis according to the three axioms that a new BN model needs to meet under the uncertain condition (Chang et al., 2021; Jones et al., 2010; Yu et al., 2020; Zaili Yang et al., 2008).

Axiom 1. A slight change in the prior probability of parent nodes should result in a relative change in the posterior probability of the child nodes.

Axiom 2. Given the variation of subjective probability distributions of each parent node, its influence magnitude to child node values should keep consistent.

Axiom 3. The total influence magnitudes of the combination of the probability variations from x attributes (evidence) on the values should be always greater than the one from the set of x-y (y ∈ x) attributes (sub-evidence).

Furthermore, sensitivity analysis can also aid in ranking the influencing factors while testing the robustness of the model. Analysis using a prior and posterior probabilities (Feng et al., 2020; Jianxing et al., 2021), as shown in Eq. (7).

$$R(X_i) = \frac{\varphi(X_i) - \psi(X_i)}{\psi(X_i)} \tag{7}$$

Where $R(X_i)$ is sensitive value, $\varphi(X_i)$ is posterior probability and $\psi(X_i)$ is prior probability.

4. Result and discussion

4.1. Calculation of FFP

According to the FT deduced in section 4.1, this study designed and distributed 40 questionnaires, and 34 valid questionnaires were collected. But experts give specific evaluation using the 7 defined linguistics terms. Triangular or trapezoidal fuzzy numbers are then used to calculation the FFP of the involved nodes. For instance, the calculation process of FFP of node X3 is introduced as follows.

Step 1: Aggregate the opinions of experts.

From the questionnaire survey, for X3 node, the opinions of 34 experts are: very small 5 votes, relatively small 6 votes, small 10 votes, medium 3 votes, relatively large 5 votes, large 4 votes and very large 1 vote. It can be calculated as:

$$\begin{aligned} f = \frac{1}{34}\cdot[&5\cdot(0,0,0.1,0.2) + 6\bullet(0.1,0.2,0.2,0.3) + 10 \\ &\bullet(0.2,0.3,0.4,0.5) + 3\bullet(0.4,0.5,0.5,0.6) + 5 \\ &\bullet(0.5,0.6,0.7,0.8) + 4\bullet(0.7,0.8,0.8,0.9) + 1\bullet(0.8,0.9,1,1)] \\ = &[0.2912,0.3765,0.4382,0.5353] \end{aligned}$$

The fuzzy number results for the aggregation of the remaining 27 parent nodes (i.e. 27 basic events in the FT) are shown in Table 7.

Step 2: Transform fuzzy numbers into FPS.

The membership function can be obtained from Eq. (2). Taking the X3 node as an example again, the aggregated membership function is obtained using Eq. (3) as shown below:

$$FPS = \frac{1}{3}\times\frac{(0.4382+0.5353)^2 - 0.4382\times0.5353 - (0.2912+0.3765)^2 + 0.2912\times0.3765}{(0.5353+0.4382-0.3765-0.2912)} = 0.4109$$

Table 7
Fuzzy number of basic events based on expert experience.

Node	Fuzzy memberships	Node	Fuzzy memberships
X1	(0.3412,0.4235,0.4882,0.5735)	X15	(0.3735,0.4618,0.5206,0.6206)
X2	(0.3235,0.4088,0.4676,0.5647)	X16	(0.4353,0.5265,0.5794,0.6706)
X3	(0.2912,0.3765,0.4382,0.5353)	X17	(0.4206,0.5118,0.5588,0.6500)
X4	(0.3235,0.4088,0.4588,0.5588)	X18	(0.3294,0.4029,0.4647,0.5500)
X5	(0.2853,0.3735,0.4324,0.5235)	X19	(0.2941,0.3618,0.4265,0.5176)
X6	(0.3147,0.4000,0.4588,0.5471)	X20	(0.2765,0.3529,0.4000,0.4971)
X7	(0.2971,0.3794,0.4441,0.5353)	X21	(0.2971,0.3735,0.4324,0.5235)
X8	(0.3676,0.4618,0.5206,0.6147)	X22	(0.4324,0.5265,0.5706,0.6676)
X9	(0.3500,0.4441,0.4853,0.5853)	X23	(0.4206,0.5147,0.5559,0.6529)
X10	(0.3441,0.4353,0.4853,0.5824)	X24	(0.3706,0.4676,0.5059,0.6029)
X11	(0.3853,0.4706,0.5206,0.6147)	X25	(0.4559,0.5529,0.5971,0.6912)
X12	(0.3794,0.4676,0.5324,0.6176)	X26	(0.4176,0.5147,0.5559,0.6500)
X13	(0.2647,0.3500,0.3941,0.4941)	X27	(0.3353,0.4324,0.4706,0.5706)
X14	(0.2676,0.3529,0.4000,0.5000)	\	\

