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Dynamic Accident Network Model for Predicting Marine Accidents in Narrow Waterways Under Variable Conditions: A Case Study of the Istanbul Strait

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Abstract: Accident analysis models are crucial tools for understanding and preventing accidents in the maritime industry. Despite the advances in ship technology and regulatory frameworks, human factors remain a leading cause of marine accidents. The complexity of human behavior, influenced by social, technical, and psychological aspects, makes accident analysis challenging. Various methods are used to analyze accidents, but no single approach is universally chosen for use as the most effective. Traditional methods often emphasize human errors, technical failures, and mechanical breakdowns. However, hybrid models, which combine different approaches, are increasingly recognized for providing more accurate predictions by addressing multiple causal factors. In this study, a dynamic hybrid model based on the Human Factors Analysis and Classification System (HFACS) and Bayesian Networks is proposed to predict and estimate accident risks in narrow waterways. The model utilizes past accident data and expert judgment to assess the potential risks ships encounter when navigating these confined areas. Uniquely, this approach enables the prediction of accident probabilities under varying operational conditions, offering practical applications such as real-time risk estimation for vessels before entering the Istanbul Strait. By offering real-time insights, the proposed model supports traffic operators in implementing preventive measures before ships enter high-risk zones. The results of this study can serve as a decision-support system not only for VTS operators, shipmasters, and company representatives but also for national and international stakeholders in the maritime industry, aiding in both accident probability prediction and the development of preventive measures.

Keywords: accident analysis; HFACS-PV; Bayesian Network; Istanbul Strait; decision making for navigation

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1. Introduction

Narrow waterways serve as critical junctures for maritime transportation, which constitutes the backbone of global trade. These areas, functioning as logistical transfer hubs, experience dense marine traffic. High traffic volumes, coupled with challenging environmental conditions and human error, render these narrow passages susceptible to marine accidents. Such incidents in narrow waterways disrupt maritime transport and have adverse economic consequences. For example, a recent accident occurred on 26 March 2024, when the container ship Dali collided with the Francis Scott Key Bridge in Baltimore, Maryland, USA. The impact caused the bridge to collapse. This bridge serves as an entry point to the Port of Baltimore, the busiest United States port for automobile exports and the ninth largest in terms of foreign cargo. Following the incident, substantial disruptions in maritime traffic ensued, sparking concerns over potential "ripple effects" across global supply chains [1]. Another notable accident occurred in the Suez Canal on 24 March 2021. The canal, which facilitates the passage of approximately one million barrels of oil products daily, remained closed for nearly a week. The damage compensation sought from the vessel's operating company reached approximately 1 billion USD [2]. Consequently, the sustainability of navigational safety in narrow waterways has become a focal point of interest for all stakeholders in the maritime sector.

Marine accidents in narrow channels cause significant direct and indirect damage to individuals, cargo, vessels, marine ecosystems, and the economy. Analyzing the distribution of marine accidents by navigational location reveals that incidents frequently occur in inland waters (53.9%), territorial waters (24.3%), and open seas (20.8%) [3]. Coastal areas, particularly narrow waterways, are especially prone to frequent marine accidents [4–6]. In global maritime transportation, numerous regulations have been issued by national and international organizations to ensure safety in narrow waterways [7–9].

Despite regulatory measures and precautions, marine accidents in narrow waterways continue to pose an ongoing threat to navigational safety [10,11]. Maritime accidents with devastating consequences represent one of the most significant obstacles to ensuring safe and sustainable maritime trade [12,13]. One of the fundamental approaches to reducing these losses is the principle of learning from past incidents and preventing future occurrences, a practice formalized in marine accident investigation and reporting, which began with the Titanic disaster. Maritime authorities conduct accident investigations to understand how and under what circumstances the system failed and why accidents occurred. The findings in investigation reports encourage maritime authorities and companies to review and revise regulations and management standards accordingly [14]. Analyzing marine accidents is one of the most effective approaches to reducing risks in maritime transportation [15,16]. Accident analysis and risk assessment models capable of accurate future forecasting are essential for accident prevention and enhancing maritime safety.

By integrating HFACS with Bayesian Networks, the proposed model uniquely addresses the gaps in existing approaches. This integrated framework systematically categorizes human errors while providing a dynamic, probabilistic understanding of accident causality pathways under varying operational conditions and human-organizational factors. Unlike previous models, this approach facilitates both descriptive and predictive analyses, enabling the estimation of accident probabilities before specific operations, such as a vessel's passage through the Istanbul Strait [6,11,12,17]. By dynamically adjusting to reflect real-time operational and contextual variables, the model offers actionable insights to support decision-making and enhance risk management. Key contributions of this model are contextualized in the light of previous accidents, expert judgments, and previous studies, to strengthen its value in advancing maritime safety modeling and decision-support systems using real-time data.

