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Research paper

Hybrid analysis of causal factors of marine accidents in ports

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ABSTRACT

Marine accidents in port areas pose significant risks due to increasing vessel traffic and operational complexity. These incidents can cause economic losses, environmental damage, and serious consequences for human life. Therefore, analysing their causes and developing preventive strategies is essential. This study proposes a hybrid approach integrating the Human Factors Analysis and Classification System (HFACS) with Bayesian Networks (BN) to examine the causes of port accidents. Based on the analysis of 150 accident reports, the model classifies human errors and organizational deficiencies and probabilistically models their causal relationships. Findings indicate that decision-based errors, rule violations, authority abuses, and procedural deficiencies are critical factors, while unsafe operational conditions frequently trigger accidents in port operations. Unlike previous studies in aviation and maritime domains, this research extends the HFACS framework into a five-level structure reflecting the high-density, spatially constrained, and multi-stakeholder nature of port environments. The additional layer represents operational constraints in port waters as a distinct causal level. Conditional probability tables are developed using a Fuzzy-SAM-based expert elicitation approach rather than conventional frequency-based estimation or simple expert averaging. This method models expert consensus under uncertainty and strengthens BN parameterization. The proposed framework supports understanding port accident causation and developing effective preventive strategies.

1. Introduction

Maritime transport constitutes the backbone of global trade and plays a vital role in ensuring the smooth functioning of the global economy (UNCTAD, 2019; UNCTAD, 2024). Growing volume demand in good and products globally reinforced the strategic importance of maritime transport, driving new requirements for port modernization, capacity expansion, and operational efficiency (Alavi-Borazjani et al., 2025; Rodrigue, 2010; Song and Panayides, 2012). However, this proportionally increased the vessel traffic and the complexity of port operations has consequently intensified the risk of accidents (Uğurlu, 2025; Yildiz, 2025; Yıldız et al., 2024; Yip, 2008). In port waters, where collisions, groundings, fires, and explosions frequently occur, a practical decision-support system based on advanced but not overly complex analytical methods is needed to identify the underlying causes of accidents and support safer port operations.

Maritime transport broadly refers to vessel movements along international shipping routes as well as port-related navigation associated with cargo and passenger transportation. However, port operations represent geographically bounded, high-traffic, and multi-stakeholder socio-technical environments within the wider maritime transport system (Palbar Misas et al., 2024). The port operational environment includes navigation activities, cargo handling processes, pilotage services, tug assistance operations, and interactions with Vessel Traffic Services (VTS), all of which occur simultaneously within restricted spatial boundaries. In this study, the term 'port area' refers to the navigational and operational zones under the administrative and operational authority of the port, including approach channels, anchorage areas, manoeuvring basins, berths and quay areas, and cargo-handling interfaces (Uğurlu et al., 2020; Yildiz, 2025). Spatial constraints,

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operational intensity, multi-actor coordination, pilotage and tug requirements, and VTS integration structurally distinguish the port environment from open-sea contexts and necessitate context-specific, multi-layer accident modelling approaches (Uğurlu and Yıldız, 2016; Fan and Yang, 2024; Wan et al., 2025).

Ports function as critical logistical hubs connecting land and sea transport, but their dynamic and complex operations expose them to significant safety risks (Lai et al., 2020). Port accidents can have severe economic, environmental, and societal consequences (Chen et al., 2013; Uğurlu et al., 2015). Studies consistently indicate that most of these incidents are caused by human error, inadequate safety measures, and unfavourable environmental conditions (Maternová et al., 2023). Hence, the enhancement of port safety management requires comprehensive strategies that integrate infrastructure improvements, risk management, equipment maintenance, and personnel training (Xu et al., 2023).

Annual reports and statistics by the European Maritime Safety Agency (EMSA) highlight that such accidents often result in irreversible environmental damage and substantial financial losses (EMSA, 2024). Human error remains as one of the leading causes of marine accidents, endangering not only onboard personnel but also disrupting the global supply chain (Dominguez-Péry et al., 2021; Hasanspahić et al., 2021). Understanding these causal mechanisms is crucial for ensuring maritime sustainability (Cao et al., 2025).

Port environments are particularly hazardous by nature due to spatial constraints, dense traffic, complex manoeuvres, and unpredictable weather and sea conditions. These challenges underscore the necessity for systematic accident analysis and the implementation of hybrid analytical frameworks that capture interrelated human, technical, and environmental factors (Qu et al., 2025). Unlike traditional accident analysis models that focus on human or technical failures, hybrid approaches integrate multiple causal dimensions and provide probabilistic insights into accident causation (Ma et al., 2023).

This study applies the Human Factors Analysis and Classification System (HFACS) in combination with Bayesian Networks (BNs) to examine port accidents within port operational areas. The integration of HFACS and BNs offers a hybrid framework for uncovering complex causal pathways and predicting accident likelihood (Yin et al., 2025). Specifically, this study aims to improve understanding of the interaction between human factors and equipment-related failures through a probabilistic hybrid model. Considering the critical role of human, organizational, and environmental factors, it is essential to establish a conceptual foundation that connects these dimensions. The accident data analysed in this study were not randomly selected from the general population of marine casualties; rather, they were systematically identified to include only events occurring within port operational areas. Accident reports obtained from relevant databases were screened based on accident location, operation type, and contextual descriptions. Cases related to approach channels, manoeuvring areas, anchorage zones, berth and quay regions, cargo-handling operations, pilotage services, and tug assistance activities were specifically filtered and included. The dataset was verified in accordance with the IMO Casualty Investigation Code standards to ensure compliance and data integrity. Given that port environments differ structurally from open-sea navigation in terms of high traffic density, multi-stakeholder interaction, VTS integration, pilot-bridge coordination, and cargo operations, the traditional HFACS structure was extended by incorporating an 'Operational Conditions' layer. Accordingly, the study was structured to reflect the contextual specificity of port-related accident mechanisms, and model variables were defined on the basis of this operational reality. The following sections present a systematic review of the literature and analytical methods forming the theoretical basis of this research.

2. Literature review

The prevention and management of port accidents have become a focal area in maritime safety research. Recent studies propose a wide range of innovative approaches from digitalization and simulation techniques to human-factor integration and environmental protection strategies (Bae et al., 2024). Improvements in port infrastructure have been shown to reduce accident risks (Khan et al., 2024). Furthermore, the influence of psychological and behavioural factors such as fatigue and stress on human performance has been repeatedly demonstrated (Hetherington et al., 2006).

2.1. Causes and complexity of port accidents

Port accidents arise from the interaction of human, technical, and environmental elements. Constrained manoeuvring spaces, the need for tugboat assistance, and sudden environmental changes exacerbate the operational complexity of ports (Uğurlu et al., 2020). Additionally, insufficient coordination among multiple stakeholders increases the probability of accidents (Chauvin, 2011). These conditions necessitate the use of analytical tools capable of representing multidimensional causal relationships and interdependencies (Chen and Huang, 2023).

Marine accident analysis methods are generally categorized into sequential, epidemiological, and systemic approaches (Uğurlu et al., 2020). Sequential models such as Fault Tree Analysis (FTA) and Event Tree Analysis (ETA) model accidents as linear chains of events (Jovanović et al., 2026). While useful for scenario-based studies, they oversimplify complex systems. Epidemiological models, including Reason's Swiss Cheese Model, address both active failures (e.g., operator errors) and latent factors (e.g., maintenance deficiencies) (Read et al., 2021). Systemic approaches, such as Leveson's System-Theoretic Accident Model and Processes (STAMP), focus on system interactions rather than isolated failures (Leveson, 2004). Each model contributes valuable insights; however, no single approach adequately captures the multidimensional nature of port accidents. Consequently, the integration of these models into hybrid frameworks is essential for comprehensive safety analysis (Giovannetti et al., 2025).

Port accidents are multidimensional because they emerge from tightly coupled interactions among human performance and cognition under high workload and time pressure; organizational conditions such as planning, staffing, supervision, and procedural design; technical and infrastructural constraints including berth geometry, tug availability, equipment reliability, and interface design; and external operating context such as traffic density, restricted waters, visibility, wind/current, and VTS-mediated coordination. In such settings, accident pathways are rarely linear: feedback loops, cross-level dependencies, and context-sensitive escalation mechanisms are common. Therefore, sequential approaches (e.g., FTA/ETA) are limited by their linear event-chain representation; epidemiological approaches capture latent conditions but remain largely descriptive; and systemic approaches provide conceptual system views but often lack probabilistic inference for quantifying how competing causal pathways change under varying port conditions. This motivates the use of hybrid approaches capable of preserving causal interpretability while enabling probabilistic reasoning under uncertainty.

2.2. Research on hybrid approaches for port accident analysis

Hybrid analytical frameworks particularly those combining HFACS and BN enable both qualitative classification and quantitative inference of causal factors (Yin et al., 2025). This integration allows for systematic evaluation of human, organizational, and environmental influences under uncertainty (He et al., 2024). The HFACS-BN model not only identifies causal patterns but also supports analytical modelling, facilitating proactive safety management (Xia et al., 2018). Although substantial progress has been made in maritime safety research, several methodological gaps persist. Most studies isolate human and technical dimensions rather than examining them as interdependent components within socio-technical systems (Dominguez-Péry et al., 2021; Ma et al., 2023). Additionally, HFACS has often been used qualitatively, limiting its predictive capacity (Ghasemi et al., 2022). Conversely, Bayesian Networks offer strong probabilistic modelling capabilities for risk inference and analytical implications; however, many applications tend to emphasize technical and operational parameters while under-representing human and organizational factors (H. Li et al., 2023). This study bridges these gaps by proposing an enhanced HFACS-BN framework that combines structured human-factor classification with probabilistic reasoning and fuzzy logic to address uncertainty. This integration provides both diagnostic and analytical insight into port accidents. The contributions of the study are methodological, introducing a hybrid HFACS-BN framework that links qualitative human factor analysis with quantitative probabilistic modelling; empirical, analysing 150 validated port accident reports from the Global Integrated Shipping Information System (GISIS), IMO, and the EMSA databases; theoretical, advancing understanding of risk emergence beyond linear causation models; and practical, offering a decision-support tool for port authorities to identify high-risk conditions and improve safety management (Meng and Lu, 2022; Yin et al., 2025).

The review of the existing literature reveals that port accident research has evolved from descriptive assessments toward data-driven, human-centred, and hybrid analytical frameworks. Table 1 summarizes recent studies that collectively highlight a convergence of methodological advancements and empirical findings emphasizing the multifactorial nature of port accidents. Building on this progression, Lyu et al. (2019) demonstrated how the HFACS-BN hybrid approach quantitatively links organizational influence on unsafe acts, achieving over 80% predictive accuracy. Dominguez-Péry et al. (2021) analysed the scope of maritime safety research studies through a systematic literature review, revealed that nearly 78% of previous studies focused narrowly on individual human errors, while only 9% adopted systemic or socio-technical perspectives. Complementing this, Ghasemi et al. (2022) integrated a Fuzzy Bayesian Network (FBN) with HFACS and showed a 31% reduction in predictive uncertainty and an accuracy level of 0.87, emphasizing the role of managerial deficiencies in accident causation. Meng and Lu (2022) further validated the predictive capacity of HFACS–BN models in aviation contexts, finding that management and supervision errors increased unsafe acts by 55%. From a conceptual standpoint, Ma et al. (2023) highlighted persistent terminological inconsistencies in maritime safety studies where the phrase human error dominates over human element, underscoring the need for a holistic socio-technical understanding. Expanding to probabilistic risk modelling, Li et al. (2023) employed data-driven Bayesian networks to analyse global marine accidents and found that environmental and operational parameters accounted for 75% of overall causal weight, leaving human and organizational factors underrepresented. Recent hybrid frameworks have addressed this imbalance. Beyond HFACS-BN, qualitative causal mapping can be conducted using systemic accident analysis approaches such as STAMP/Causal Analysis based on System Theory (CAST), AcciMap, and Functional Resonance Analysis Method (FRAM), while quantitative inference may rely on regression-based models, structural equation modelling, machine-learning classifiers, or purely data-driven Bayesian networks. However, these alternatives typically involve a trade-off between interpretability and inference: systemic mapping methods often remain non-probabilistic, whereas data-driven analytical models may achieve classification performance but provide limited transparency and weaker linkage to human-factor taxonomies. In contrast, an HFACS-based BN combines *(i)* a theoretically grounded, hierarchical classification of human and organizational failures with *(ii)* probabilistic reasoning that explicitly represents uncertainty and interdependence across layers. This enables diagnostic tracing of risk propagation (from organizational influences to unsafe acts), scenario-based updating, and sensitivity-based prioritization of intervention points-capabilities that are particularly valuable in port environments where operational conditions and stakeholder coordination dynamically reshape accident likelihood.

Table 1
Studies related to port accidents.

Author(s)	Scope of the Study	Methodology	Findings
Lyu et al. (2019)	Quantitative evaluation of air-traffic incidents via HFACS-BN.	HFACS-BN probabilistic analysis.	Organizational influences indirectly affected 73% of unsafe acts; model achieved prediction accuracy >80%.
Dominguez-Péry et al. (2021)	Bibliometric review of human-error research in shipping safety.	Scientometric analysis of 530 articles.	78% of studies analysed individual errors; only 9% adopted systemic or socio-technical models.
Ghasemi et al. (2022)	Human and organizational failure analysis in process industries.	Fuzzy BN integrated with HFACS.	Fuzzy Bayesian Network (FBN)-HFACS reduced predictive uncertainty by 31% and achieved accuracy = 0.87 in accident-likelihood estimation.
Li et al. (2022)	Analysis of human and organizational factors in ship collision accidents on the Yangtze River.	Modified HFACS integrated with Bayesian Network using historical collision data and sensitivity analysis.	Human and organizational factors were dominant contributors to accidents. The BN model revealed that organizational influence → supervision → unsafe acts formed the most critical causal chain.
Meng and Lu (2022)	Analysis of human factors in CFIT aviation accidents.	HFACS-BN hybrid model.	Management and supervision deficiencies increased unsafe acts by 55%, improving prediction accuracy by 27% over HFACS.
Ma et al. (2023)	Conceptual use of human-factor terms in maritime safety.	Bibliometric + semantic analysis.	"Human error" appeared in 63% of papers vs "human element" 12%, showing conceptual imbalance.
Li et al. (2023)	Probabilistic modeling of global marine accidents.	Data-driven BN (23 Risk Influential Factors (RIFs) from GISIS).	Environmental/ operational variables dominated risk paths; human/ organizational factors <25% of total influence weight.
Yin et al. (2025)	Data-driven causal-chain analysis of waterborne traffic accidents using HFACS-BN.	Improved HFACS + BN applied to 200 GISIS/EMSA accidents.	Hybrid model achieved R^2 = 0.82; human-organizational interactions explained 68% of accident variability.
Qu et al. (2025)	Risk analysis of open-sea marine accidents using a data-driven approach.	Multi-source Data-Driven Bayesian Network (DDBN) built from AIS,	The model achieved 84% predictive accuracy and quantified how

(continued on next page)

Table 1 (*continued*)

Author(s)	Scope of the Study	Methodology	Findings
		weather, and accident data.	vessel tonnage, route density, and human error jointly drive accident probabilities.