Table 8
FFP of root node.

Node	FPS	FFP	Node	FPS	FFP	Node	FPS	FFP
X1	0.4567	0.0036	X10	0.4621	0.0038	X19	0.4011	0.0023
X2	0.4417	0.0033	X11	0.4983	0.0049	X20	0.3827	0.0020
X3	0.4109	0.0025	X12	0.4991	0.0050	X21	0.4073	0.0025
X4	0.4383	0.0032	X13	0.3766	0.0019	X22	0.5494	0.0070
X5	0.4038	0.0024	X14	0.3809	0.0020	X23	0.5362	0.0064
X6	0.4303	0.0030	X15	0.4947	0.0048	X24	0.4868	0.0045
X7	0.4144	0.0026	X16	0.5530	0.0072	X25	0.5741	0.0083
X8	0.4912	0.0047	X17	0.5353	0.0064	X26	0.5344	0.0063
X9	0.4665	0.0039	X18	0.4373	0.0031	X27	0.4524	0.0035

Step 3: Transform the FPS into FFP.

According to Eq. (4), FPS is 0.4109, so the value of K is 2.5946. Therefore, the FFP of node X3 is 0.0025. Similarly, the FFP of other nodes can be calculated, and the calculation results are shown in Table 8.

In this paper, the FFP is taken as the prior probability of the BN, and the prior probability is the result of the expert's initial judgement. As shown in Table 8, the largest FFP is "Heavy traffic on the channel" (node X25), followed by "Situational judgement ability" (node X16). This is because of the mix of MASS and conventional ships on the channel, when the traffic volume is too heavy, MASS has to constantly change routes. However, the traditional manned ships and MASS need to carry out constant information exchange, and in this process, collision accidents could likely to happen. Besides, it is evident that situational judgement is also an important factor leading to collision accidents.

4.2. CPT calculation using Noisy-OR

As the conditional probability is affected by the number and state of nodes, the number of CPT increases exponentially with the number of nodes. To simplify the calculation process and reduce the difficulty of experts' scoring, this paper uses Noisy-OR to calculate the conditional probability of each node. Taking the A2 node as an example, the calculation process of conditional probability is introduced. Based on the questionnaire results and fuzzy theory outlined in Section 3.2, the possibility of each root node (X6 and X7) causing the failure of the child node (A2) can be converted into a specific probability, known as the connection probability P_i. After performing calculations, the connection probabilities of nodes X6 and X7 are determined to be 0.5754 and 0.5787, respectively. The conditional probability of A2 can be calculated using Eq. (6):

$$\mathrm{P}(A_2 = yes|X_6 = yes, X_7 = yes) = 1 - (1 - 0.5754)(1 - 0.5787) = 0.8211$$

$$\mathrm{P}(A_2 = yes|X_6 = yes, X_7 = no) = 1 - (1 - 0.5754) = 0.5754$$

$$\mathrm{P}(A_2 = yes|X_6 = no, X_7 = yes) = 1 - (1 - 0.5787) = 0.5787$$

$$\mathrm{P}(A_2 = yes|X_6 = no, X_7 = no) = 1 - (1 - 0)(1 - 0) = 0$$

Thus, according to the above calculation process, the complete CPT of the A2 node can be obtained. Similarly, we can obtain the conditional probabilities of other nodes.