2. Overview of Accident Analysis Models

Modern ships are equipped with advanced technologies and supported by numerous regulations; nonetheless, human factors continue to play a significant role in the occurrence of accidents. The complex social, technical, and psychological nature of human elements complicates accident and incident analysis. The available literature offers over a hundred analytical approaches, yet there is no consensus on the superiority of any single approach. Human errors, environmental factors, technical failures, and mechanical malfunctions are commonly highlighted as traditional causes of accidents [15,17,18]. In determining the approach for accident analysis, factors such as the type of accident, the pattern of occurrence, the causes to be analyzed (e.g., human errors, technical failures, mechanical malfunctions, operational conditions), and causal factors should be considered. In maritime literature, the most effective approaches for developing models that accurately predict accident-causing factors, and their impacts are those based on historical accident data. By using actual incidents and data, these models yield more accurate and consistent results [19,20]. Hybrid approaches, such as the one proposed in this study, address the limitations of traditional models by combining the systematic classification of human errors from HFACS with the probabilistic capabilities of Bayesian Networks. Unlike conventional models, this hybrid framework dynamically predicts accident probabilities based on real-time operational and human-organizational factors, offering practical applications for narrow waterways such as the Istanbul Strait. Methods can be categorized by their approach to accidents and underlying assumptions into sequential, epidemiological, and systemic approaches [21,22], with a fourth category comprising hybrid approaches. These hybrid approaches, designed to analyze complex accidents and factors, often provide more consistent results when the other three approaches alone are insufficient.

When selecting the most suitable method or methods for a study, first identifying the accident analysis approach can be beneficial. The key consideration in determining the approach is the general pattern of the accidents being analyzed and the fundamental characteristics of the industrial system in which these accidents occur. For example, in the manufacturing industry, sequential approaches may be more appropriate for analyzing accidents and incidents with relatively simpler patterns, often resulting from technical, electronic, or mechanical failures. If epidemiological or systemic approaches were applied in such a context, the analysis method could become overly complex, with many details of the method not fitting within the accident's actual pattern. This mismatch could result in gaps in the accident analysis model produced. Therefore, it is essential to choose the approach by evaluating each method's core principles and objectives (Table 1), considering the industrial application's characteristics [11,22,23].

Table 1. Approaches used in accident analysis.

Approach	Main Principle	Main Objective	Example Methods
Sequential	Specific causes and well-defined connections.	Identification or elimination of causes.	• Linear event chain (Domino) • Tree models • Network models
Epidemiological	Carriers, barriers, and latent conditions.	Reinforcement of defenses and barriers.	• Swiss cheese • Bowtie model • Pathological Systems
Systemic	Tight couplings and complex interactions.	Monitoring and controlling performance variability.	• Control theory models • Chaos models • Stochastic resonance
Hybrid	Combination of the most robust approaches for analysis.	Accurate accident modeling and consistent forecasting.	• Fuzzy logic-network model hybrids • Fuzzy logic-hierarchical model hybrids • Systemic-epidemiological model hybrids • Fuzzy logic-systemic model hybrids

Hybrid approaches involve a sequential or simultaneous combination of multiple methods from the same or different categories to more accurately model accident causation (Table 1) [11,22,23]. The greatest advantage of these approaches lies in their flexibility and adaptability, allowing for the development of more robust accident and risk analysis models. In hybrid applications, methods are typically combined in a way that mitigates or strengthens each other's weaknesses [11,13,24]. Numerous hybrid methods exist in the literature, designed to facilitate application and deliver more consistent qualitative-quantitative analyses. The complexity of human behavior, influenced by social, technical, and psychological aspects, makes accident analysis challenging. Therefore, a research gap still exists in the ability of existing models to dynamically predict accident probabilities under varying operational conditions in real-time, particularly in high-risk environments such as narrow waterways. The research questions addressed in this study are: (1) How can a hybrid model effectively integrate human and operational factors to predict accident probabilities in a real-time manner? (2) What are the limitations of existing models in dynamic accident prediction, and how can they be addressed? (3) How can the proposed model enhance decision-making for vessel traffic operators in confined and high-risk areas? By the end of a study, hybrid models enhance the accuracy of predictions made by accident or risk analysis models.

In this study, a combined dynamic accident network structure has been developed based on past marine accident data and expert opinions, intended for use by vessel traffic operators to predict accident occurrence in narrow waterways. The construction of this network utilized a hybrid approach combining the HFACS with the Bayesian Network (BN). The HFACS-BN hybrid approach proposed in this study exemplifies the benefits of hybrid models by integrating the strengths of both systemic and probabilistic approaches. Its ability to predict accident probabilities in real-time before a ship passes through narrow waterways, such as the Istanbul Strait, marks a significant advancement in maritime accident analysis and decision support. The network structure proposed in this study assists vessel traffic operators in predicting the sector-based risk posed by a ship before its passage through a narrow waterway, thereby enabling them to determine and implement preventive measures accordingly.