Yin et al. (2025) achieved an R^2 of 0.82 when integrating improved HFACS categories with Bayesian inference across 200 IMO and EMSA cases. R-squared (R^2), or the coefficient of determination, is a statistical measure showing the percentage of variance in a dependent variable that is explained by the independent variables in a regression model, indicating how well the model fits the data (0 to 1 or 0% to 100%). Higher R^2 (closer to 1) means the model explains more of the data's variability, suggesting a better fit, while 0 means it explains none. It quantifies how much prediction error is reduced by using the model compared to just using the average. While Li et al. (2022) identified organizational influence → supervision → unsafe acts as the most critical causal chain in ship collisions on the Yangtze River. Similarly, Qu, Wang, Zhao, Fang, and Xie (2025) applied a multi-source, data-driven Bayesian network and achieved 84% predictive accuracy, illustrating the growing convergence of human-centred and computational safety modelling within port-accident research.

Although several studies have used HFACS and BN together in maritime and aviation safety research (Lyu et al., 2019; Li et al., 2022; Yin et al., 2025), most of these studies retain the traditional four-layer HFACS structure and mainly focus on open-sea navigation contexts, such as collisions and groundings. However, port environments are geographically constrained and operationally complex socio-technical systems. They are characterised by dense vessel traffic, coordination between pilots and tugboats, cargo handling operations, and strong dependence on port authorities and VTS systems. For this reason, the causal mechanisms leading to port accidents differ significantly from those observed in open-sea navigation accidents. To address this gap, the present study provides three main contributions to the literature. First, the classical HFACS hierarchy is structurally extended by introducing an explicit Operational Conditions layer, which reflects the spatial constraints and multi-actor coordination dynamics of port operations. In addition, factors specific to port accidents are incorporated into the framework. Second, the conditional probability tables are constructed using an aggregation approach based on Hesitant Fuzzy Linguistic Term Sets (HFLTS). This allows epistemic uncertainty in expert judgments to be modelled systematically, beyond traditional frequency-based estimations. Third, the Bayesian structure is evaluated through axiom-based logical validation and sensitivity-based structural assessment, demonstrating the explanatory capacity of the proposed framework for analysing the causal pathways of port accidents. Taken together, these contributions provide an analytical framework that is sensitive to real operational processes and capable of explaining the complex causal relationships involved in the formation of port accidents.

3. Methodology

This study adopts a hybrid methodological framework integrating the HFACS with BNs to systematically identify and quantify the causal mechanisms underlying port accidents. The methodology is designed to bridge qualitative and quantitative analytical perspectives by combining structured human factor analysis with probabilistic modelling. This integration provides both diagnostic and analytical capabilities, enabling the identification of root causes and the assessment of potential future risks under uncertainty (Fenton and Neil, 2018). The proposed methodology consists of four sequential and interdependent stages, each representing a critical step of the analytical workflow. These stages are illustrated in Fig. 1 and explained in detail below.

3.1. *Definition of research scope and data collection*

The first stage involves defining the scope and boundaries of the study and establishing the data foundation for subsequent analyses. Marine accident data were collected from GISIS and national investigation reports, in accordance with the standards set by IMO (2020) and EMSA (2024).

A total of 776 port related accidents were reviewed, and after data validation and completeness screening, 150 reports were selected for detailed analysis. These reports contain variables such as accident type, location, environmental conditions, vessel attributes and human involvement factors. This dataset forms the empirical basis for exploring the interrelations among human, organizational, and environmental risk elements (Chauvin et al., 2013). The systematic and standardized data collection ensures representativeness and comparability across cases, which is essential for the reliability of subsequent probabilistic modelling.

Only marine accidents that occurred within port areas and were documented by official accident investigation reports were considered. During the preliminary screening, accidents occurring outside port areas, records containing only statistical summaries, and reports lacking sufficient qualitative information on human, organizational, or operational factors were excluded from the dataset. Following verification, completeness, and comparability checks conducted in accordance with the accident reporting and investigation principles published by the International Maritime Organization (IMO, 2020), 150 verified and methodologically consistent accident investigation reports suitable for detailed content analysis were selected as the final sample. The institutional distribution of these reports is presented in Table 2. Methodological consistency was evaluated based on the structural integrity of the report, the clarity of cause-effect relationships, and the systematic identification of human and organizational factors. To reduce potential reporting differences among countries and institutions, all reports were converted into a standardized coding scheme prior to analysis, and incomplete or ambiguous statements were interpreted in alignment with the analytical framework used in this study. These reports provide structured information on vessel characteristics, environmental and meteorological conditions, human involvement, and operational context, forming the empirical basis of this research (Li et al., 2023). Accordingly, the study seeks to generate causal and analytical insights into port-area accidents rather than statistical generalization. However, numerical imbalances in the distribution of reports across countries and vessel types limit the statistical generalizability of the findings. Therefore, the results are interpreted within the framework of the Bayesian Network model's capacity to explain structural and causal relationships. These quantitative relationships establish the empirical foundation for the subsequent BN modelling of human organizational interdependencies within port safety analysis.

The dataset includes variables such as country of origin, vessel name, date and time of the accident, daylight condition, involvement of other vessels (if applicable), vessel flag, vessel type, tonnage, accident magnitude, coordinates, port country, accident site, reporting date, casualty/injury information, pilot presence during the incident, and final outcomes. Systematic selection and classification process is essential for ensuring the reliability and validity of the analyses. GISIS and national investigation reports offer multidimensional data including vessel characteristics, accident type and location, meteorological conditions, and temporal details. These data not only present technical information but also reveal the environmental and operational context which are critical for identifying root causes. Furthermore, the reports provide additional insights into causal factors and accident severity, allowing for deeper and more detailed analyses.

The classification provides a foundation for examining the complex structure of port related accidents. Maintaining dataset balance was

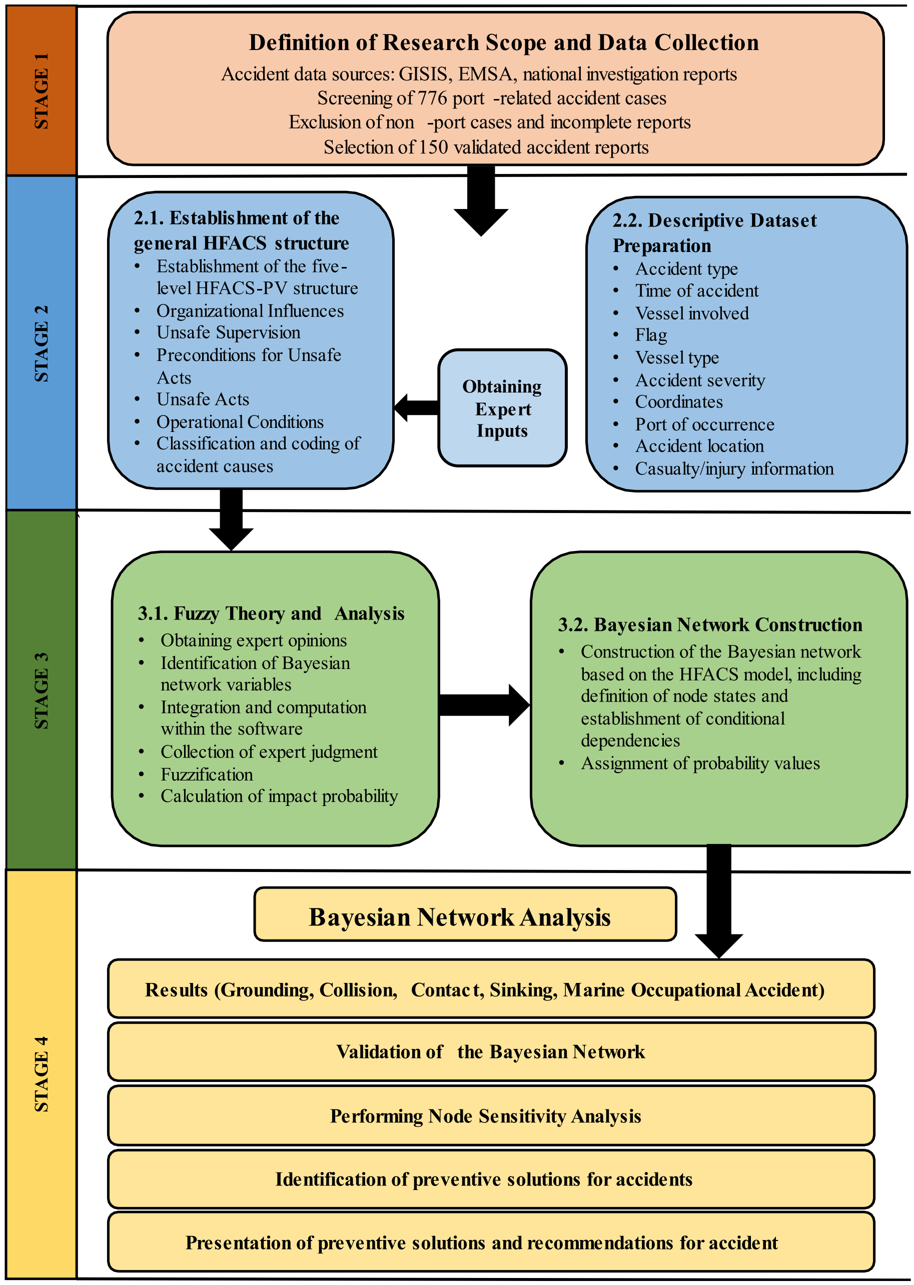

Fig. 1. Workflow diagram.

adopted as a key principle to enhance the accuracy of the analyses. Special care was taken to ensure that each accident factor was proportionally represented. For example, environmental factors such as high waves, fog, and sea ice were grouped under the category of adverse sea conditions to enable more focused and meaningful analysis. Lastly, all accident factors were systematically categorized into four primary domains: human factors, vessel-related issues, environmental conditions, and managerial factors. This structured framework facilitates a holistic understanding of accident formation processes and contributes not only to retrospective assessments but also to the development of forward-looking strategies for accident prevention.

3.2. Human Factors Analysis and Classification System

The HFACS offers a systematic framework for analysing the complex nature of human factors and has found wide application across various disciplines. by Shappell and Wiegmann (2001) to investigate human errors in naval aviation, HFACS has evolved into a versatile analytical model widely applied across safety-critical sectors including maritime transport, healthcare, energy production, construction, and information technology (Patriarca, Bergström, Di Gravio & Woltjer, 2018).

In the healthcare domain, for instance, it has been effectively employed to investigate the causes of surgical errors and patient safety incidents (ElBardissi et al., 2007). In the energy industry, it has been applied to analyse accidents in the oil and gas sector, particularly by examining organizational and human level contributing factors (Nwankwo et al., 2022). Moreover, in the field of information technology, it has been utilized to understand the origins of software development errors and to identify deficiencies in team communication and coordination. By classifying both active and latent failures, it provides a systematic framework that allows researchers and practitioners to identify breakdowns at multiple system levels, ranging from individual decision-making and unsafe acts to supervisory shortcomings and organizational climate, thereby facilitating more comprehensive risk

Table 2
Distribution of accident reports by databases.

Marine Accident Investigation Organization	Country	Number of Reports
Antigua and Barbuda Department of Marine Services and Merchant Shipping	Antigua and Barbuda	1
Bahamas Maritime Authority (BMA)	Bahamas	2
Belgian Marine Accident Investigation Unit (MAIU)	Belgium	1
Bundesstelle für Seeunfalluntersuchung	Germany	5
Bureau d'Enquêtes sur les Événements de Mer (BEAmer)	France	4
Canadian Transportation Safety Board	Canada	1
Commissariat aux Affaires Maritimes (CAM)	Luxembourg	2
Danish Maritime Accident Investigation Board Authority	Denmark	4
Dutch Safety Board (Onderzoeksraad voor Veiligheid)	Netherlands	1
Gabinete de Investigação de Acidentes Marítimos e da Autoridade para a Meteorologia Aeronáutica (GAMA)	Portugal	3
Hellenic Bureau for Marine Casualties Investigation (HBMCI)	Greece	9
Japan Marine Accident Inquiry Agency	Japan	5
Liberian Maritime Authority (LiMA)	Liberia	9
Lithuanian Maritime Safety Administration	Lithuania	2
Marine Accident Investigation Branch	United Kingdom	14
Marine Accident Investigation Committee (MAIC)	Cyprus	7
Marine Accident Investigation Section	Hong Kong/ China	2
Malta National Transportation Safety Board	Malta	46
Panama Maritime Authority	Panama	13
Prefectura Naval Argentina (PNA)	Argentina	1
Safety Board of Canada	Canada	1
Swedish Accident Investigation Authority	Sweden	3
Transport Accident and Incident Investigation Division	Lithuania	2
Transport Safety Investigation Bureau (TSIB)	Singapore	1
Total		**150**

assessments and targeted interventions.