4.3. Collision probability prediction and diagnosis

Based on the BN structure established in Section 4.1, simulation inference was carried out in GENIE software. Combining Section 3.4, the prior probability, conditional probability can be imported into GENIE. The results are shown in Fig. 5, collision probability is 0.0192. In BN, the posterior probability represents the updated probability distribution of a node, given observed evidence. The posterior probability is shown in Fig. 6. From Fig. 7, the trend of the prior and the posterior probability is basically the same. But the a prior probability of "Radar sensing system failure" (X10) has an opposite trend to the a posterior probability. Experts believe that the risk of collisions caused by the failure of sensing systems such as radar is low, however MASS are more dependent on sensing systems.

According to fault diagnosis, node X4, influenced by nodes B1 and A1, shows an increased posterior probability, highlighting significant impacts from operational errors and management issues among shore-based personnel and underscoring inadequate training. Similarly, node X8, influenced by nodes B2 and B1, also exhibits an increased probability, reflecting system and equipment failures and management lapses, revealing the grave consequences of neglecting regular maintenance of ship equipment. Additionally, there is a call for stronger training of shore-based personnel at MASS and regular maintenance of systems and equipment. Lastly, node X21, serving as an indicator of external physical attacks, shows a significantly elevated posterior probability when faced with actual threats, emphasizing the need for heightened attention to such risks in security measures.

This paper takes node T as the target node, and changes the occurrence probability of the event to observe the sensitivity analysis results,

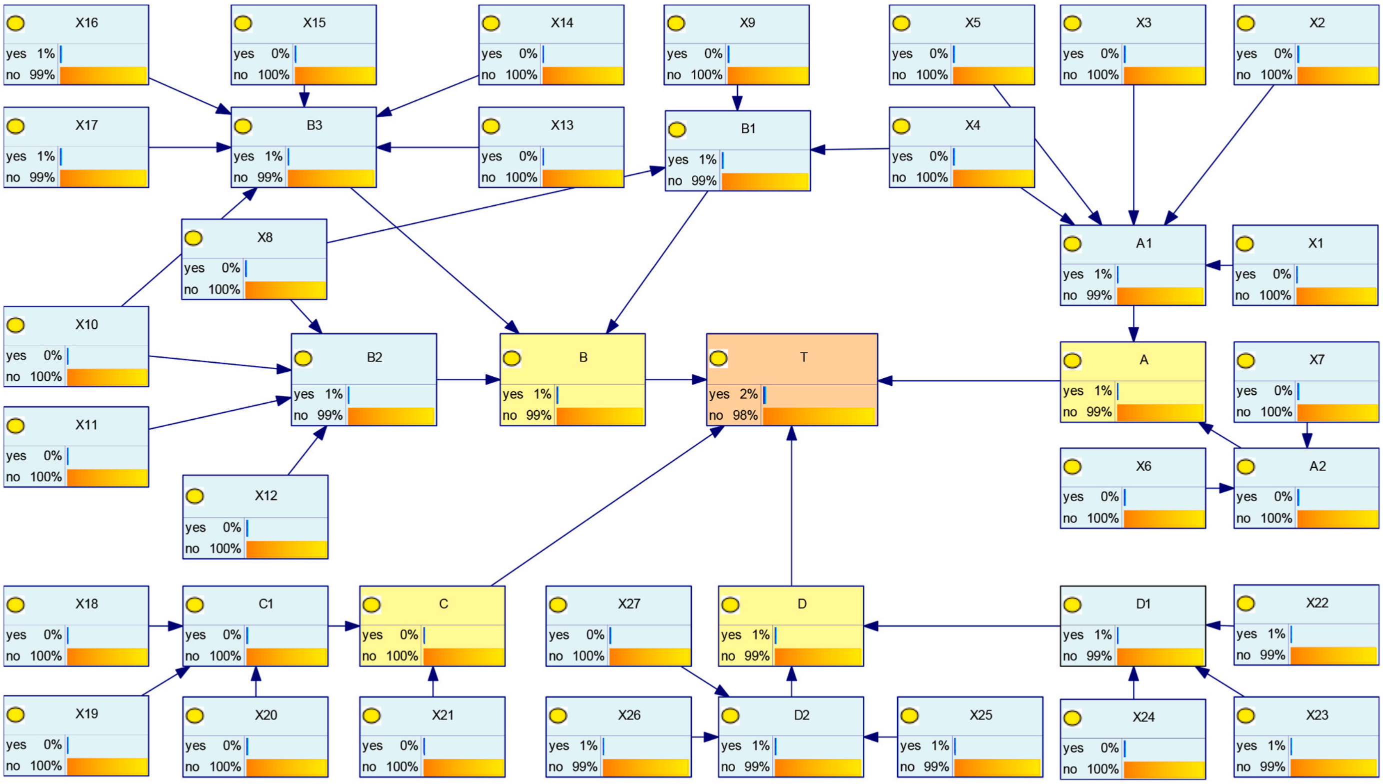

Fig. 5. BN reasoning results.