3. Models Used in the Study

3.1. HFACS-PV Model

HFACS was developed based on Reason's Swiss Cheese Model and a systems approach to human factors in accidents [25,26]. Beyond the primary levels outlined in the Swiss Cheese Model, HFACS incorporates sub-levels within its structure that allow for a hierarchical classification of accident causes. The original framework of HFACS consists of four main levels: Unsafe Acts, Preconditions for Unsafe Acts, Unsafe Supervision, and Organizational Influences. Similar to Reason's Swiss Cheese Model, HFACS categorizes Human and Organizational Factors (HOFs) contributing to accidents into two sub-groups: active errors and latent failures [27]. HFACS has proven to be a reliable and applicable taxonomy for human factors analysis across various sectors, as demonstrated in numerous studies [28–32]. One of the distinguishing features of HFACS, in comparison to other accident causation models, is its ability to highlight the role of managerial and organizational factors within complex systems, such as accident causation [26,33]. A key advantage of the HFACS framework is its capability to stratify human error-related factors according to the accident causation structure and to enable the interrelation of causal factors through quantitative models [34–37].

In this study, the HFACS-PV (HFACS for passenger vessel accidents) structure was used to classify accident causes (Figure 1). The fundamental distinction between the HFACS-PV framework and other HFACS structures, as well as approaches to human factors analysis in accidents, is its treatment of Operational Conditions as a separate level. Operational Conditions refer to the environmental factors surrounding vessels during operations such as navigation, anchoring, maneuvering, loading, and discharging. HFACS-PV was initially developed by Uğurlu et al. (2018) using a dataset of passenger vessel accidents. However, over the recent years, this framework has been applied in more than 10 research studies involving different datasets and types of ships, including collisions, contacts, fire explosions, offshore accidents, and other accident types [11,13,17,20,31,32,36,38,39]. Those applications demonstrated its adaptability and applicability to various types of vessels and accident scenarios. Thus, while the framework's name (HFACS-PV) reflects its origin, its utility has been validated across a wide range of contexts, making it suitable for analyzing human and organizational factors in accidents beyond passenger vessels.