3.2.1. *Structuring the framework*

HFACS provides a framework for examining the underlying mechanisms of human error across complex socio-technical systems. Its integration with hybrid analytical methods such as BNs, fuzzy logic, and machine learning algorithms has significantly expanded the analytical capacity of traditional accident modelling, shifting it from descriptive and retrospective assessment toward analytical and system-oriented evaluation (Rostamabadi et al., 2019). Through this integration, HFACS bridges the gap between qualitative human-factor taxonomy and quantitative probabilistic reasoning, allowing for the modelling of interdependent causal relationships that underlie marine accidents (Wang et al., 2024)

In the maritime context, HFACS serves as a diagnostic framework for identifying both latent conditions (e.g., organizational culture, inadequate supervision, policy gaps) and active failures (e.g., operator errors, procedural violations). By categorizing these factors into four hierarchical levels, Organizational Influences, Unsafe Supervision, Preconditions for Unsafe Acts, and Unsafe Acts the framework enables a holistic understanding of how managerial, environmental, and individual factors interact to produce operational failures (Yıldırım et al., 2019)

The theoretical foundation of HFACS is rooted in Read et al. (2021)'s Swiss Cheese Model, which conceptualizes accidents as the result of multiple, interacting system deficiencies rather than isolated human mistakes. This approach emphasizes that failures propagate through organizational layers, aligning latent vulnerabilities and active errors in ways that ultimately compromise system safety. Accordingly, the framework supports the development of data-driven training programs, safety culture evaluations, and targeted intervention strategies addressing deficiencies at all organizational levels (Li et al., 2023; Liao et al., 2023)

When incorporated into hybrid analytical environments, this approach enhances diagnostic accuracy and analytical capacity by quantifying the interdependencies between human, organizational, and environmental variables. This synthesis transforms accident investigation from a reactive process into a proactive, evidence-based analytical discipline, capable of assisting maritime authorities and policymakers in identifying hidden risk patterns and optimizing safety management systems. Consequently, the structured integration of human-factor frameworks with probabilistic reasoning particularly through Bayesian modelling represents a pivotal advancement in contemporary marine accident prevention and safety governance (Fan et al., 2024; Li et al., 2022).

In the maritime context, the structured analytical framework was operationalized to examine how human, organizational, and environmental interactions contribute to the emergence of accidents in port operations. The model enabled the systematic mapping of causal relationships derived from validated accident reports, integrating quantitative probabilities with qualitative human-factor categorizations. This implementation revealed that accident causation in maritime domains is rarely the product of a single event or error; rather, it emerges through the alignment of procedural deviations, supervisory lapses, and management inefficiencies within complex operational systems (Patriarca et al., 2018; Ma et al., 2023). The probabilistic inference derived from Bayesian analysis provided insights into the relative influence of each causal layer, identifying organizational control and supervisory oversight as dominant determinants of risk (Priatno et al., 2025),

The integration of structured human-factor classification with data-driven inference further allowed the simulation of risk propagation across safety layers, demonstrating how seemingly minor procedural oversights can escalate into major incidents under specific environmental or operational conditions (Peng et al., 2025). Such an approach not only deepens diagnostic understanding but also supports predictive safety management by quantifying how variations in supervision, training, or communication affect overall system resilience (Pillay, 2017). The findings underscore the necessity of transitioning from reactive post-accident assessments to proactive safety governance frameworks ones capable of anticipating risk evolution before operational thresholds are breached.

Ultimately, the model's implementation within the maritime sector illustrates the transformative potential of hybrid analytical methods in advancing safety performance. By linking probabilistic reasoning with organizational learning, it offers an adaptive, evidence-based decision support mechanism for maritime authorities and port operators seeking to minimize systemic vulnerabilities and foster sustainable safety cultures (Li et al., 2023).

3.2.2. *Systematic application of HFACS*

In the empirical analysis of 150 validated marine accident investigation reports, distinct nonconformities were identified and categorized across the HFACS structure. Studies such as Qiao et al. (2020) demonstrate that combining hierarchical human-factor classification with probabilistic Bayesian modelling enables the estimation of how failures propagate across system layers and influence overall accident probability. In this study, the factors identified in accident reports were systematically categorized and coded in accordance with the HFACS framework. This coding process, based on the primary categories and subcategories of HFACS, served as the core analytical structure of the study by enabling qualitative accident-report evidence to be transformed into structured categorical variables for subsequent Bayesian Network modelling. The coding procedure aimed to classify human, organizational, and environmental factors contributing to accident occurrence and to identify their roles within the progression of incident scenarios. The analysis of these factors within a hierarchical structure across different levels allowed the interrelationships among causal factors to be examined systematically. Consequently, the framework provided a methodological basis for linking observed operational errors with broader supervisory, organizational, and operational conditions in the subsequent BN analysis.

The hierarchical structure and inconsistencies were identified through a rigorous, multi-stage process integrating literature synthesis and empirical data analysis. First, a review of previous HFACS-based maritime studies (Chauvin et al., 2013; Hasanspahić et al., 2021) was conducted to identify recurring human and organizational factors. Subsequently, content analysis was performed on 150 verified port accident reports obtained from the GISIS and EMSA databases to identify contributing causal elements. These elements were classified under the HFACS-PV framework and structured within the relevant levels. The resulting classification was then reviewed and finalized through a structured and iterative evaluation process involving five domain experts. Throughout this process, emphasis was placed on ensuring both internal consistency and alignment with the HFACS-PV structure, with necessary revisions implemented based on expert feedback.

3.3. Classification and coding using the framework

To systematically analyse the multidimensional and hierarchical causal structure of marine accidents, this study adopts the HFACS-PV framework, which provides a holistic approach to Human and Organizational Failures (HOFs). HFACS is grounded in Reason's Swiss Cheese Model and explains accident occurrence through the interaction between latent conditions and active failures (Uğurlu et al., 2018; Zhang et al., 2024). Within this structure, organizational influences, unsafe supervision, and preconditions for unsafe acts represent latent factors, while unsafe acts correspond to active failures (Uğurlu et al., 2020). However, empirical findings in marine accident research suggest that environmental factors (operational conditions) cannot be adequately conceptualized as either latent failures or simple preconditions within the traditional four-level structure. Studies based on HFACS-PV indicate that environmental and operational factors do not directly trigger unsafe acts; instead, they operate as complementary conditions that allow existing unsafe acts to evolve into accidents (Yildiz et al., 2021; Uğurlu, 2025; Başkan et al., 2025). For this reason, unlike the classical HFACS structure, operational conditions are treated in HFACS-PV as a distinct fifth level representing the final enabling stage in accident occurrence. This approach preserves the causal chain between latent and active failures while more explicitly incorporating the physical, environmental, and operational realities of maritime activities. As a result, the model provides a more accurate and explanatory representation of accident formation processes in both port and open-sea operations.

In this stage, accident-related factors were systematically coded using an adapted version of the Human Factors Analysis and Classification System (HFACS), a hierarchical framework that categorizes human and organizational failures into five interrelated levels: i. Organizational Influences, ii. Unsafe Supervision, iii. Preconditions for Unsafe Acts, iv. Unsafe Acts, and v. Operational Conditions (Shappell and Wiegmann, 2001; Uğurlu et al., 2018).

The inclusion of Operational Conditions as a fifth tier extends the traditional four-level HFACS structure to account for external and internal environmental constraints that are particularly significant in port and offshore operations. This extension enables a more comprehensive understanding of how technical, environmental, and organizational factors interact in complex maritime systems.

Each accident report was meticulously reviewed to identify both active failures (e.g., decision errors, procedural violations) and latent conditions (e.g., supervisory lapses, training or procedural deficiencies) (Read et al., 2021; Alexander, 2019). The coding process transformed qualitative evidence into structured categorical data, making it suitable for probabilistic modelling within the BN framework.

3.4. Construction and validation of the Bayesian Network

The third stage involved the development of a Bayesian Network (BN) model to represent and quantify the probabilistic relationships among the identified causal factors. Within this framework, each causal factor defined under the HFACS-PV structure was treated as a node in the BN, and causal dependencies among nodes were established through directed links based on literature evidence, accident reports, and expert judgment. The initial coding of accident causes into HFACS levels and subcategories was conducted by the research team. The appropriateness and accuracy of these preliminary classifications were then evaluated by five experts with experience in marine accidents, human factors, and risk analysis, and with established familiarity with HFACS-based studies and structure. The evaluation process was carried out using the Delphi method (Danacı and Yıldırım, 2023; Arican, 2025; Arıcan and Ünal, 2025). In this process, experts were asked to independently review the proposed coding in terms of their suitability for the corresponding HFACS levels and subcategories. The collected feedback was compiled and reviewed through iterative rounds until a stable consensus was achieved. Conditional Probability Tables (CPTs) were constructed using historical accident data, structured expert elicitation obtained through the Delphi process, and relevant literature, in order to address uncertainty. The developed BN model was validated following the axiom-based testing framework proposed by Pristrom et al. (2016), ensuring systematic verification of the model's logical consistency and causal structure.

Axiom 1. A slight increase or decrease in the probabilities of each parent node must strictly result in a corresponding relative increase or decrease in the posterior probabilities of its child node.

Axiom 2. The influence of changes in the subjective probability distributions of parent nodes on their child nodes must be continuous and consistent. In other words, variations in parent nodes (increase or decrease) should be reflected correspondingly in the child nodes (increase-increase / decrease-decrease).

Axiom 3. The combined magnitude of the total effects resulting from variations in the probability distributions of any attribute set "x" (evidence) must always be greater than that of a single attribute "$x - y$" (where $x \in y$). In other words, the aggregate impact of probability variations derived from multiple attributes should always exceed the individual effects of a single parent node.

These tests were complemented by expert validation to confirm that the model structure accurately reflected operational realities in port environments (Nikghadam et al., 2023). The integration of qualitative expert judgment and quantitative testing enhanced both the validity and reliability of the constructed BN model (Fenton and Neil, 2018). In addition to the axiom-based validation procedure, the robustness of the Bayesian Network was also examined through sensitivity analysis. Sensitivity analysis evaluates how changes in the probabilities of parent nodes influence the posterior probabilities of outcome nodes, and it is widely used to assess the stability and explanatory capacity of probabilistic models. The three-stage sensitivity analysis conducted in this study enabled the identification of the most influential causal pathways within the accident network and provided quantitative support for the logical consistency of the model structure. This complementary validation step strengthens the methodological reliability of the proposed HFACS-BN framework.

3.5. Construction of the BN structure and associated models

BNs have been extensively applied across diverse disciplines due to their ability to model causal relationships and manage uncertainty in complex systems. In the maritime field, they serve as an effective analytical tool for accident risk evaluation, operational safety management, and maintenance optimization (Yang and Haugen, 2018). By representing interdependencies among accident contributing factors, BNs provide a structured means for probabilistic reasoning and the identification of risk propagation paths (Wang et al., 2021). In this study, the construction of the BN model followed a systematic, stepwise methodology consisting of six key stages.

3.5.1. Problem definition and scoping

The process began with defining the analytical objectives, which included identifying the types of marine accidents (e.g., collisions, groundings, and contact incidents), delineating the geographical scope (port and coastal environments), and determining the desired resolution level of analysis. This step ensured that the BN model would align with the study's overall aim of quantifying accident likelihoods in port operations (Li et al., 2024)

3.5.2. Variable identification and data collection

Relevant variables were identified through a synthesis of accident reports, statistical databases, and expert consultations. The review of previous studies (Jiang et al., 2024; Liao et al., 2023; Qiao et al., 2020; Li et al., 2022; Qu et al., 2025) informed the selection of human, mechanical, environmental and organizational factors influencing marine accidents. These variables were then encoded as nodes in the BNs model, establishing the foundation for causal dependency mapping.

3.5.3. Structure design

The structural design involved mapping the relationships among variables based on both empirical correlations and expert judgment. Causal links were directed from root causes (e.g., organizational influence, supervision quality) toward outcome variables (e.g., collision or grounding). The resulting structure reflected the hierarchical interaction among human, technical, and environmental factors and provided a logically coherent representation of the accident causation process.

3.5.4. Parameter learning

In cases where quantitative data were insufficient, Fuzzy Set Theory (FST) was applied to incorporate expert opinions into the BN structure (Zadeh, 1965). The integration of fuzzy logic allows the conversion of linguistic evaluations into quantitative expressions, thereby enabling the representation of uncertainty in a mathematically consistent way. In this study, experts expressed their judgments regarding the likelihood and influence of specific factors using linguistic variables such as very low, low, medium, high, and very high. These qualitative expressions were then transformed into triangular fuzzy numbers (TFNs) to estimate conditional probabilities within the BN model. The fuzzy approach thus facilitated the modeling of uncertainty where empirical data were unavailable or incomplete, improving the representativeness of human related factors.

To ensure the consistency and credibility of expert input, the Similarity Aggregation Method (SAM) was employed for combining expert opinions (Liu and Yang, 2022). This method simultaneously considers the relative importance (weight) of each expert and the degree of consensus among all experts. By integrating these two dimensions, SAM enables a more robust and objective aggregation compared to conventional averaging methods. The aggregated fuzzy probabilities obtained through this process were then used to populate the CPTs of the BN, forming the quantitative foundation of the model.

The linguistic scale utilized in this study for converting qualitative expert assessments into numerical values is presented in Table 3, which defines seven linguistic levels and their corresponding triangular fuzzy number ranges. This scale ensured uniformity and comparability among different expert judgments, minimizing subjectivity in the evaluation process.

The use of fuzzy linguistic terms provided flexibility for experts to express uncertainty more intuitively and to handle cognitive hesitation during the elicitation process. Furthermore, to capture ambiguous or overlapping perceptions among experts, the approach adopted the principles of Hesitant Fuzzy Linguistic Term Sets (HFLTSs), which allow multiple linguistic terms to be assigned to a single evaluation when confidence in a single descriptor is limited (Liao et al., 2023). This enriched representation increased the accuracy and realism of expert-based probability estimation. Ultimately, embedding FST within the BNs construction process ensured a seamless integration between qualitative expert knowledge and quantitative probabilistic reasoning.

Table 3
Seven-point fuzzy numbers linguistic assessment scale and corresponding values.

Linguistic Variable	Triangular Fuzzy Numbers			
	A	B		C
Very Low	VL	0	0.04	0.08
Low	L	0.07	0.13	0.19
Medium-Low	ML	0.17	0.27	0.37
Medium	M	0.35	0.5	0.65
Medium-High	MH	0.63	0.73	0.83
High	H	0.81	0.87	0.93
Very High	VH	0.92	0.96	1

The integration of fuzzy theory within the BNs structure ensured that both subjective expert judgment and quantitative reasoning were seamlessly combined, thereby addressing data scarcity while maintaining analytical consistency across the entire modelling process.

3.5.5. Model validation

The constructed BNs was validated through comparisons with historical accident records and expert evaluations. Validation metrics included consistency checks between predicted and observed outcomes. When discrepancies arose, the network structure and CPTs were iteratively refined to improve accuracy and reliability (Rostamabadi et al., 2019).

3.5.6. Implementation and application

The validated BNs was implemented as a decision support tool for port safety management. It enabled scenario-based forecasting, probabilistic reasoning, and the evaluation of intervention strategies. For example, in a grounding scenario, the model could estimate the probability of hull damage or environmental pollution by incorporating variables such as visibility, sea state, and vessel type. Such analytical capabilities allow decision-makers to allocate resources more efficiently and to develop proactive risk mitigation strategies.