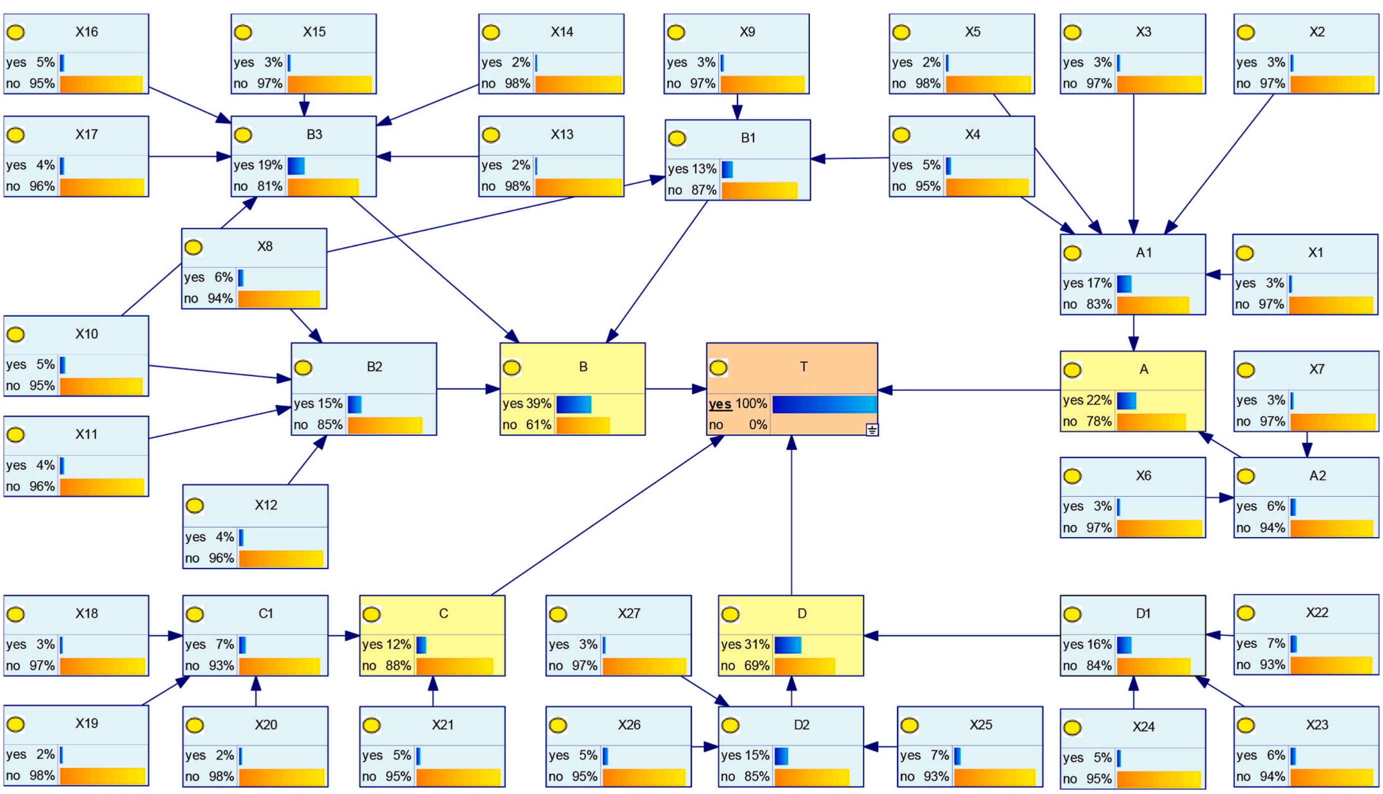

Fig. 6. Posterior probability of BN.