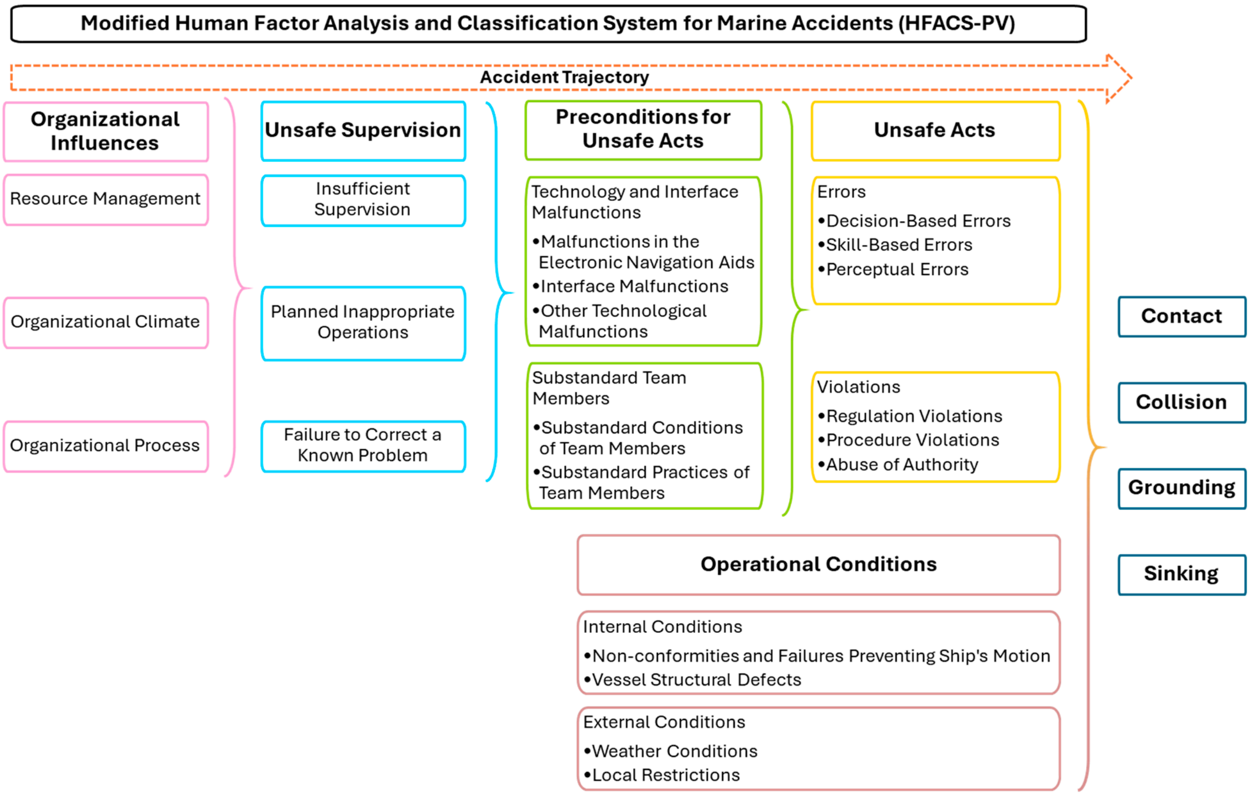

Figure 1. Core structure of HFACS-PV used in the study.

Operational conditions were divided into internal (main engine failure, rudder failure, structural defects of the vessel, etc.) and external (e.g., presence of shallow areas in the region, strong currents, wind, heavy traffic, etc.) factors. Structurally, these factors differ from the human and organizational factors found in other levels of HFACS and act as complementary elements to Unsafe Acts in the causation of marine accidents (Figure 1) [11,13]. Due to its high compatibility with marine accidents, the HFACS-PV framework has found extensive application in the literature, including the analysis of passenger ship accidents [31], accidents resulting from failures in electronic navigational aids [17], analysis of marine accidents in the Black Sea [11], analysis of engine room fires [20], and the analysis of various types of accidents (collision, grounding, and sinking) [13,17,36] as well as in pilotage accident analysis [32].

3.2. Bayesian Network Approach and Applications in Accident Analysis

Bayes' theorem, introduced by Thomas Bayes, is a conditional probability approach rooted in the concept of subjective probability [40,41]. This model represents the likelihood of adverse events within a network structure through conditional probabilities. The BN approach enables both qualitative and quantitative assessments. The constructed BN model reveals the causal structure of relationships between nodes and facilitates causal reasoning among nodes, representing a qualitative approach to network building [42]. The quantitative aspect involves determining numerical values through Conditional Probability Tables associated with each node (parent, child, or root) within the network [11,38,43]. One of the key advantages of BN is its adaptability to the specific application domain, allowing the model to be updated with each new piece of information to better reflect real-world conditions. Additionally, BN provides a framework for modeling and reasoning under uncertainty.

The mathematical expression of Bayes' theorem is the probability of event A occurring, given the knowledge of event B, where A and B are two events linked by conditional probability dependence. This is represented by Equation (1) [42,44,45].

$$P(A|B) = \frac{P(A \cap B)}{P(B)},\ \mathrm{P(B)} > 0 \tag{1}$$

Here, $P(B)$ = Probability of event B happening, and $P(A \cap B)$ = Probability of happening of both A and B. Finally, the term $P(B)$ represents the probability of B occurring independently, which conditionally influences the probability of event A_i. The probability of event B occurring given the knowledge of event A is represented by Equation (2).

$$P(B|A) = \frac{P(A \cap B)}{P(A)},\ \mathrm{P(A)} > 0 \tag{2}$$

Here, $P(A)$ = Probability of event A happening, and $P(A \cap B)$ = Probability of happening of both A and B. To express these conditional probability formulas in a general form, let us assume there are k number of mutually exclusive events A_i intersecting with event B. The probability of event A_i occurring, given the knowledge of event B, can be calculated using Equation (3).

$$P(A_i|B) = \frac{P(A_i)\ P(B|A_i)}{P(B)},\ i = 1,\ 2,\ 3,\ 4, \ldots,\ k \tag{3}$$

where k is the number of states of event A.

In this equation, the term $P(A_i|B)$ represents the posterior probability of the hypothesis (i.e., the probability of A_i occurring in a given B scenario). The term $P(A_i)$ denotes the prior probability of the hypothesis, meaning the probability of A occurring in a specific i condition. The term $P(B|A_i)$ is the conditional probability of "B" given A_i (the likelihood of the evidence supporting the hypothesis being tested).

The BN model enables the representation of complex events, such as accident causation, as a network structure using nodes and directed arrows (edges). This model can thus be tested on a case study, allowing the user to understand accident causation and make predictions based on variable conditions. In this study, the BN approach was employed to develop a network model that represents accident causation in narrow waterways through conditional probability relationships. This network model will dynamically display the potential accidents a vessel may encounter (influences threatening safety) based on variable conditions during transit. Additionally, the network model can be used to understand and interpret the relationship between Operational Conditions and HOFs contributing to accidents in narrow waterways.

4. Materials and Methods

In this study, a dynamic network structure was developed to predict marine accident causation under variable conditions by utilizing collision, contact, grounding, and sinking accident data, as well as expert opinions for narrow waterways, which are critical junctions in maritime trade. The Istanbul Strait, with approximately 50,000 vessels transiting annually, was selected as the example application area. The accident data analyzed in the study comprises 240 vessel incidents that occurred between 2004 and 2021. Hybrid approaches were employed for accident analysis, specifically using the HFACS-PV and fuzzy BN approaches.