Overall, this structured construction process ensures a logical and traceable methodological flow, satisfying both analytical rigor and practical applicability in maritime safety assessment.

3.6. Fuzzy modelling and validation process

3.6.1. Fuzzification

In this study, all adverse conditions associated with the parent nodes of each child node within the network structure were individually evaluated by subject-matter experts. The expert judgments were systematically recorded using a seven-point Likert scale within the HFACS framework. The primary rationale for selecting this scale lies in its strong psychometric properties and its alignment with the methodological requirements of decision-making processes.

The seven-point Likert scale allows for more nuanced distinctions among expert opinions. This sensitivity is particularly important when ranking risks and priorities related to human factors. Compared to five-point scales, the seven-level structure enables more detailed evaluations, thereby enhancing the analytical power of the dataset (Preston and Colman, 2000). In addition, the presence of a midpoint (i.e., the neutral option at level 4) allows experts to express indecision or neutrality, which enhances the scale's balance and contributes to the reliability and representativeness of the collected data (Likert, 1932). Therefore, the seven-point Likert scale was adopted in this study to ensure that expert evaluations were collected systematically, validly, and reliably.

After collecting expert evaluations for all negative conditions of the child nodes in the network, the expert opinions, originally given using a seven-point verbal scale, were converted into triangular fuzzy numbers. A triangular fuzzy number expresses the probability of a condition as a set of three values representing the lower bound, most likely value, and upper bound of the estimated probability. For example, (a_1, a_2, a_3). For all x ∈ A, A is a fuzzy number, $\mu\tilde{A}(x)$ is a membership function, and the R value interval is defined as R→[0,1]. The standard triangular number $\tilde{A}$ = (a_1, a_2, a_3) has a membership function defined as:

$$\left\{\begin{array}{c} 0 \quad x \le a_1 \\ (x-a_1)/(a_2-a_1) \quad a_1 \le x \le a_2 \\ (a_3-x)/(a_3-a_2) \quad a_2 \le x \le a_3 \\ 0 \quad x \ge a_3 \end{array}\right\} \tag{1}$$

Let us assume that each expert Ek (where k = 1, 2, …, M) expresses their opinion using predefined linguistic terms based on prior experience. These linguistic terms can be converted into corresponding fuzzy numbers. The collected fuzzy numbers are then processed using an algorithm explained below in six steps:

Step 1. Calculate the degree of agreement (similarity degree) for each pair of experts' opinions. and represent the standard triangular fuzzy numbers corresponding to the opinions of experts E_u and E_v, respectively. The similarity function S is defined using Equation (2).

$$S(\tilde{R}_u, \tilde{R}_v) = 1 - \frac{1}{J=3}\sum_{i=1}^{3}|a_i - b| \quad i = 1,2,3 \tag{2}$$

where J is the number of fuzzy set members, meaning that it should be 3 for a triangular fuzzy number.

Step 2. The similarity value $S(\tilde{R}_u, \tilde{R}_v) \in [0,1]$. A higher value indicates greater agreement between two experts. For triangular fuzzy numbers, the Average Agreement (AA) level of an expert's opinion can be calculated as:

$$AA(E_u) = \frac{1}{M-1}\sum_{\substack{u \ne v \\ v=1}}^{J} S(\tilde{R}_u, \tilde{R}_v) \tag{3}$$

Step 3. The Relative Agreement (RA) level for each expert is given by:

$$E_u(u = 1, 2, \ldots, M) \text{ as } RA(E_u) = \frac{AA(E_u)}{\sum_{u=1}^{M} AA(E_u)} \tag{4}$$

Step 4. The Consensus Coefficient (CC) for each expert is calculated using Equation (5):

$$CC(E_u) = \beta \times W(E_u) + (1-\beta) \times RA(E_u) \tag{5}$$

The coefficient β (0 ≤ β ≤ 1) is a relaxation factor indicating the relative importance of expert weight W(Eu) compared to RA(Eu). In this study, β = 0.5 was adopted (Hsu and Chen, 1996; Sarıalioğlu et al., 2020; Yıldız et al., 2024).

Step 5. The aggregated result of the experts' judgment can be found as follows by adopting Equation (6).

$$\tilde{R}_{AG} = CC(E_1) \times \tilde{R}_1 + CC(E_2) \times \tilde{R}_2 \ldots + CC(E_M) \times \tilde{R}_M \tag{6}$$

3.6.2. Defuzzification

In fuzzy set theory, the defuzzification process converts the aggregated fuzzy number into a measurable and interpretable result. It aims to transform the combined fuzzy number into a Fuzzy Probability Score (FPS), derived from the membership function resulting from the aggregation of expert opinions.

Several defuzzification techniques are available, such as the centroid, centre of area, mean of maximum, and weighted average methods (Merigó and Gil-Lafuente, 2010). In this study, the Centre of Area (CoA) method was selected for its clarity and simplicity (Sugeno, 1999).

The mathematical expression for a triangular fuzzy number $\tilde{R}$ = (a_1, a_2, a_3) is given in Equation (7):

$$FPS = \frac{\int_{a_1}^{a_2}\frac{x-a_1}{a_2-a_1}x\,dx + \int_{a_2}^{a_3}\frac{a_3-x}{a_3-a_2}x\,dx}{\int_{a_1}^{a_2}\frac{x-a_1}{a_2-a_1}dx + \int_{a_2}^{a_3}\frac{a_3-x}{a_3-a_2}dx} = \frac{1}{3}(a_1 + a_2 + a_3) \tag{7}$$

3.6.3. Dynamic accident network modelling and validation

After completing the fuzzification and defuzzification stages, the conditional probabilities derived for port ship accidents were imported into GeNIe 4.1 Academic Bayes software (Bayes Fusion, 2024) to execute the hybrid HFACS-BN model. The developed model dynamically estimated the probability of marine accidents under various operational, environmental, and organizational conditions. This dynamic capability allowed the network to continuously update causal dependencies, reflecting changes in supervision quality, environmental stressors, and human performance across time. In this study, however, the model's dynamic analytical capacity was used not to generate forward-looking out-of-sample forecasts, but to analyse how accident probabilities and causal pathways behave under different scenarios.

A hybrid multi-layer validation strategy was implemented to ensure the model's robustness, accuracy, and operational relevance. Beyond structural and logical coherence checks, dynamic validation procedures were designed to evaluate the model's analytical stability and adaptability under uncertain maritime environments. The network's inferential behaviour was tested using cross-validation and posterior probability checks to ensure consistent alignment between simulated and observed accident patterns (Fenton and Neil, 2018; Vehtari et al., 2017). Furthermore, global sensitivity and elasticity analyses quantified the degree of influence of parent nodes such as organizational management quality, supervision effectiveness, and environmental hazards on terminal accident probabilities. These analyses confirmed that small perturbations in high-level nodes resulted in proportional and coherent changes in downstream probabilities, validating the network's internal consistency and causal integrity (Yang and Haugen, 2018; Pristrom et al., 2016).

The model's reliability was further reinforced through expert elicitation and domain validation, involving iterative consultations with maritime safety specialists. Experts verified that the directional dependencies, probability strengths, and conditional relationships represented in the network accurately reflected real-world accident dynamics in port environments (Hossain et al., 2019). The resulting structure, presented in Fig. 2, demonstrates the hierarchical and interdependent nature of causal mechanisms across the HFACS framework ranging from organizational influences (pink) and unsafe supervision (blue) to preconditions for unsafe acts (green), unsafe acts (orange), and operational or environmental conditions (yellow). The red outcome nodes represent the final accident states, including collisions, groundings, sinkings, and marine occupational accidents.

This validated structure not only supports diagnostic interpretation but also provides an analytical decision-support tool for maritime authorities and port operators. Through scenario simulation and probabilistic inference, the model enables evidence-based prioritization of preventive strategies, transforming traditional accident investigation into a proactive and data-driven safety management system (Fenton and Neil, 2018).

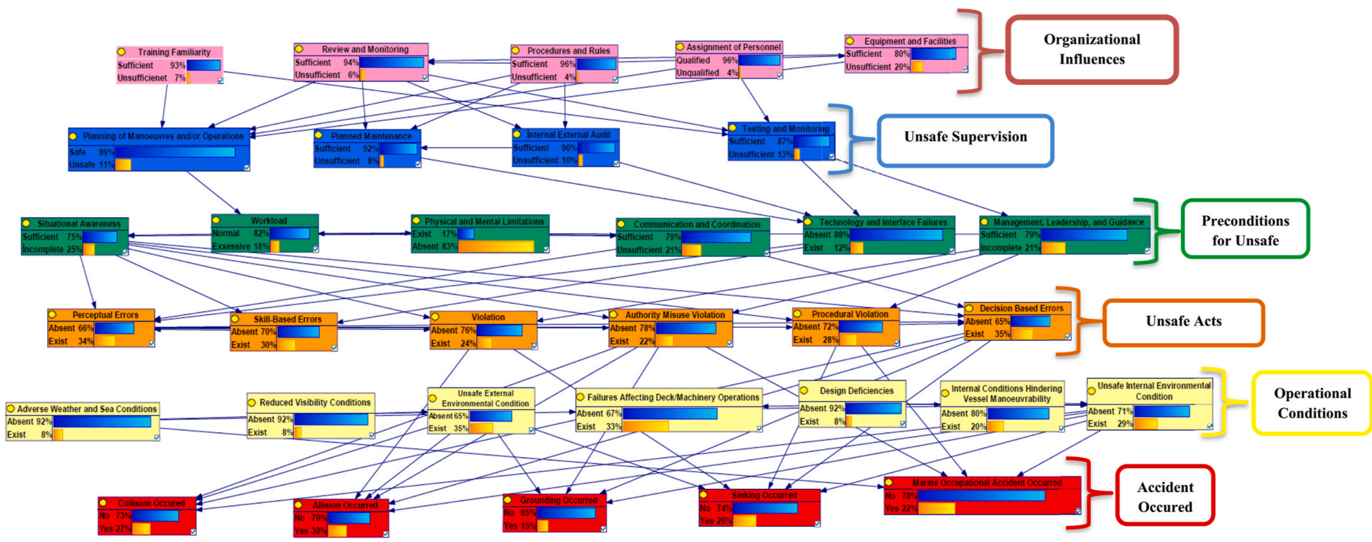

Fig. 2. Bayesian Network model structure integrating causal relationships for marine accidents.

3.7. Sensitivity analysis and scenario simulation

Sensitivity analysis is employed in areas such as accident analysis, risk assessment, nonconformity analysis, and failure modelling to examine the impact of variations in data or nonconformities within a system on the final outcomes. This type of analysis reveals the effects of preventive measures taken against adverse events on the system or assists in estimating the level of damage the system may encounter under a worst-case scenario (Uğurlu and Yıldız, 2016).

In BNs studies, sensitivity analysis is applied to determine the influence of changes in root, parent, or child nodes on the outcome nodes. In other words, it provides the capability to estimate how variations in the system's inputs are reflected in its outputs (Kjaerulff and Madsen, 2008).

The sensitivity analysis conducted in this study aims to reveal the effects of changes in system inputs on the corresponding outputs. The outputs of the network include the probabilities of collision, contact, grounding, sinking, and marine occupational accidents. The inputs, on the other hand, are defined as the latent and active failures contributing to the occurrence of these accidents. BNs based sensitivity analysis enables the identification and assessment of risk factors by thoroughly examining the effects of these contributing elements within the accident occurrence processes.

The final stage applies sensitivity analysis and scenario simulation to examine how changes in causal variables influence the likelihood of specific accident outcomes. Sensitivity analysis was conducted to determine the relative impact of parent nodes (e.g., human errors, environmental hazards, supervisory deficiencies) on outcome nodes such as collisions, groundings, and sinking (Liao et al., 2023). Scenario simulations were performed using the GeNIe 4.1 Academic Bayes software (Bayes Fusion, 2024), which allows dynamic manipulation of variable probabilities to test alternative operational conditions. These analyses enable the identification of critical risk pathways and key intervention points for effective port safety management (Badjadi et al., 2023). The results obtained in this stage provide additional analytical insights into the behaviour of the model and offer practical implications for decision-makers. In this way, the approach supports a transition from reactive accident analysis to proactive and data-driven risk mitigation strategies (Fan et al., 2020).

4. Test case

To demonstrate the fuzzy logic and BN processes in a case study, the child node "Workload" was selected. This node has two parent nodes: "Planning of Manoeuvres and/or Operations" and "Management, Leadership, and Guidance" (Fig. 3). These parent nodes generate four conditional probability scenarios for the "Workload" node. For each of these scenarios, the current state of workload was evaluated by experts using linguistic terms. These linguistic assessments were quantified using the seven-point fuzzy linguistic scale presented in Table 4. As in the overall network (Fig. 2), Fig. 3 includes directed arrows only between nodes that have direct conditional dependencies, which is consistent with the BN approach.

To improve the consistency and reliability of the evaluation, the approach used to combine expert opinions has been clearly defined. In the literature, expert assessments are often weighted differently based on criteria such as experience, profession, and professional position, in order to reflect differences in knowledge and authority among experts. However, in this study, all five experts have similar academic backgrounds, comparable professional experience, and similar levels of responsibility in the fields of maritime safety, human factors, accident investigation, and port operations. Therefore, a hierarchical weighting of experts was not considered methodologically necessary.

For this reason, an equal-weighting approach was adopted in combining expert contributions, and each expert's opinion was included in the analysis with a weight coefficient of 0.20. This approach prevented the creation of artificial prioritization among experts and ensured that all expert opinions were represented in a balanced manner

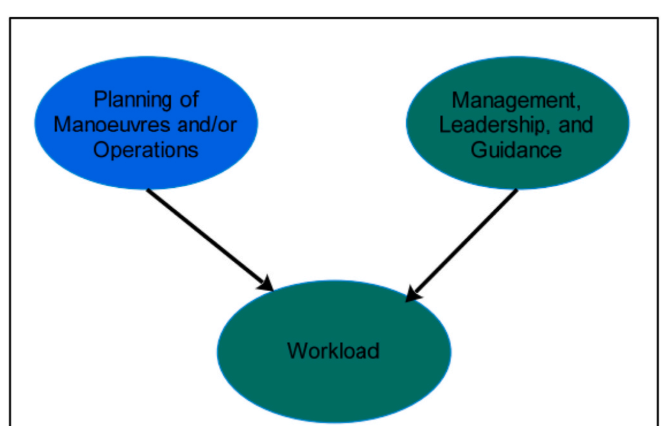

Fig. 3. "Workload" node and its parent nodes.