as shown in Fig. 8 and Fig. 9. In Fig. 8, the red color represents sensitivity, with darker shades indicating higher sensitivity. Fig. 9 provides a ranking of the sensitivity for each basic event. The findings show that bad environment (D) is the most critical factor influencing the safety of MASS. For one thing, severe weather conditions, including sudden storms, can disrupt the ship's communication system, leading to

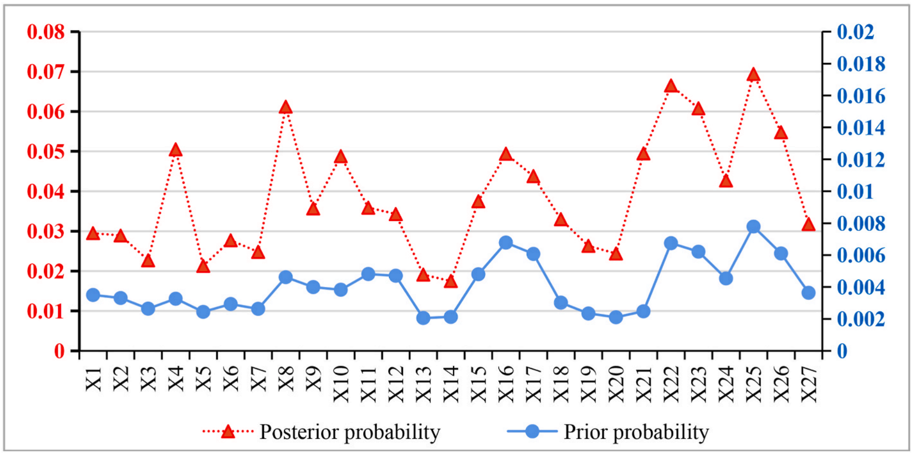

Fig. 7. Prior probability and posterior probability of BN.