Unlike accident studies based solely on theoretical applications and analytical assessments, this study conducted a theoretical-practical comparison by involving an expert group composed of experienced professionals in narrow waterways, officials from national maritime authorities, and maritime academics. Results obtained at each stage of the study were evaluated with this group, thereby identifying the final risks for the Istanbul Strait. This approach aims to include practical risks, often overlooked in the qualitative analysis of accident reports and analytical assessments, ensuring that these real-world risks are incorporated into the study. This approach aims to minimize the data gaps, referred to as "uncertainties" in safety assessment and risk analysis studies in the literature. As a result of this study, an accident network model has been developed to predict the probability of accidents for a vessel transiting the examined narrow waterway under variable conditions. If utilized by vessel traffic operators in the relevant regions, this network model has the potential to increase awareness and reduce accidents. Unlike BN studies in the literature, the network structure developed in this study is specifically designed to assess real-time accident risk based on variables such as internal and external environmental conditions prior to transit.

The unique value of this study can be understood by examining the potential short-, medium-, and long-term impacts of its outcomes. The short-term impact of the accident network presented in this study is to ensure that mariners making their first transit through the Istanbul Strait are informed of existing hazards via vessel traffic operators. Additionally, maritime authorities in countries with narrow waterways and all stakeholders in the maritime sector can benefit from this accident network and the study's findings when providing region-specific training. The medium-term impact is for coastal state maritime authorities (such as coast guard officials, vessel traffic operators, etc.) to use the proposed network model as a decision support tool for identifying risk factors and determining risk control options. Furthermore, the accident network can be adapted to other narrow waterways with necessary modifications or further optimized for existing narrow channels, enabling its use in managing traffic in other narrow waterways with more consistent results. The long-term impact of the study's outcomes is to reduce maritime accidents, thereby ensuring the sustainability of navigational safety and minimizing disruptions in maritime trade. The steps of the study are presented below.

4.1. Identification of Accident-Triggering Factors in the Istanbul Strait and Development of a Dynamic Accident Network

In the first phase of the study, 240 official accident reports recorded in the Global Integrated Shipping Information System (GISIS) and Transport Safety Investigation Center (UEIM) databases for incidents in the Istanbul Strait were reviewed. During this phase, the root causes and contributing factors for each accident were identified and classified individually within the HFACS-PV framework (Figure 1). This framework was used to categorize and code the causes and causal factors of accidents derived from the reviewed maritime accident reports. After hierarchically classifying the causes under the HFACS-PV structure, the relationships between accident causes for each incident were modeled using the BN approach, considering the pattern of each accident's occurrence. This approach aims to concretely reveal the relationships among factors causing the accident and enable analytical evaluation through Bayes' conditional probability approach. Subsequently, the BNs created for each accident were combined to develop an accident network for predicting accident occurrence (sinking, contact, collision, and grounding) in narrow channels (Figure 2). Bayes Fusion Genie 4.1 Academic Bayes software was used to model the BN and process conditional probabilities [46], ensuring consistent and efficient modeling and mathematical processing.

There are three critical elements in developing a BN model: identifying the nodes in the network, placing the directional arrows that define relationships between nodes, and determining the conditional probabilities associated with each node [44,47,48]. The following outlines how these critical elements were addressed in this study. In the BN, nodes were defined to encompass all nonconformities identified in the 240 accident reports, classified under the HFACS-PV framework, ensuring no nonconformities were omitted. Accordingly, the BN model in this study was categorized based on the primary and sub-levels of the HFACS-PV structure (Figures 1 and 2). This organization allows potential users of the network (e.g., ship masters and traffic operators) to easily understand the level of each node and its interactions with other levels at a glance.