Table 4
Linguistic expressions and their corresponding triangular fuzzy number values.

Linguistic Expression	Abbreviation	Triangular Fuzzy Number		
		a_1	a_2	a_3
Very Low	VL	0.00	0.04	0.08
Low	L	0.07	0.13	0.19
Reasonably Low	ML	0.17	0.27	0.37
Medium	M	0.35	0.50	0.65
Reasonably High	MH	0.63	0.73	0.83
High	H	0.81	0.87	0.93
Very High	VH	0.92	0.96	1.00

during the evaluation process. In this way, expert assessments were treated as equal in terms of knowledge and experience, and the objectivity of the model inputs was preserved.

The linguistic terms provided by the experts were converted into numerical values and processed using fuzzy logic procedures to construct the CPTs. For example, conditional probability scenario 68 (CPT 68) for the unsafe state of the Workload node is presented in Tables 5 and 6, together with the expert evaluations and the related calculations.

The fuzzy probability values calculated for CPT 68 are then defuzzified using Equation (7).

$$\textit{Defuzzification of CPT } 68 = \left(\frac{1}{3}\right) \times \left(\mathrm{a}_{1_{\tilde{\mathrm{R}}_{\mathrm{AG}}}} + \mathrm{a}_{2_{\tilde{\mathrm{R}}_{\mathrm{AG}}}} + \mathrm{a}_{3_{\tilde{\mathrm{R}}_{\mathrm{AG}}}}\right)$$

$$\left(\frac{1}{3}\right) \times (0.24 + 0.36 + 0.48) = 0.36$$

The posterior probability value for the unsafe state of the Workload node was calculated as 0.36. Accordingly, the posterior probability for the safe state of the Workload node was calculated as 0.64 (1-0.36). In the BN developed in this study, conditional probability scenarios are generated by 33 nodes. The calculations presented for CPT 68 were repeated for all other scenarios in the model, and CPTs containing both fuzzy and defuzzified probability values were constructed for each case. The conditional probability table for the "Workload" node, which includes four related scenarios, is presented in Table 7.

To illustrate the general formulation of CPTs within the BN, the CPT of the child node "Workload" is presented as an example. This node has two parent nodes: "Planning of Manoeuvres and/or Operations" and "Management, Leadership, and Guidance." The possible states of these parent nodes are safe or unsafe, and sufficient or incomplete. The state of the "Workload" node depends on the combinations of these two parent node states (Fig. 4).

The posterior probability of the "Planning of Manoeuvres and/or Operations" node being in the "safe" state is 89%, while the posterior probability of the "Management, Leadership, and Guidance" node being in the "sufficient" state is 79% (Fig. 4).

According to the BN developed in this study, there are four parent node combinations representing the normal or excessive states of the "Workload" node. The conditional probability values for these four combinations are presented in Table 8. Based on these conditions, the probability of the "Workload" node being in the normal state is calculated as 82%, while the probability of being in the excessive state is calculated as 12%.

Table 5
Experts' linguistic evaluations for CPT 68.

Expert No	Linguistic Evaluation	Triangular Fuzzy Numbers
Expert 1	M	(0.35, 0.50, 0.65)
Expert 2	ML	(0.17, 0.27, 0.37)
Expert 3	ML	(0.17, 0.27, 0.37)
Expert 4	ML	(0.17, 0.27, 0.37)
Expert 5	M	(0.35, 0.50, 0.65)

The probability of the "Workload" node being in the safe state is calculated as follows:

Let; W = Workload (normal), PMO = Planning of Manoeuvres and/or Operations (safe), MLG= Management, Leadership, and Guidance (sufficient), and let $\widetilde{\mathrm{W}}$,$\widetilde{\mathrm{PMO}}$, $\widetilde{\mathrm{MLG}}$ denote their respective complementary states (i.e., excessive, unsafe, and incomplete).

$\mathrm{P\backslash(W)} = [(\mathrm{P(W \mid PMO, MLG)} \times \mathrm{P(PMO)} \times \mathrm{P(MLG)}] + [(\mathrm{P(T \mid PMO}, \widetilde{\mathrm{MLG}}) \times \mathrm{P(PMO)} \times \mathrm{P}(\widetilde{\mathrm{MLG}})] + [(\mathrm{P(T} \mid \widetilde{\mathrm{PMO}}, \mathrm{MLG}) \times \mathrm{P}(\widetilde{\mathrm{PMO}}) \times \mathrm{P(MLG)}] + [(\mathrm{P(T} \mid \widetilde{\mathrm{PMO}}, \widetilde{\mathrm{MLG}}) \times \mathrm{P}(\widetilde{\mathrm{PMO}}) \times \mathrm{P}(\widetilde{\mathrm{MLG}})]$

$\mathrm{P(W)} = (0{,}94 \times 0{,}89 \times 0{,}79) + (0{,}55 \times 0{,}89 \times 0.21) + (0.64 \times 0.11 \times 0.79) + (0.23 \times 0.11 \times 0.21) = 0.82\ (82\%)$

$\mathrm{P}(\widetilde{\mathrm{W}},) = 1 - 0.82 = 0.18\ (18\%)$

5. Results

This section presents the research findings in three analytical domains: HFACS analyses (Section 5.1), BNs analyses (Section 5.2), and sensitivity analyses (Section 5.3). Section 5.1 presents the identified unconformities, the structure, and corresponding explanations. Section 5.2 provides the BNs construction process, model results, and validation procedures, while Section 5.3 includes the results of sensitivity analyses evaluating the impact of causal factors on port accident likelihood.

The HFACS-BN framework described in Section 3 was applied to classify nonconformities and model their probabilistic relationships.

5.1. The results of HFACS analyses

Through systematic analysis of the validated dataset, 298 distinct nonconformities were identified and categorized according to the HFACS framework. These nonconformities reflect a broad spectrum of organizational, supervisory, operational, and human deficiencies observed in port accident investigations.

At the operational and individual levels, unsafe acts such as excessive vessel speed, improper mooring operations, and non-compliance with navigational protocols were among the most frequent causes of incidents. These behaviours often co-occurred with preconditions such as fatigue, reduced situational awareness, and cognitive overload induced by heavy traffic density or poor visibility conditions.

As illustrated in Fig. 5, the hierarchical distribution of HFACS levels and subcategories provides a multidimensional understanding of the systemic nature of port nonconformities. Organizational influences account for the largest proportion of contributing factors, underscoring the decisive impact of management systems, procedural frameworks, and safety culture on operational outcomes. Within this category, procedural deficiencies, insufficient training, and gaps in infrastructure and safety management systems (SMS) emerged as the most prevalent latent conditions. The next major contributors, unsafe acts and unsafe supervision, represent the active and intermediate stages through which organizational shortcomings manifest in daily operations. Frequent subcategories such as violations, decision errors, and inadequate supervision reflect behavioural and managerial weaknesses that directly influence frontline safety performance. Preconditions for unsafe acts, including fatigue, communication failures, and workload imbalance, highlight the interplay between human limitations and operational demands, consistent with the socio-technical perspective of accident causation. Finally, operational conditions such as equipment failures, design flaws, and environmental constraints demonstrate the influence of technical and contextual variables on human reliability.

At the organizational level, the most frequent issues included inadequate risk assessment procedures, missing or outdated safety management documentation, insufficient maintenance oversight, and lack of standardized operational guidelines. Additionally, inadequate resource allocation such as limited personnel and protective equipment emerged as a recurrent factor, reflecting systemic weaknesses in port safety management.

Table 6
Aggregation calculations for CPT 68.

Step 1. Similarity degree for CPT 68 is calculated using Equation 2.

$S(E_1, E_2)$	0.77			$S(\tilde{R}_u, \tilde{R}_v) = 1 - (1/3)\sum_{i=1}^{3} \lvert a_{1i} - a_{2i} \rvert$ $S(E_1, E_2) = 1 - \left(\frac{1}{3}\right)(0.18 + 0.23 + 0.28) = 0.77$
$S(E_1, E_3)$	0.77	$S(E_2, E_5)$	0.77	
$S(E_1, E_4)$	0.77	$S(E_3, E_4)$	1.00	
$S(E_1, E_5)$	1.00	$S(E_3, E_5)$	0.77	
$S(E_2, E_3)$	1.00	$S(E_4, E_5)$	0.77	
$S(E_2, E_4)$	1.00			

Step 2. Average agreement for CPT 68 is calculated using Equation (3).

$AA(E_1)$	0.8275	$AA(E_u) = \frac{1}{M-1}\sum_{u \neq v}^{M} S(\tilde{R}_u, \tilde{R}_v)$ $AA(E_1) = \left(\frac{1}{5-1}\right)(0.77 + 0.77 + 0.77 + 1.00) = 0.8275$
$AA(E_2)$	0.8850	
$AA(E_3)$	0.8850	
$AA(E_4)$	0.8850	
$AA(E_5)$	0.8275	

Step 3. Relative agreement for CPT 68 is calculated using Equation (4).

$RA(E_1)$	0.1920	$RA(E_u) = \frac{AA(E_u)}{\sum_{u=1}^{M} AA(E_u)}$ $RA(E_1) = \frac{0.8275}{0.8275 + 0.8850 + 0.8850 + 0.8850 + 0.8275} = 0.1920$
$RA(E_2)$	0.2053	
$RA(E_3)$	0.2053	
$RA(E_4)$	0.2053	
$RA(E_5)$	0.1920	

Step 4. Consensus coefficient for CPT 68 calculated using Equation (5).

$CC(E_1)$	0.1960	$CC(E_u) = \beta \cdot w(E_u) + (1 - \beta) \cdot RA(E_u)$ $CC(E_1) = 0.5 \times 0.2 + 0.5 \times 0.1920 = 0.1960$
$CC(E_2)$	0.2027	
$CC(E_3)$	0.2027	
$CC(E_4)$	0.2027	
$CC(E_5)$	0.1960	

Step 5. Aggregation of expert opinions for CPT 68 using Equation (6).

$$\tilde{R}_{AG} = CC(E_1) \times \tilde{R}_1 + CC(E_2) \times \tilde{R}_2 + \ldots + CC(E_M) \times \tilde{R}_M$$

$$0.2 \times (0.35, 0.50, 0.65) + 0.2 \times (0.17, 0.27, 0.37) + 0.2 \times (0.17, 0.27, 0.37) + 0.2 \times (0.17, 0.27, 0.37) + 0.20 \times (0.35, 0.50, 0.65) = (0.24, 0.36, 0.48)$$

Table 7
Fuzzy and defuzzified probabilities for the conditional probability scenarios of the "Workload" node.

Conditional Probability No	Fuzzy Probability			Defuzzified Probability
66	0.01	0.06	0.10	0.06
67	0.31	0.45	0.59	0.45
68	0.24	0.36	0.48	0.36
69	0.69	0.77	0.86	0.77

At the unsafe supervision level, the dataset revealed frequent instances of insufficient monitoring of maintenance operations, delayed inspections, unplanned or poorly coordinated activities, and ineffective oversight of crew performance, particularly during complex manoeuvres and cargo handling. The preconditions for unsafe acts category were primarily characterized by fatigue, stress, poor situational awareness, communication breakdowns, and environmental challenges such as heavy seas, strong winds, and poor visibility that impaired operational judgment.

Within the unsafe acts level, the most common errors included improper mooring and anchoring operations, failure to comply with navigational regulations, unsafe working postures during loading activities, and procedural deviations. At the operational conditions level, deficiencies were related to equipment failures, design flaws in machinery and ship access structures, and the absence of systematic inspection or testing programs. Taken together, these findings illustrate that port accidents result from a complex interaction of human, technical, and managerial factors, rather than isolated operational mistakes.

As shown in Fig. 6, these 298 nonconformities are distributed across five hierarchical HFACS levels: Organizational Level (32.2%), Unsafe

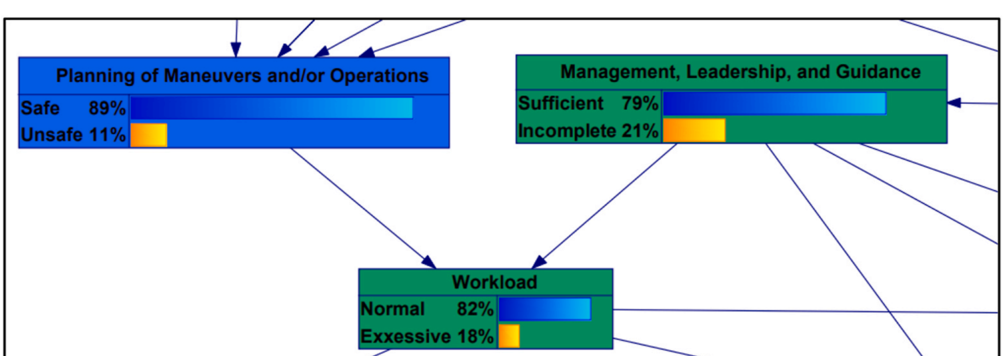

Fig. 4. Posterior probabilities of the "Workload" node and its parent nodes.

Table 8
Conditional probability scenarios and values for the safe state of the "Workload" node.

Conditional Probability No	Planning of Manoeuvres and/or Operations	Management, Leadership, and Guidance	Defuzzified Probability
66	Safe	Sufficient	0.94
67	Safe	Incomplete	0.55
68	Unsafe	Sufficient	0.64
69	Unsafe	Incomplete	0.23

Acts (23.2%), Unsafe Supervision (17.4%), Preconditions for Unsafe Acts (15.1%), and Operational Level (12.1%). This distribution reveals that organizational and human-action-related factors collectively account for more than half of all recorded nonconformities, emphasizing both the systemic and behavioural dimensions of safety failures in port operations. The predominance of organizational and unsafe act categories underscores the dual necessity of reinforcing institutional safety culture and enhancing individual operational discipline.

At Level 1 (Organizational Influences), Procedural Deficiencies (PD) and Improper Planning (IP) were dominant, particularly in cargo operation and manoeuvring incidents. These findings reveal systemic weaknesses in organizational processes, safety documentation, and resource allocation, indicating the need for structured management oversight. At Level 2 (Unsafe Supervision), inadequate supervision (IS) and insufficient maintenance (IM) were frequently identified in cargo handling and manoeuvring accidents. These results emphasize the critical role of supervisory monitoring and maintenance scheduling in preventing cascading human and technical errors. At Level 3 (Preconditions for Unsafe Acts), communication deficiencies (CD) and situational awareness gaps were prominent, particularly during cargo operations and high traffic manoeuvring. Such deficiencies reflect limited coordination among teams and insufficient information flow between bridge and port control. At Level 4 (Unsafe Acts), perceptual errors (PE) and decision errors (DE) emerged as major contributors, especially in fall-from-height and navigation-related cases. These errors underline the cognitive and psychological dimensions of operator performance under complex and dynamic conditions. At Level 5 (Operational Conditions), personnel assignment (PA) deficiencies were most evident in collision and manoeuvring cases, highlighting the necessity of matching crew competence and experience with task complexity.