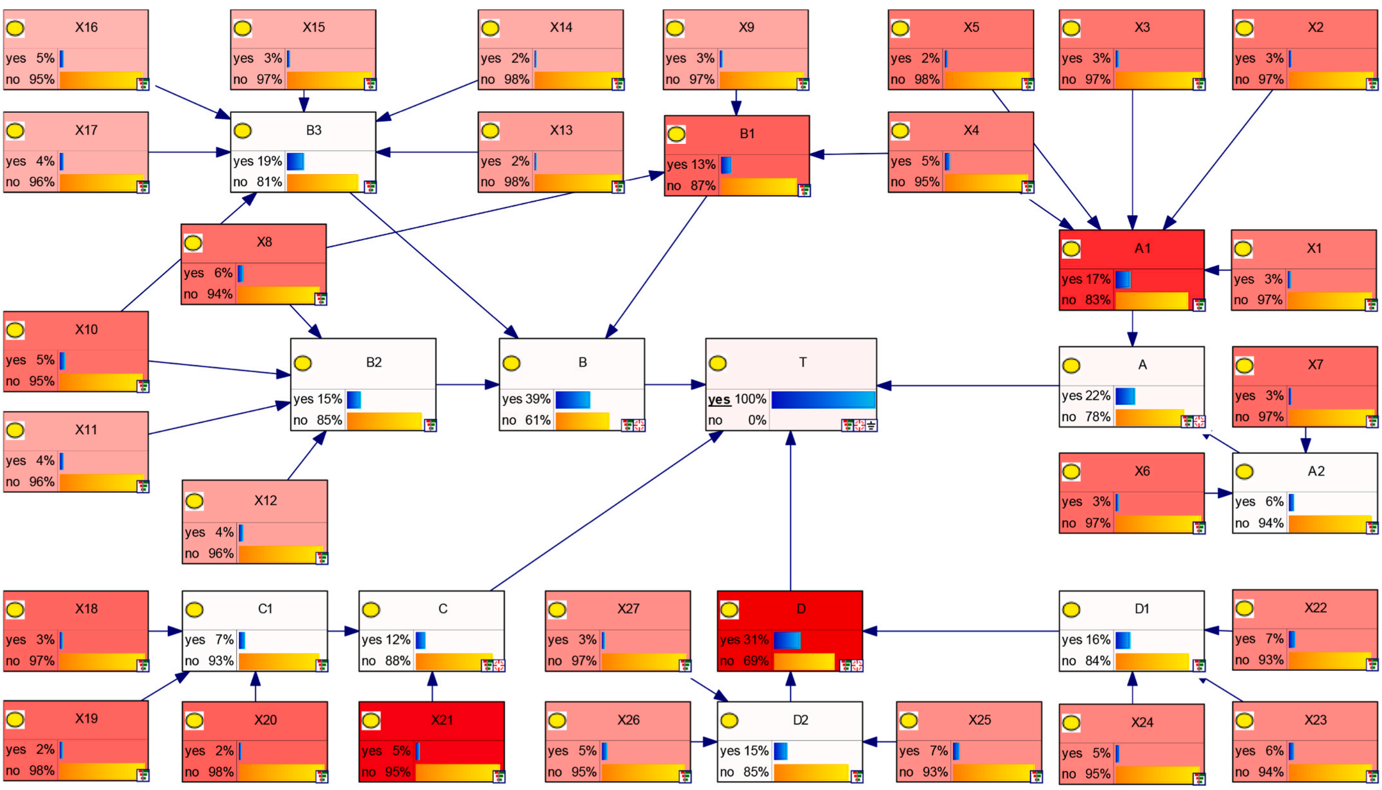

Fig. 8. The results of the sensitivity analysis with T as the target node.

potential delays in shore-based signals and an increased risk of collision with other vessels. Furthermore, in high-traffic scenarios, inadequate interaction between MASS and manned ships can result in collisions (Chang et al., 2021).

Among the secondary indicators, shore-based manipulation errors (A1) and management problems (B1) are the most sensitive factors. These issues arise from the negligent or inadequate knowledge of shore-based operators. In comparison to traditional manned ships, MASS are more dependent on equipment, and their external equipment and devices are vulnerable to the comprehensive impact of external forces such as seawater erosion, wind, and waves. If the ship's equipment is not regularly inspected and maintained, it is likely to lead to equipment failure, leading to collision accidents.

In the third level indicators, there are several issues that need attention. These include external physical attacks (X21), inadequate training of shore-based operators (X4), neglecting regular inspections and maintenance of ship equipment (X8), and failures in radar and other sensing systems (X10). Reducing the crew weakens the prevention and control of external physical attacks, thereby increasing the risk of such incidents. Additionally, the collision accidents are also caused by the lack of control skills and emergency response ability of shore operators, as well as their insufficient ship driving qualifications. The difference between MASS and traditional ships is that equipment replaces human operation, such as sensing equipment replacing human observation. Consequently, MASS are more reliant on equipment. To mitigate risks, shipping companies should adhere to relevant regulations and conduct regular inspections and maintenance of ship equipment, including radar, sensors, and other critical systems.

Moreover, the spread of false information (X20), remote hijacking (X19), and hacking (X18) are also concerns. By attacking the control

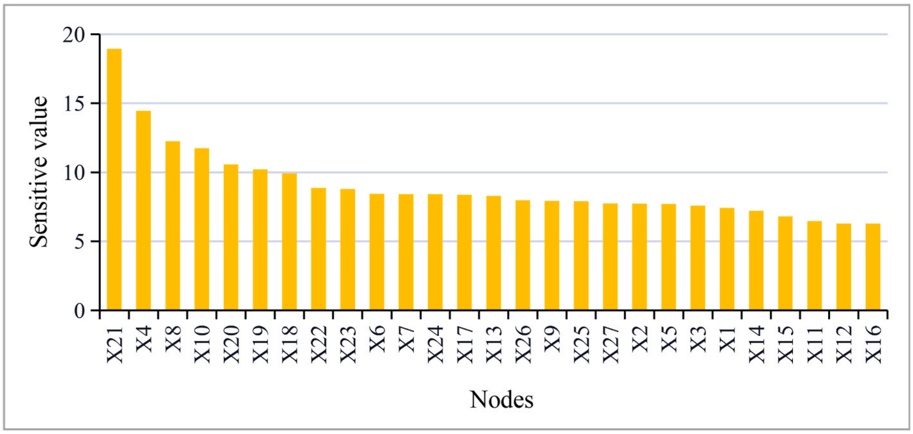

Fig. 9. Sensitivity analysis value.

center's IT system, hackers can paralyze it or spread false information to the shore base. This could lead to misjudgment by operators and potentially result in destruction or hijacking of MASS.