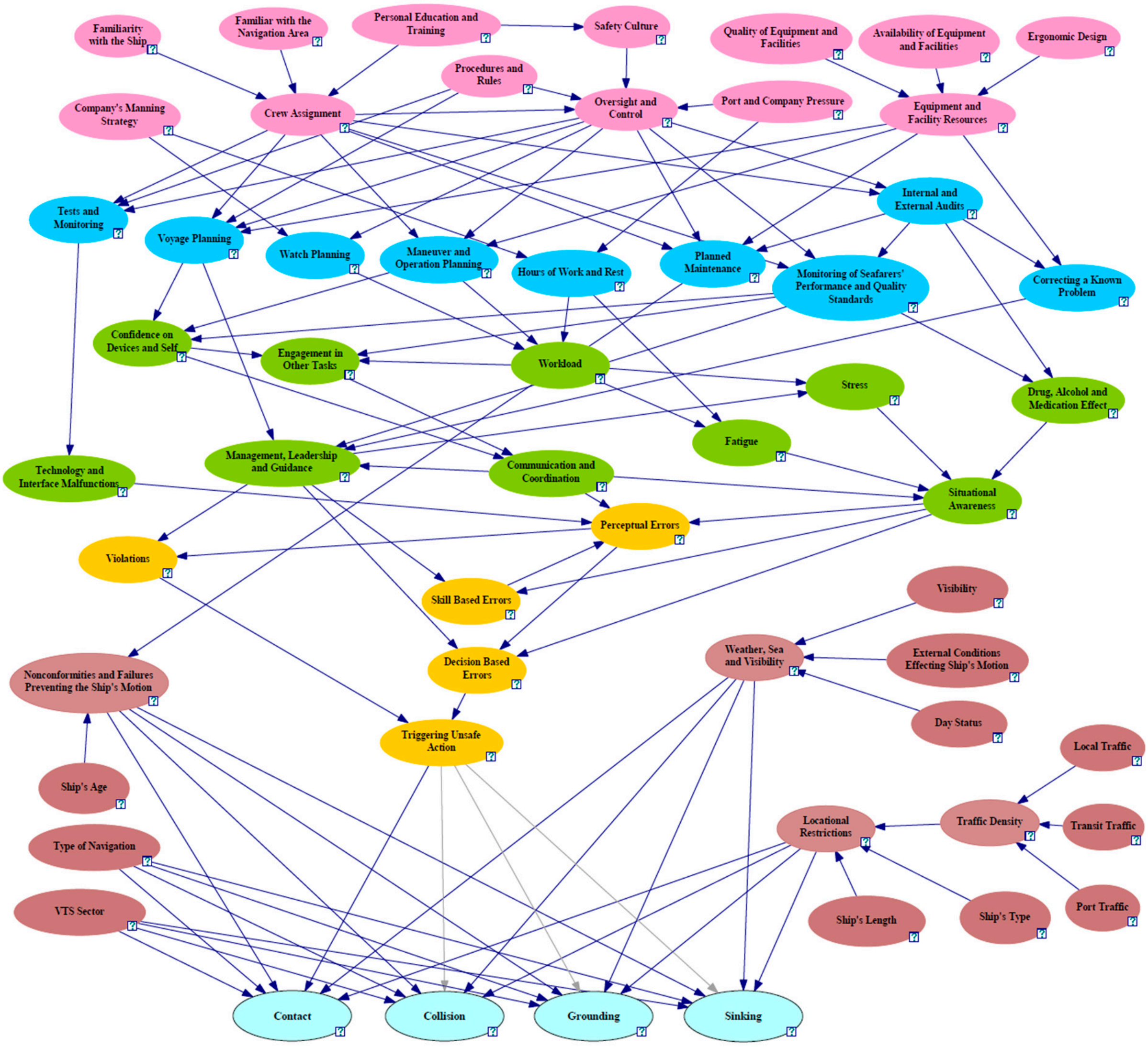

Figure 2. Bayesian Network model of the accidents in Istanbul Strait.

The placement of relationship arrows in a BN is also a critical aspect of its development. In this study, to ensure consistency and avoid overlooking existing relationships, a separate BN was created for each accident (a total of 240 networks). When constructing each network, the HFACS-PV nonconformities contributing to the accident and the causal structure of the incident were used as the foundation. The network was modeled to be directional from node to node without forming loops. In the final configuration of the accident network, arrows were placed between nodes that appeared in association with each other in 5% or more of the incidents. For example, in the Istanbul Strait, 143 of the 240 accidents analyzed (59.6%) involved both the "Insufficient Review and Control" and "Unsafe Maneuver and Operation Planning" nodes, which played a role in the occurrence of these incidents. Consequently, a relationship arrow was placed between these two nodes in the final accident network. The specificity of the accident network to narrow waterways is due to variations in operational conditions (such as traffic density, size of transiting vessels, and vessel traffic sectors). Various approaches exist in the literature for determining the probabilities associated with nodes in a BN [49–53]. The most commonly used approaches include statistical data (frequency analysis) and expert opinions. Researchers may select the approach best suited to the study and its dataset or use a hybrid of both approaches [38,39,47,54]. Due to the non-homogeneous distribution of accident data in narrow waterways, a hybrid approach was adopted in this study. The application of this approach is described below.

4.2. Establishment of Dynamic Accident Network and Fuzzy Bayesian Implementation

Accident data was used as the basis for root nodes, with the probability assignment for each root node calculated as the ratio of the frequency of the relevant nonconformity to the total number of accidents. For child nodes, expert opinions were used. Expert assessments were gathered using the Fuzzy Numbers Probability approach, and Fuzzy Probability was calculated for each condition of each node. Five experts were consulted for the Istanbul Strait. Their responses were weighted based on their professional positions, experience in their roles, maritime experience, and the number of vessels transits they had conducted through the Istanbul Strait (Table 2). The consulted experts and their weight scores for the Istanbul Strait are presented below (Table 3).