Fig. 7 presents the frequency distribution of the most dominant HFACS subcategories associated with different types of port-related marine accidents. The findings clearly demonstrate that unsafe acts remain the most influential causal mechanisms across all accident categories, reinforcing the primacy of human behavioural and procedural deviations in accident causation.

Among the identified subcategories, procedural violations were the most frequent, particularly in grounding incidents (n = 47). This outcome underscores the critical impact of inadequate compliance with operational procedures, navigation rules, and cargo-handling protocols on maritime safety. Rule violations and decision-based errors also exhibited high frequencies in collision and sinking events (n = 32 and n = 23, respectively), indicating that cognitive overload, misjudgement under time pressure, and inconsistent adherence to safety protocols significantly affect operational reliability.

By contrast, authority abuse violations while comparatively less frequent (n = 11) were most often linked to contact accidents, reflecting localized deficiencies in leadership control, task delegation, and interdepartmental communication. These results collectively emphasize that

Fig. 5. Port ship accidents HFACS nonconformity distribution.

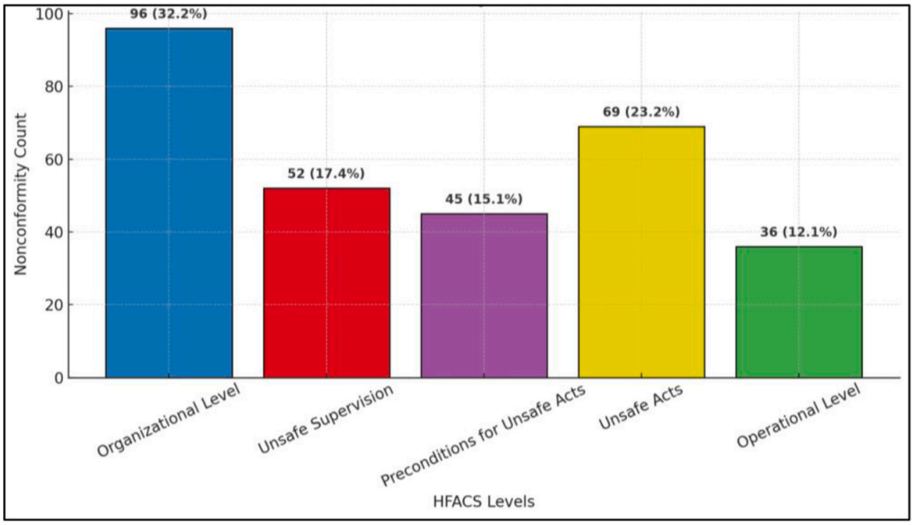

Fig. 6. Distribution of nonconformity counts across HFACS levels.

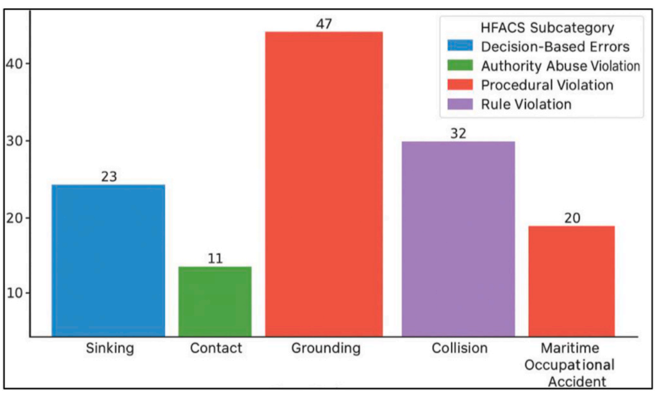

Fig. 7. Dominant subcategories affecting accident types.

noncompliance behaviours and procedural lapses remain the dominant precursors of marine accidents in port operations. Therefore, establishing behaviour-based safety systems and adaptive supervision mechanisms is essential to mitigate latent organizational vulnerabilities and promote a culture of procedural discipline and accountability.

Table 9 presents the detailed classification of accident causes identified throughout the investigation. Each causal factor was mapped to its corresponding HFACS level based on documentary evidence, field interviews, and safety reports gathered during Stage 1. This structured approach ensured a consistent and traceable linkage between individual operational errors and the broader systemic weaknesses from which they emerged.

The analysis revealed that Organizational Influences represented the largest proportion of contributing factors approximately 32% of all identified elements, including lack of protective equipment, inadequate Safety Management System (SMS) implementation, and deficiencies in procedures and risk management. These results indicate that many marine and offshore accidents stem not from isolated human errors but from latent organizational weaknesses embedded within management systems.

Similarly, Unsafe Supervision factors such as insufficient oversight during tank-cleaning operations, improper crane handling, and inadequate planning illustrate the cascading effects of managerial shortcomings on operational safety.

Within the Preconditions for Unsafe Acts layer, common issues included lack of situational awareness, communication failures between ship and port, and operator fatigue. These findings underscore the human-performance dimension of maritime safety, emphasizing the need for continuous training, effective coordination, and workload management to sustain operational resilience.

The Unsafe Acts category encompassed recurrent decision and perceptual errors, such as non-compliance with established procedures and failure to recognize imminent risks that represent the final manifestations of upstream systemic deficiencies. The Unsafe Acts category was structured with a clear distinction to avoid conceptual ambiguity. In line with the HFACS framework, unsafe acts were classified into two main groups: errors and violations. Errors refer to unintentional and unintended actions. Decision-based errors include, for example, incorrect assessment of environmental conditions during berthing; skill-based errors refer to performance deficiencies during cargo handling operations; and perceptual errors involve misjudging distance under restricted visibility or high traffic density. In contrast, violations refer to the deliberate disregard of rules or procedures. Rule violations include knowingly exceeding port speed limits; procedural violations involve skipping mandatory operational control steps; and authority abuse refers to ordering the continuation of operations despite safety warnings. The key distinction between these categories is intentionality: errors represent unintended performance deviations, whereas violations reflect conscious noncompliant behaviour. This distinction prevents overlap between categories and ensures analytical consistency within the model.

Finally, the Operational Conditions layer captured environmental and technical constraints, including adverse weather, mechanical failures, and design deficiencies, that interact with human and organizational factors to influence accident probability. HFACS-based categorization provides a structured, hierarchical understanding of the interplay between human, technical, and organizational contributors. It establishes a quantitative foundation for subsequent Bayesian Network modelling by linking observable operational errors with their latent systemic origins. The findings strongly suggest that enhancing organizational safety culture, supervision quality, and procedural compliance offers the most effective pathway toward reducing accident occurrence in maritime and offshore operations.

5.2. *The results of BN analyses*

The BN model was constructed based on the hybrid HFACS-BN framework to quantify the probabilistic relationships among the contributing factors influencing marine accidents (Fenton and Neil, 2018; Kabir and Papadopoulos, 2019; Jiang et al., 2024). The model

Table 9
HFACS-detailed accident causes.

HFACS-Main Category	Accident Cause	Subcategory	Accident Type	*f*
Operational Conditions	Strong wind	External Conditions	Cargo Manoeuvre	7
	Strong current		Manoeuvre	3
	Fog		Navigation	1
	Engine failure	Internal Conditions	Manoeuvre	2
	Rudder failure		Manoeuvre	3
	Crane design deficiency	Design Deficiencies	Cargo Operation	1
	Ladder design deficiency		Fall from Height	2
Unsafe Supervision	Lack of test and control (Radar/ Electric Chart and Information System (ECDIS))	Inadequate Supervision	Navigation	3
	Lifeboat test deficiency		Life Saving	6
	Insufficient maintenance - Crane	Inadequate Maintenance	Cargo Operation	6
	Lack of supervision during tank cleaning operations	Inadequate Supervision	Enclosed Space	2
	Improper crane operation	Inappropriate Planning	Cargo	5
	Insufficient pilot/ tug support	Planning Deficiency	Manoeuvre	2
Preconditions for Unsafe Acts	Lack of situational awareness	Cognitive Factors	All Operations	15
	Physical fatigue	Physical Condition	Manoeuvre	3
	Alcohol consumption	Physiological Condition	All Operations	4
	Lack of communication between Captain and Pilot	Communication Breakdown	Manoeuvre	8
	Lack of communication between Ship and Port	Coordination Breakdown	Loading	6
	Lack of pre-voyage briefing	Team Management	Preparation	1
Unsafe Acts	Incorrect manoeuvre - Pilot	Decision Error	Manoeuvre	3
	Failure to perceive accident risk	Perceptual Error	Cargo & Manoeuvre	14
	Crane operation error	Skill-Based Error	Cargo Operation	2
	Non-compliance with procedures	Violation	General	5
	Not using safety harness	Routine Violation	Fall from Height	1
	Deactivating tank alarm	Exceptional Violation	Tank Operation	1
	Procedure exists but not followed (e.g., risk analysis skipped)	Procedural Violation	Loading, Manoeuvre	4
Organizational Influences	Lack of training (Lifeboat)	Training Deficiency	Life Saving	4
	Lack of familiarity (Crew change)	Familiarity Deficiency	General	6
	Assignment of unqualified personnel	Human Resources	All Operations	14
	Insufficient staffing	Human Resources	Operational	4
	Lack of protective equipment	Equipment Resources	Cargo & Rescue	29
	Poorly maintained handrail	Equipment Resources	Fall from Height	11
	Missing alarm/ detector system	Equipment Resources	Fire	4
	No risk analysis performed	Procedures & Risk Management	Loading	8
	Lack of working-at-height procedure	Procedures & Risk Management	Fall from Height	6
	Ignoring the SMS (Safety Management System)	Procedures & Risk Management	Management	3
	General procedural deficiencies	Procedures & Risk Management	General	15
	Lack of general procedures (organization-wide)	Deficiency in Procedures & Risk Management	All Operations	15
	No risk assessment conducted	Risk Management Deficiency	Loading, Manoeuvre	8
	Disregarding SMS	Safety Culture & Management	Management	3
	Inadequate SMS	Safety Culture & Management	Corporate	1
	Absence of accident risk assessment	Risk Management Deficiency	Manoeuvre, Loading	4
	Lack of mooring procedure	Procedural Deficiency	Cargo & Manoeuvre	2
	Lack of cargo handling procedure	Operational Process Deficiency	Cargo Operation	1
	Lack of safe work procedure (onboard)	Procedural Deficiency	All Operations	3

development process encompassed node identification, parameter estimation, and structural validation, ensuring that causal dependencies among human, organizational, and environmental dimensions were represented logically and consistently.

5.2.1. Validation outcomes

5.2.1.1. Axiom 1 validation: Independent Influence of parent nodes. Axiom 1 assesses whether variations in parent node probabilities lead to corresponding changes in their respective child node probabilities. This test ensures that the BN structure responds dynamically and logically to input variations, thereby confirming the model's local causal sensitivity (Pristrom et al., 2016). As shown in Table 10, the results across accident categories including External Environmental Unsafe Condition (EEUC), Decision-Based Mistakes (DBM), Abuse of Authority Effect (AOAE), and Internal Environmental Unsafe Condition (IEUC)exhibited consistent behavioural trends. Under normal, worst, and best conditions, changes in parent nodes produced proportional responses in accident occurrence probabilities. Specifically, higher unsafe condition levels corresponded with increased accident likelihoods across all nodes, validating that each factor independently affects the system as theoretically required by Axiom 1.

5.2.1.2. Axiom 2 validation: Continuous and monotonic influence. Axiom 2 examines whether the relationships between parent and child nodes are continuous and monotonic, ensuring that incremental increases in parent node probabilities consistently yield corresponding increases in the dependent nodes. The validation results for the grounding scenario are illustrated in Fig. 8, demonstrating a stable and monotonic increase across three parent factors: Unsafe External Environmental Condition,

Table 10
Testing of Axiom 1 across all accident categories.

Status	EEUC	Collison	Status	DBM	Contact
Normal	Observed	Yes	Normal	Observed	Yes
	35	27		35	27
Worst	100	31	Worst	100	33
Best	0	25	Best	0	24
	AOAE	**Contact**	**Status**	**IEUC**	**Contact**
Status	Observed	Yes	Normal	Observed	Yes
Normal	22	27		29	27
Worst	100	36	Worst	100	29
Best	0	25	Best	0	26

EEUC: External Environmental Unsafe Condition, **DBM**: Decision Based Mistakes, **AOAE**: Abuse of Authority Effect, **IEUC**: Internal Environmental Unsafe Condition.

Decision Errors, and Authority Abuse Violation. The slopes of these curves confirm that the model adheres to the principle of causal continuity no inverse or discontinuous trends were observed. This outcome reinforces that the BN structure accurately represents dynamic relationships among operational and human-performance variables under varying risk conditions.

5.2.1.3. Axiom 3 validation: Cumulative effect of Combined nodes. Axiom 3 verifies whether the joint influence of multiple parent nodes on an outcome exceeds the effect of any individual node. This ensures that the BN model effectively captures cumulative and interactive effects among factors a crucial feature in complex socio-technical systems such as port operations. As presented in Table 11, the sinking accident scenario revealed that when all contributing factors (IEUC, EEUC, PV, RV, and DBE) were set to 100%, the probability of sinking increased to 0.92, confirming Axiom 3 compliance. This result validates the model's capacity to reproduce realistic escalation patterns under compounding risk conditions, where multiple human and environmental weaknesses align simultaneously.

5.3. The results of sensitivity analyses

Sensitivity analyses were performed to evaluate the relative influence of human, organizational, and environmental factors on the probability of port-related marine accidents. By systematically varying parent node probabilities within the validated HFACS-BN framework, the analysis quantified how incremental changes in causal variables affected the likelihood of specific accident outcomes. This procedure enabled the identification of high-impact nonconformities and the prioritization of intervention areas critical to accident prevention.