4.4. Model validation

The FTA-FBN model was further validated based on facial validity, by combining expert experience with previous studies to discuss the rationality and reliability of the MASS collision model. The results demonstrate that the developed BN aligns well with the findings of previous studies (Chang et al., 2021; C. Fan et al., 2020; Wahlström et al., 2015), not only do the identified navigational risk factors cover all possible areas, but their relationships also align with the understanding of MASS navigational safety. Furthermore, individual risk factors have been refined and enhanced based on expert guidance. To summarize, the gathered data and methodologies are dependable and effectively incorporate insights from prior studies, aligning well with existing knowledge.

To validate the model's reliability, it can be partially confirmed using the three axioms outlined in Section 3.4, along with sensitivity analysis. Taking node D1 as an example, its parent node includes X22 (Low visibility), X23 (Bad weather), and X24 (Hydrology (large swells)). During the sensitivity analysis, the prior probabilities of these parent nodes were increased by a step of 5%, observing the change in the posterior probability of child node D1. Table 9 shows the change in the probability of node D when the prior probabilities of nodes X22, X23, and X24 are simultaneously increased to 5%, 10%, 15%, and 20%. From Table 9, a slight increase in the prior probability of the parent node results in a corresponding increase in the posterior probability of the child node, thus satisfying axiom 1. When the increased amplitude of parent nodes X22, X23, and X24 are consistent, the posterior probability of child node D1 also exhibits a consistent increase, thereby satisfying axiom 2. If the parent nodes increase to 5% at the same time, the posterior probability of D1 also increases to 7.95%. This indicates that the probability of the parent nodes changing concurrently is greater than when it changes alone and it satisfies axiom 3. Overall, these findings support the reliability and validity of the model.

4.5. Implications

After conducting a literature survey and summarizing accident reports, the risk factors of MASS collision accidents are summarized from four perspectives: human, ship equipment, cyber security, and environment. Compared to prior studies, this study specifically addresses management risks. For instance, there is still room for enhancement in the safety management system of autonomous ships. MASS require more comprehensive safety management systems and regular maintenance of ship equipment. Additionally, it was found that factors such as target recognition ability, comprehension of the navigational environment, and situational judgement ability are among the potential risks that contribute to MASS collisions. The proposed FTA-FBN model predicts the probability of MASS collisions. The prediction results can serve as a valuable reference for researchers to conduct further studies on the risks associated with MASS navigation. This includes the identification, causal analysis, quantitative assessment, and prevention and control of collision risk factors. Additionally, these results can aid ship companies in establishing a comprehensive safety system, which can be beneficial for maritime safety agencies in developing effective navigational safety strategies.

The FTA-FBN model is an effective tool for assessing navigation risk in MASS by establishing logical relationships between risk factors, even in the absence of data. Additionally, it enhances the system's ability to diagnose faults. The model can help ship engineers quickly locate and troubleshoot problems by analyzing various system parts to identify possible failures and their causes and effects. Failure to yield to vessels and promptly avoid collisions are crucial. The government and maritime regulators can gain a deeper understanding of the sources and transmission paths of MASS navigational risks and improve the collision

Table 9
Accident rate of the change in variables.

	+5%				+10%			
X22	+5%	\	\	+5%	+10%	\	\	+10%
X23	\	+5%	\	+5%	\	+10%	\	+10%
X24	\	\	+5%	+5%	\	\	+10%	+10%
D1	3.71%	3.59%	3.73%	8.87%	6.44%	6.21%	6.49%	16.33%
	+15%				+20%			
X22	+15%	\	\	+15%	+20%	\	\	+20%
X23	\	+15%	\	+15%	\	+20%	\	+20%
X24	\	\	+15%	+15%	\	\	+20%	+20%
D1	9.18%	8.83%	9.24%	23.38%	11.91%	11.45%	12%	30.1%

avoidance rules and related policies and measures for MASS navigational safety. In order to improve ship design, product quality, and reliability, ship manufacturers and suppliers can enhance the situational awareness and target recognition capabilities of ships. This will help meet the needs of the shipping market and increase sales and cooperation opportunities.