Table 2. Expert judgments weighing scale.

Designation	Weight Factor	Experience in Designation	Weight Factor	Sea Service	Weight Factor	Number of Strait Transits	Weight Factor
Pilot	3	7≤ years	3	10≤ years	3	100≤ times	3
VTS operator	3	4–6 years	2	6–9 years	2	50–99 times	2
Master mariner	2	0–3 years	1	0–5 years	1	0–49 times	1

Table 3. Characteristics and weight scores of experts who participated in the study.

Expert No	Designation	Experience in Designation	Sea Service	Number of Strait Transits	Weight Factor				Aggregated Weight	Weight Score
IS-E1	Pilot	15	28	1000≤ times	3	3	3	3	12	0.20
IS-E2	VTS operator	7	12	100≤ times	3	3	3	3	12	0.20
IS-E3	Pilot	16	20	1000≤ times	3	3	3	3	12	0.20
IS-E4	Pilot	30	30	1000≤ times	3	3	3	3	12	0.20
IS-E5	VTS operator	13	20	100≤ times	3	3	3	3	12	0.20
Total								60		1.00

This study involved two distinct expert sessions to enhance the robustness of the accident network and ensure diverse expert insights were incorporated. In the first session, five experts, including pilots, vessel traffic service (VTS) operators, and master mariners with extensive experience in the Istanbul Strait, were consulted to develop the initial network structure and assign weights to accident-triggering factors. The input data of their assessments were processed based on their professional qualifications, experience, and familiarity with the specific operational challenges of narrow waterways.

In the second session, 19 experts were involved to validate and refine the conditional probabilities within the Bayesian Network. This larger group was composed of a broader range of professionals, including additional pilots, shipmasters, and VTS operators. Their role was to provide input on the impact of operational conditions identified in the study on maritime accidents, allowing for the aggregation of a more comprehensive and representative dataset. The second session ensured that the model incorporated a wider variety of expert perspectives, improving the overall reliability and applicability of the findings on operational conditions in the Istanbul Strait.

Expert assessments were collected individually from each expert using the Fuzzy Numbers 7-point evaluation scale (Table 4). Initially, each expert was briefed on the structure and functioning of the BN. Subsequently, the conditional probability table for the child nodes was presented to each expert, who was asked to evaluate the adverse impact of each condition.

Table 4. Fuzzy numbers 7-point linguistic evaluation scale and corresponding values.

		Triangular Fuzzy Numbers		
Evaluation Scale	**Abbreviation**	**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

After gathering expert assessments for all adverse conditions of the child nodes in the network, the expert opinions provided on the 7-point verbal scale were converted into triangular Fuzzy Numbers. A triangular Fuzzy Number represents the probability of a condition as a triplet set of Fuzzy Probability values of conditional probability, such as (a_1, a_2, a_3). For each x ∈ A, A is a fuzzy number, $\mu_{\check{A}}(x)$ is a membership function and the range of R values was defined as $R \to [0,1]$. Assuming the value of A lies within the interval $[a_1, a_3]$, the membership function $\mu_{\check{A}}(x)$ was calculated using Equation (4) [20,55,56]:

$$\mu_{\check{A}}(x) = K_{I(i+1)} = \left\{ \begin{array}{cc} 0 & x \le a_1 \\ (x - a_1)/(a_2 - a_1) & a_1 \le x \le a_2 \\ (a_3 - x)/(a_3 - a_2) & a_2 \le x \le a_3 \\ 0 & x \ge a_3 \end{array} \right\} \quad (4)$$

After all expert opinions were converted from the verbal scale to a numerical scale (triangular fuzzy numbers), the fuzzy logic processing steps were sequentially followed to obtain fuzzy probabilities for each condition, as presented below. Combining expert opinions is essential, as experts in a heterogeneous group, as in this study, may have varying levels of experience, knowledge, and expertise, leading to different interpretations and conclusions about a conditional probability. Therefore, consolidating the data obtained from expert assessments and integrating their opinions is crucial. In this regard, Hsu and Chen (1994) proposed an algorithm for combining views from homogeneous and heterogeneous expert groups, which is frequently used in the literature [18,20,57]. The aggregated expert opinions was calculated by following the steps outlined below using Equations (5)–(9). Assume that each expert, E_l (l = 1, 2, . . ., M) expresses his/her viewpoints about a specific attribute in a certain context by use of a predefined set of qualitative terms. The qualitative terms are converted to the corresponding fuzzy numbers.