The results of the detailed sensitivity analysis for port-related maritime occupational accidents are presented in Fig. 9. Among the evaluated HFACS categories, Procedural Violations exhibited the highest

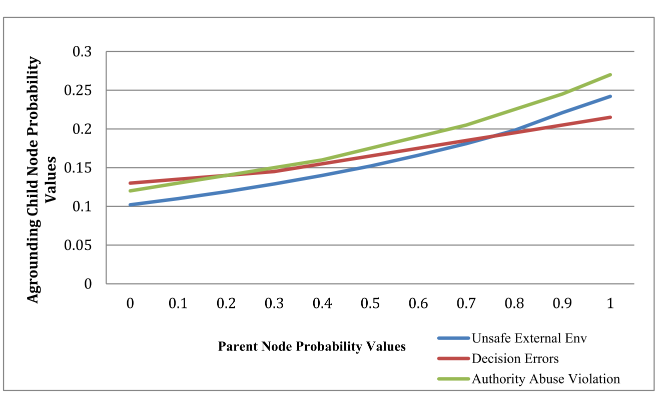

Fig. 8. Probability distribution of grounding node based on parent nodes.

Table 11
Axiom 3 assessment for the sinking accident.

IEUC	EEUC	VOP	RV	DBE	SINKING
0.29	0.35	0.28	0.24	0.35	0.26
1	0.36	0.28	0.24	0.35	0.3
0.29	1	0.28	0.24	0.35	0.33
0.29	0.35	1	0.44	0.66	0.37
0.29	0.35	0.51	1	0.62	0.41
0.29	0.35	0.52	0.43	1	0.41
1	1	1	1	1	0.92

UIEC: Unsafe Internal Environmental Condition, **UEEC**: Unsafe External Environmental Condition, **PV**: Procedure Violation, **RV**: Regulation Violation and, **DBE:** Decision-Based Errors.

sensitivity index, confirming their dominant contribution to occupational incidents. Workload and Situational Awareness followed closely, revealing that cognitive strain and perceptual degradation substantially increase the risk of human-performance breakdowns during high-intensity port operations.

Variables related to Technology and Interface Failures, Deck/Machinery Operational Faults, and Unsafe Internal Environmental Conditions exhibited moderate influence, suggesting that while technical reliability is important, it is human-centred procedural adherence and workload management that most strongly dictate accident likelihood. Lower-level factors, such as Equipment Sufficiency, Personnel Assignment, and Review and Monitoring, had comparatively minor impacts but still serve as critical precursors in cascading error propagation.

The heatmap presented in Fig. 10 visualizes the interaction between accident types and HFACS noncompliance factors, offering an intuitive overview of how different unsafe behaviours and system deficiencies cluster across incident categories. The coloured intensity represents the relative frequency of each factor, with darker shades corresponding to higher occurrence levels. Notably, Decision Errors (DE) and Procedural Deficiencies (PD) exhibit the highest concentration during cargo operations and manoeuvring, indicating that cognitive misjudgements and procedural lapses are the primary precursors to operational accidents. Similarly, Rule Violations (RV) and Lack of Training and Familiarity (LTF) appear most prominently in collision and capsize/take-on scenarios, emphasizing the direct relationship between regulatory nonconformance and navigational instability.

Moreover, Inadequate Supervision (IS) and Poor Planning (IP) emerge with moderate to high frequencies across multiple categories, particularly grounding and cargo-handling operations, highlighting the cross-layered impact of organizational oversight on frontline safety behaviour. The relative clustering of these high-frequency cells suggests that unsafe acts rarely occur in isolation but rather co-occur with supervisory and organizational weaknesses.

Overall, the heatmap underlines a multi-level causal interdependence: operational deviations such as decision and procedural violations often coincide with latent management and environmental deficiencies, confirming the systemic nature of human error in port accident causation. This visual evidence strengthens the argument that preventive strategies should target not only individual errors but also the supervisory and organizational contexts that enable them.

The results of the sensitivity analysis provide additional support for the internal consistency and explanatory capacity of the proposed Bayesian structure. The analysis shows that changes in higher-level causal factors, particularly organisational influences and supervisory conditions, lead to measurable changes in accident probabilities at lower levels. These findings confirm that the model structure appropriately represents the causal relationships between latent conditions and the operational errors and violations of operators (including ship personnel and port personnel). The analysis also demonstrates, both qualitatively and quantitatively, how latent conditions lead to operational errors and violations, and how these factors interact with environmental conditions to produce port accidents.

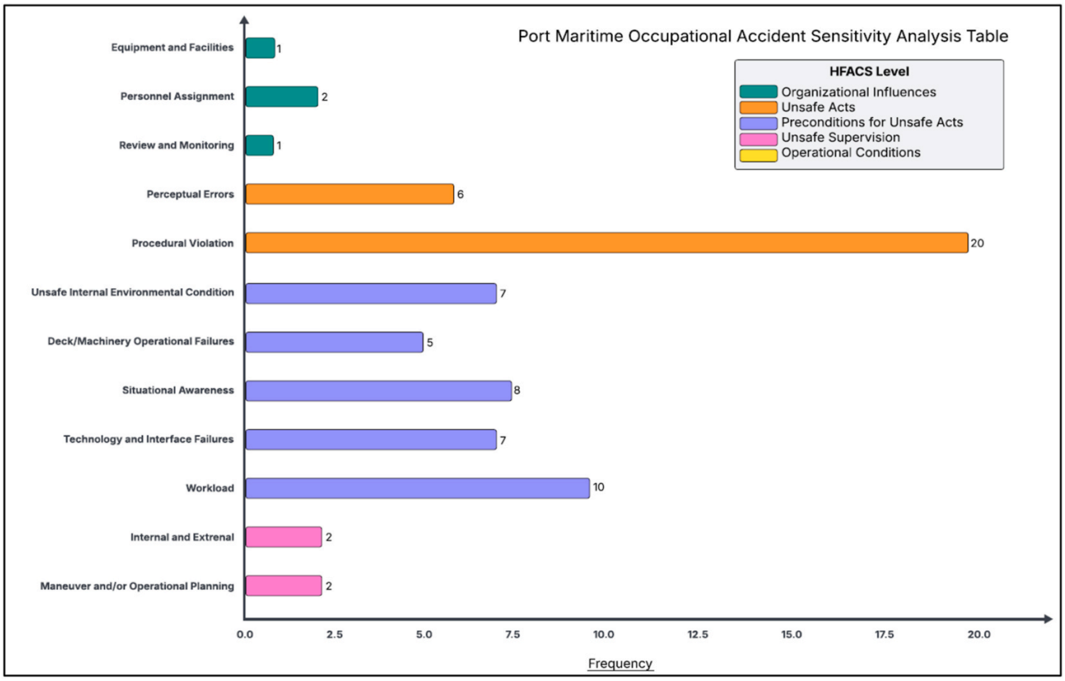

Fig. 9. Sensitivity analysis table for port marine occupational accidents.

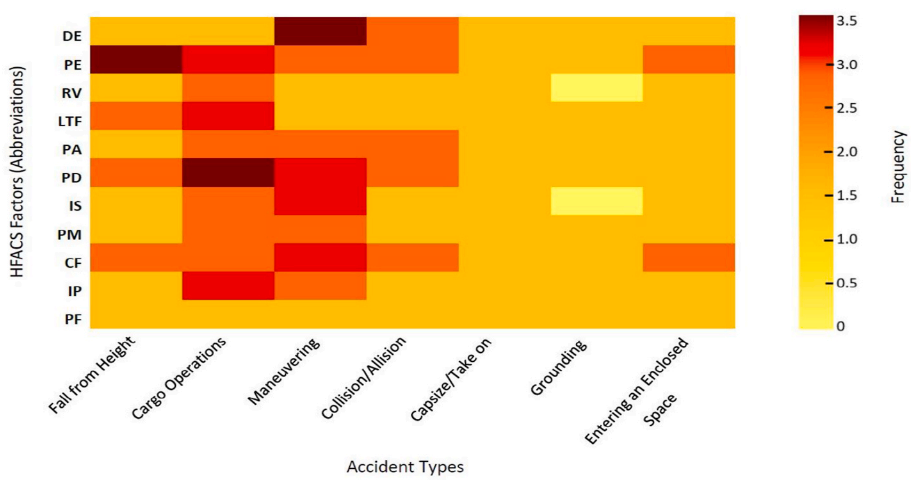

Fig. 10. Heat map of accident type frequencies according to nonconformity factors.

6. Practical implications

This section translates the study's analytics into concrete moves that ports can make now. The hybrid HFACS-BN approach turns scattered incident data into a diagram that updates with conditions, highlights possible leverage points and supports decision making can measurably reduce accident likelihoods.

6.1. *Implications for port safety management*

Sensitivity analysis quantitatively reveals the relative impact of latent and active failures on accident probabilities within the BN model, showing where risk is concentrated across the system. In this study, factors identified as highly sensitive are treated not only as key risk indicators but also as actionable managerial and operational leverage points. In other words, sensitivity results are used to determine which organizational, supervisory, and operational elements should be prioritized in port safety management. Accordingly, highly sensitive nodes are directly linked to practical interventions. For example, risks concentrated in organizational and supervision layers are translated into concrete managerial actions such as strengthening procedures, improving planning processes, and restructuring communication mechanisms. Similarly, sensitivity findings related to workload and situational awareness provide the basis for recommendations concerning personnel capacity management, pre-operation briefings, and additional control mechanisms for critical operations.

The frequency and sensitivity analyses presented in Figs. 7 and 9 show that risk in port accidents is concentrated in specific HFACS subcomponents. In particular, procedural violations emerge as the node with the highest sensitivity in relation to accident probability, followed by workload and situational awareness. This finding suggests that intervention priorities in port safety management should focus less on individual operator performance and more on system-level factors such as procedural design, task allocation, and operational capacity planning. Operationally, this implies that safety investments and managerial attention should prioritize reviewing the practicality of procedures, defining mandatory pre-operation control steps, and establishing capacity buffers during high-workload periods, rather than simply increasing training intensity.

The results indicate that nonconformities cluster at the organizational and supervisory layers before surfacing as unsafe acts. Port leaders should therefore treat procedural gaps, planning weaknesses, and thin communication channels as primary risks. Regular HFACS-based audits tied to corrective-action dashboards help shift attention from "who erred" to "what in the system made the error likely," consistent with modern resilience and just-culture principles. Where workload and situational awareness repeatedly precede incidents, managers should build capacity buffers, staffing thresholds for weather/traffic peaks, short pre-task briefs, cross-checks for high-consequence operations, so that the performance can adapt under changing demands. Finally, BN sensitivities should guide prioritization of controls: emphasize procedural discipline for grounding, decision-support for collision, and supervision quality for contact, directing training, supervision time, and inspection hours to those high-yield nodes.

6.2. Policy and regulatory implications

The policy and regulatory implications presented in this section are developed on the basis of risk factors identified as highly influential in the BN-based sensitivity analysis. Regulators can embed BN indicators into safety monitoring so that inspection intensity scales with modelled risk, aligning oversight with performance-based regulation. Agencies should adopt leading, probabilistic metrics forecasted collision probability under specific weather/traffic states and supervision quality to drive adaptive pilotage limits, dynamic speed guidance, or conditional tug requirements. Policies that foster just culture and shared learning will improve reporting of nonconformities and near misses, sustaining the data-model-decision feedback loop (Marino et al., 2023). The findings of this study indicate that rule-based and threshold-oriented regulatory approaches may not adequately capture the contextual variability of port operations. The HFACS-accident type mappings presented in Fig. 10 demonstrate that the same operation can produce different risk profiles under varying environmental, traffic, or organizational conditions. Therefore, regulatory frameworks should move beyond static compliance checks toward context-sensitive, risk-weighted oversight mechanisms.

6.3. Practical application of the BN framework

In operations planning, the BN can be linked to VTS/port MIS feeds (visibility, wind/sea state, traffic density) to display live risk by berth, fairway, and operation type, with "what-if" sliders for staffing, tugs, and sequencing. For training, node-level posteriors inform targeted scenario drills, decision-making under time pressure for bridge teams, workload management for cargo operations, and authority-gradient checks for contact-prone situations. For resource allocation, the ranked list of sensitive nodes (e.g., Procedural Violation, Workload, Situational Awareness) shows where marginal investment buys the largest risk reduction, and the same evidence base helps align contractors, stevedores, pilots, towage so that controls are system-wide. In this context, the proposed BN-based decision-support approach can be gradually implemented by restructuring existing VTS records, incident reporting systems, and inspection data, without requiring new infrastructure investment. This demonstrates that the model is not only a theoretical analytical tool but also a practical risk monitoring mechanism that can be integrated into current port information systems.

6.4. Recommendations for future implementation

Future implementation of the proposed hybrid HFACS-BN framework requires a systematic and collaborative approach that connects empirical evidence, analytical modelling, and managerial practice. Establishing an integrated safety data hub should be prioritized as a foundational step. Linking HFACS-coded investigation reports, near-miss databases, Vessel Traffic Service (VTS) logs, and maintenance records to a shared BN backbone will enable continuous, data-driven safety monitoring. Regular recalibration of network parameters conducted quarterly or semi-annually will ensure that the model remains reflective of evolving operational realities, including seasonal variations, changing traffic density, and procedural updates.

Another critical aspect involves the automation of BN recalibration. Employing structured data pipelines and Expectation Maximization (EM) algorithms allows the network to adaptively update conditional probabilities as new data are incorporated. This continuous learning mechanism strengthens the analytical validity of the model, allowing it to evolve alongside the port's dynamic risk environment.

In parallel, integrating machine learning augmentation into the BN framework can further enhance analytical sensitivity. Through anomaly detection and ensemble-based classification, the model can identify emergent precursor patterns such as the simultaneous rise of workload, low visibility, and communication delay and use these as priors to anticipate accident-prone scenarios. This hybrid synergy between probabilistic reasoning and data-driven intelligence significantly advances early-warning capabilities.

Furthermore, fostering cross-port collaboration is essential for collective learning and model refinement. A federated data-sharing network among ports would allow the BN to learn from distributed datasets while preserving data privacy. This collaboration can produce harmonized predictive indicators, establish comparative benchmarks, and accelerate the global standardization of data-driven maritime safety management.

Finally, the establishment of a dedicated risk analytics unit within port administrations is crucial for sustainable implementation. Such a unit would maintain the HFACS coding process, perform continuous BN updates, and generate operational intelligence briefs for management. By institutionalizing these analytical capacities, ports can transition from reactive safety management to a proactive, adaptive, and learning-oriented safety culture.