The MASS collision risk assessment uses expert empirical judgement as a data source, which has implications for the safety of MASS navigation. Shipping companies operate in a high-risk industry, and for this reason, they need to perform risk assessments to ensure safe ship operations. This includes developing strategies to combat piracy and terrorist attacks, providing training to shore-based personnel, and regularly inspecting and maintaining ship equipment. Insurance companies need to conduct a risk assessment of a ship in order to determine the appropriate amount and rate of insurance coverage. A marine risk assessment can provide insurers with valuable insights regarding the ship's risks, enabling them to set insurance rates and amounts accurately. Additionally, a risk assessment can also help the insurers make informed risk control recommendations.

Furthermore, shipbuilders and shipyards can utilize it to identify risks and enhance safety measures. It has been discovered that MASS has a high risk of malfunctioning radar and other sensing systems, spreading false information, remote hijacking, irrational design of ship systems, and human coding errors. 1) Optimal design and manufacture: improve ship design and manufacturing processes to enhance the safety and performance of ships, thereby reducing the risk of hardware failure of MASS. Introduce advanced design principles and measures to optimize the design of the sensing system and reduce the possibility of failure. 2) Improved technology: designers and developers should continuously improve their technical level and introduce advanced technologies and processes to improve the safety and performance of vessel systems and reduce risks such as irrational system design and human coding errors. 3) Strengthened supervision and management: strengthening supervision and management is the key to ensuring ship safety. Strengthen the cybersecurity system, establish a sound management system, and enhance the supervision of ship construction and operation to ensure the safety and quality of ships. Strengthening the monitoring and review of cybersecurity systems and enhancing cooperation with government and regulatory bodies can reduce the risk of cyberattacks.

5. Conclusions

This paper is dedicated to the identification and quantitative assessment of the risk of collisions with MASS, the conclusions are as follows.

(1) As most of the current research on MASS is focused on technology development and system algorithm design, there is a lack of research on risk assessment of MASS, and the methods are mostly from a qualitative perspective, which cannot be quantitatively assessed. This paper aims to fill this gap and promote the research progress of MASS risk assessment.
(2) Previous studies on traditional manned ships have found that human error is the most important risk factor. However, in MASS, shipping companies should pay more attention to preventing external physical attacks, enhancing training for shore-based controllers, and improving emergency response capabilities. Secondly, the ship's equipment should be regularly overhauled and maintained to avoid device failure due to long-term corrosion and wear. Besides, cyber security management should be strengthened to prevent hackers from attacking and hijacking MASS. The results can provide some reference for shipping companies and relevant maritime agencies.
(3) Method, mapping FT into BN, solves the problem that the BN cannot establish a DAG graph due to lack of historical data. Using a Noisy-OR model to calculate the CPT avoids a complex calculation process and reduces the difficulty of expert scoring. Additionally, this paper is the only study to apply the combined FTA-FBN approach to the collision risk assessment of MASS.
(4) In terms of the number of participants, 34 feedbacks are reflected by the MASS development constrains (i.e. limited implementation in practice worldwide). It thoroughly checked the published papers in the field and found that all the MASS risk analysis works had involved a limited number of domain experts (Fan et al., 2024; Lim et al., 2024; Sezer et al., 2024). Future work could expand the amount of data from experts to enhance the generalisability of the findings. With the MASS development and implementation in the real world, experimental data especially those relating to human factors shall be further explored. Furthermore, future research could employ dynamic Bayesian networks to analyse multiple dynamic nodes and investigate the probabilities of state transfer among them. This approach would allow for a dynamic representation of the entire change process of MASS collisions as time progresses.

CRediT authorship contribution statement

Pengchang Li: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yuhong Wang:** Writing – review & editing, Supervision, Resources, Project administration, Investigation, Formal analysis. **Zaili Yang:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Zaili Yang reports financial support was provided by European Research Council. Yuhong Wang reports financial support was provided by Natural Science Foundation of Ningbo.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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