Collectively, these recommendations reinforce the insights drawn in the Discussion section, where the analysis demonstrated that human, organizational, and environmental factors interact dynamically to shape accident probabilities. By operationalizing these recommendations, the findings of this study can be transformed into actionable strategies that strengthen resilience, enhance predictive safety governance, and close the gap between theoretical modelling and real-world maritime safety performance. In this way, the hybrid HFACS-BN framework not only explains the mechanisms of accident causation but also provides a tangible pathway toward the next generation of intelligent, data-driven port safety management systems.

7. Discussion

The integration of the HFACS with BN represents a significant methodological advance in maritime safety research, offering a coherent bridge between qualitative human factor taxonomies and quantitative probabilistic reasoning. The findings of this study demonstrate that the proposed hybrid HFACS-BN framework not only captures the hierarchical nature of accident causation in port environments but also provides a dynamic and analytical decision support mechanism for risk assessment. Through empirical validation, axiom-based testing, and sensitivity analyses, the model was shown to reliably reproduce causal dependencies among organizational, supervisory, human, and environmental factors thereby fulfilling both theoretical and operational expectations of systemic accident modelling.

7.1. Interpreting the hierarchical dynamics of port accidents

The distribution revealed that Organizational Influences and Unsafe

Supervision jointly accounted for nearly half of the total, indicating that systemic management deficiencies and procedural inconsistencies play a central role in accident causation. For instance, several reports cited the absence of updated risk assessments, ineffective coordination between bridge teams and port control, and delayed decision-making during critical manoeuvres as recurring precursors to accidents. These findings align with the results of Maternová et al. (2023), who demonstrated that communication failures and inadequate supervision significantly elevate the likelihood of navigational and berthing incidents in port waters.

The hierarchical distribution of nonconformities within the HFACS framework revealed a pronounced concentration at the organizational and supervisory levels, confirming that systemic and managerial deficiencies precede unsafe operational behaviours. Procedural deficiencies, planning weaknesses, and inadequate supervision emerged as the most influential latent precursors, corroborating earlier studies that highlight the centrality of institutional governance and leadership in maritime safety performance (Hasanspahić et al., 2021; Ma et al., 2023). The dominance of unsafe acts particularly decision errors and procedural violations further validates the premise that human performance degradation often represents the final expression of upstream structural weaknesses. This dual pattern reflects the multi-layered nature of accident formation, where organizational climate and safety culture modulate individual behaviour through feedback loops of policy, training, and supervision.

7.2. Validation of the bayesian model and its theoretical coherence

Bayesian Networks quantitatively represent probabilistic dependencies among variables; however, causal interpretations in such models depend on the underlying theoretical assumptions of the network structure and the guidance of domain knowledge. In this study, the directed links between nodes and the interpreted effects are grounded not only in statistical associations but also in the hierarchical causal logic of the HFACS-PV framework, the temporal sequencing of accident reports, and structured expert justification. Therefore, the findings presented here should be understood not as claims of absolute causality, but as causally interpretable probabilistic relationships.

The results of the axiom-based validation reinforce the internal coherence and logical soundness of the BN model. The successful compliance with Axioms 1 and 2 confirms that the network maintains monotonicity and continuity key properties of valid probabilistic inference systems (Pristrom et al., 2016). Axiom 3 verification, where the joint activation of multiple parent nodes amplified accident likelihoods beyond individual effects, further demonstrates the model's capacity to capture cumulative and interactive influences. This finding underscores the nonlinear escalation pattern of maritime risk, particularly under simultaneous exposure to human, environmental, and supervisory deficiencies. By replicating real-world causal complexity within a transparent and interpretable probabilistic structure, the model transcends traditional deterministic frameworks and aligns with contemporary safety paradigms emphasizing emergent behaviour and systemic resilience.

7.3. Sensitivity and causal influence: human error at the core

The sensitivity analysis revealed that unsafe acts especially procedural violations, decision errors, and rule violations, are most strongly associated with accident probabilities across categories and emerge as dominant contributors within the model. These findings are consistent with the broader human reliability literature, which indicates that task errors and cognitive overload systematically co-occur with operational failures (Stanton et al., 2017). Yet the co-occurrence of these behaviours with supervisory deficiencies, such as inadequate monitoring and ineffective communication suggests that human errors should not be interpreted as isolated events. Rather, they are shaped and amplified within a network of organizational constraints and resource limitations. The heatmap visualization (Fig. 10) clearly illustrates that procedural and decision-based nonconformity clusters probabilistically align with weak planning and supervision nodes, and that their interaction jointly increases accident probabilities. These visual and quantitative results reinforce the interpretation that port accidents cannot be reduced to single operator errors but should be understood as emergent outcomes of multi-layered socio-technical interactions. Accordingly, the findings do not assert isolated causal claims but present causally interpretable probabilistic patterns that support a systematic understanding of port accident mechanisms.

7.4. Theoretical and methodological contributions

From a theoretical standpoint, this study advances maritime safety modelling by embedding HFACS within a probabilistic graphical structure, thus enabling a dual explanatory-analytical capability. Whereas conventional HFACS applications remain largely diagnostic and qualitative, the hybrid HFACS-BN framework quantifies interdependencies, allowing dynamic updates as new data or expert knowledge become available. Methodologically, the incorporation of fuzzy logic enhances robustness against uncertainty and subjective bias in expert elicitation, addressing one of the main limitations of Bayesian approaches in safety research (Fenton and Neil, 2018). The demonstrated success of the model in reproducing known accident mechanisms while offering forward-looking simulations underscores its potential as a decision-support architecture for port authorities and maritime regulators.

Compared with traditional HFACS-based accident analysis approaches, which mainly provide qualitative classifications of human and organisational errors, the integration of Bayesian Networks enables the probabilistic analysis of relationships between causal factors. This allows the model to move beyond descriptive classification and supports the quantitative examination of causal pathways within accident systems. In particular, the Bayesian Network structure makes it possible to analyse how changes in higher-level conditions influence accident outcomes through multiple intermediate layers. Such analysis cannot be achieved using traditional HFACS approaches alone.

The findings obtained from the Bayesian Network analysis show that the proposed HFACS-BN framework can represent the hierarchical propagation of accident risk across organisational, supervisory, operational, and human action layers. Unlike traditional accident analysis approaches based on linear causal chains, the probabilistic structure of the Bayesian Network allows the examination of interdependencies among multiple causal factors. This structure enables the tracing of how latent organisational deficiencies are reflected through supervisory and operational conditions, eventually leading to unsafe actions and accident outcomes. In this way, the model improves the interpretability of accident formation processes in port environments by clearly illustrating how risk propagates across different levels of the socio-technical system.

The proposed framework does not aim to develop a purely prediction-oriented model. Instead, it focuses on improving the causal interpretation of accident mechanisms in complex port environments. By integrating the HFACS classification structure with probabilistic Bayesian inference, the framework enables both qualitative understanding and quantitative evaluation of accident formation processes. In this context, the main contribution of the model is its ability to support scenario-based safety analysis and to help identify critical intervention points for port safety management. The addition of the Operational Conditions layer further improves the explanatory capacity of the proposed Bayesian Network framework in understanding how operational deviations within port areas lead to accidents.Ports are spatially constrained and operationally complex environments where ship manoeuvres, cargo operations, pilotage services, and coordination among port authorities occur simultaneously. By explicitly incorporating operational conditions within the causal hierarchy, the model provides a more realistic representation of port accident formation processes compared with previous HFACS applications developed mainly for open-sea navigation contexts.

7.5. Practical reflections and path toward resilient port safety

The original contribution of this study lies not in simply reaffirming the dominant role of organizational factors, but in probabilistically analysing how these factors interact with specific human errors under particular operational contexts and evolve into different accident types. Through the integration of HFACS and BN, accident causation is transformed from a static and retrospective classification into a context-sensitive, analytical, and intervention-oriented decision-support framework.

The analytical outcomes collectively point to a paradigm shift from reactive post-accident assessment to proactive risk forecasting. The practical application of the model enables continuous monitoring of operational conditions, analytical evaluation of emerging hazards, and strategic allocation of preventive resources. By highlighting the high sensitivity of procedural and supervisory variables, the results advocate for behaviour-based safety systems, enhanced oversight protocols, and real-time performance feedback mechanisms. Moreover, the probabilistic transparency of the model facilitates risk-informed decision-making, allowing authorities to calibrate inspection frequency, training intensity, and policy intervention according to quantifiable risk gradients. This evidence-based governance approach aligns with international regulatory frameworks emphasizing adaptive, data-driven safety management (Hossain et al., 2019; IMO, 2024; EMSA, 2024).

7.6. Integrating findings into broader safety theory

Beyond its immediate maritime context, the study contributes to the broader discourse on complex socio-technical system safety. The HFACS-BN integration exemplifies how theories of organizational error, human performance, and system resilience can be operationalized within a unified analytical model. By showing that human errors are not merely end events but dynamic symptoms of upstream structural weaknesses, the study reinforces the conceptual shift toward resilience engineering and safety-II thinking (Read et al., 2021). The framework's adaptability also suggests applicability across other high-risk domains such as offshore drilling, aviation, and logistics fields where multi-factorial causation and uncertainty are inherent.

8. Limitations of the study

Along with the methodological contributions of this study, several limitations should be acknowledged. First, the analysis is based on 150 accident investigation reports. Although these reports were systematically selected and verified, they may not fully represent the global diversity of port accidents. Therefore, the findings should be interpreted within the analytical scope of the dataset, rather than as statistically generalisable results. Second, the parameterization of the Bayesian Network partly relies on expert judgement, due to the limited availability of consistent and comprehensive quantitative accident data. Although the use of fuzzy linguistic aggregation and the Similarity Aggregation Method improves the reliability of expert assessments, the model is still influenced to some extent by subjective expert knowledge. Third, the proposed HFACS-BN framework is primarily designed to support causal interpretation and scenario-based inference, rather than to develop a prediction-oriented model. Therefore, the model should be considered an analytical decision-support tool, rather than a pure predictive model. Future research may address these limitations by using larger accident datasets, applying machine-learning-based parameter learning methods, and conducting cross-validation with alternative accident modelling approaches.

9. Conclusions

This study presented an integrated analytical framework that combines the HFACS with BNs to model and supports understanding of the causal dynamics of port accidents. By systematically linking hierarchical human factor classifications with probabilistic inference, the research offers a multidimensional understanding of how human, organizational, environmental, and supervisory factors interact to shape accident outcomes in complex port environments.

The empirical findings derived from 150 validated accident investigation reports revealed that organizational and supervisory deficiencies are the primary latent precursors of operational failures. Procedural violations and decision errors consistently emerged as the most dominant unsafe acts, underscoring that human error is rarely an isolated phenomenon but rather the emergent outcome of systemic management weaknesses. The Bayesian Network analysis quantified these relationships, demonstrating that accident probability escalates sharply when multiple high-level deficiencies such as poor supervision, inadequate planning, and environmental hazards converge. These results affirm the nonlinear and cumulative nature of marine accident causation and highlight the critical need for system-oriented safety management.

The validation stage confirmed the logical and structural accuracy of the proposed model through compliance with three axioms of causal consistency. Axiom 1 verified that parent nodes exerted monotonic influence on dependent variables; Axiom 2 demonstrated continuity in causal propagation across environmental and human-performance domains; and Axiom 3 validated the model's ability to capture the compounded effects of interacting risk factors. Together, these results confirm that the HFACS-BN framework is not only theoretically coherent but also operationally reliable for decision making and diagnostic related applications in maritime safety assessment.

Sensitivity analyses further emphasized the dominant influence of unsafe acts and organizational failures across accident types. Decision errors, procedural deficiencies, and rule violations exhibited the highest sensitivity indices, while supervisory and environmental factors acted as amplifiers of latent vulnerabilities. These findings provide quantitative evidence supporting the principle that effective maritime safety depends not only on procedural compliance but on cultivating resilient organizational structures, adaptive supervision, and continuous information flow within port operations.

From a methodological standpoint, the integration of fuzzy logic into the Bayesian inference process represents a key innovation. This approach mitigated uncertainty and subjectivity in expert judgments, enhancing both transparency and analytical precision. The hybrid HFACS-BN model thus transcends traditional linear accident investigation tools by offering a probabilistic, learning-based, and continuously updating system capable of supporting proactive risk governance.

The implications of this study extend beyond theoretical advancement. For maritime regulators and port authorities, the model provides a practical decision-support instrument capable of forecasting accident probabilities, testing "what-if" scenarios, and prioritizing preventive interventions under uncertainty. By identifying high-sensitivity factors such as supervision quality, procedural compliance, and environmental control, the framework enables resource optimization and evidence-based policymaking aligned with the International Maritime Organization's human element strategy and risk-based safety regulations.

At a broader level, the research contributes to the emerging paradigm of resilience engineering and Safety-II thinking, shifting the focus from error attribution toward system adaptability and learning. The proposed hybrid methodology demonstrates how human reliability theory, probabilistic reasoning, and organizational behaviour can be seamlessly integrated to advance the analytical capability of maritime safety systems.

The HFACS-BN framework developed in this study establishes a scientifically grounded, empirically validated, and practically applicable foundation for next-generation port accident analysis. Its analytical power, interpretability, and adaptability make it an essential tool for transforming maritime safety management from a reactive process into a proactive, data-driven, and resilient safety ecosystem. However, several limitations should be acknowledged. The proposed model is developed and validated using historical accident investigation data and expert elicitation, and it has not yet been implemented within live port operational environments. Accordingly, its primary contribution lies in providing a structurally adapted and quantitatively validated analytical decision-support framework tailored to port accident mechanism. Future research should explore model scalability across other high-risk maritime domains such as offshore platforms, container terminals, and ferry operations and integrate real-time data streams to develop intelligent, self-learning maritime safety management systems capable of continuously evolving with operational complexity.

In this study, accidents occurring within port areas were analysed within a general framework, and different accident types were evaluated together. The main reason for this approach is the lack of sufficiently homogeneous and detailed data at this stage to focus on a single accident category. Therefore, the analysis was structured to reflect the overall risk profile of port operations by including all accident types. In future research, if sufficient and comparable datasets for a specific accident type become available, the model can be adapted to that particular category to produce more detailed results.

CRediT authorship contribution statement

Hüseyin Tolga Sanal: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Fatih Emre Boran:** Writing – review & editing, Validation, Supervision. **Serdar Yıldız:** Writing – original draft, Visualization, Methodology, Formal analysis. **Özkan Uğurlu:** Writing – review & editing, Validation, Supervision, Software, Methodology, Formal analysis. **Xinjian Wang:** Writing – review & editing, Validation, Methodology. **Jin Wang:** Writing – review & editing, Validation, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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