Step 1. Calculate the degree of similarity (degree of agreement). ($S_{UV}(\widetilde{R}_u, \widetilde{R}_v)$ is defined as opinions (degree of agreement) between each pair of experts, E_u and E_v. According to this, consideration for ($S_{UV}(\widetilde{R}_u, \widetilde{R}_v)$, $\widetilde{A} = (a_1, a_2, a_3)$ and $\widetilde{B} = (b_1, b_2, b_3)$ being the two standard triangular fuzzy numbers, the degree of agreement function of S is defined by Equation (5):

$$S(\widetilde{A}, \widetilde{B}) = 1 - \frac{1}{J = 3} \sum_{i=1}^{3} |a_i - b| \; i = 1,\ 2,\ 3 \quad (5)$$

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

Step 2. When $(\widetilde{A}, \widetilde{B}) \in [0,\ 1]$ the greater the value of $S(\widetilde{A}, \widetilde{B})$, the higher similarity between two experts with respect to fuzzy numbers, $\widetilde{A}$ and $\widetilde{B}$. Accordingly, for two standard triangular fuzzy numbers, in the above equation, the Average of Agreement degree of experts ($AA(E_u)$) is calculated using Equation (6):

$$AA(E_u) = \frac{1}{m-1}\sum_{\substack{u \neq v \\ v=1}}^{J} S(\widetilde{R}_u, \widetilde{R}_v) \tag{6}$$

Step 3. The relative agreement (RA) degree of all experts ($RA(E_u)$) is calculated using Equation (7):

$$E_u(u = 1, 2, \ldots, M) \text{ as } RA(E_u) = \frac{AA(E_u)}{\sum_{u=1}^{m} AA(E_u)} \tag{7}$$

Step 4. The consensus coefficient (CC) degree of expert opinions ($CC(E_u)$), where $E_u(u = 1, 2, \ldots, M)$, is calculated using Equation (8):

$$CC(E_u) = \beta \times W(E_u) + (1-\beta) \times RA(E_u) \tag{8}$$

In Equation (8), coefficient $\beta(0 \leq \beta \leq 1)$ is referred to as a relaxation factor of the proposed method. Based on the cases of Hsu and Chen (1996), β is a critical factor to balance the RA degree and the degree of importance (weight) W of each expert. Since β indicates which is more critical between the $W(E_u)$ and $RA(E_u)$ assigned by the decision-maker, the value of β need to be predetermined by the decision-maker according to their preferences. The influence of expert agreement increases as β decreases. If $\beta = 0$, the weight factor of the experts is disregarded, assuming a homogeneous distribution among the experts. Conversely, when $\beta = 1$, it is assumed that the experts share the same consensus coefficient (CC) and weight importance. In this study, β is given a value of 0.5 [18,20,57].

Step 5. The weighted results of the opinions of M number of experts ($\widetilde{R}_{AG}$) are calculated using Equation (9) below:

$$\widetilde{R}_{AG} = CC(E_1) \times \widetilde{R}_1 + CC(E_2) \times \widetilde{R}_2 \ldots + CC(E_M) \times \widetilde{R}_M \tag{9}$$

After calculating the weighted results of expert opinions ($\widetilde{R}_{AG}$), it is necessary to perform defuzzification to obtain interpretable and measurable results. Transforming fuzzy numbers into clear, comprehensible values through defuzzification is critical for the decision-making process. If calculations are performed using triangular fuzzy numbers, the result will also be in the form of triangular fuzzy numbers. To fully understand the relationship among these values, a fuzzy number should be converted into a precise score, termed the "Fuzzy Probability Score" (FPS) [58,59]. The FPS for each condition is derived from a membership function calculated during the aggregation of expert opinions. Defuzzification methods include the mean of maximum membership method, centroid method, weighted average method, center of area method, and center of sums method [20,55,56,60]. In this study, the "center of area" method, which is widely used due to its simplicity and clarity, has been employed to calculate the fuzzy probability values for each condition [61–63]. The defuzzification equation (X^*) is presented below in Equation (10):

$$X^* = \frac{\int \mu_i(x)x\,dx}{\int \mu_i(x)\,dx} \tag{10}$$

The defuzzification process of triangular fuzzy numbers ($\widetilde{A}_1 = (a_1, a_2, a_3)$) can be described as follows (Equation (11)):

$$X = \frac{\int_{a_1}^{a_2} \frac{x-a_1}{a_2-a_1} x\,dx + \int_{a_2}^{a_3} \frac{a_3-x}{a_3-a_2} x\,dx}{\int_{a_1}^{a_2} \frac{x-a_1}{a_2-a_1} dx + \int_{a_2}^{a_3} \frac{a_3-x}{a_3-a_2} dx} = \frac{1}{3}(a_1 + a_2 + a_3) \tag{11}$$

After determining the probabilities for all conditions as described above, the probabilities for the narrow channel (Istanbul Strait) were entered into the Genie 4.1 Academic Bayes software, and the network was executed. In BN studies, the analytical validation of the developed network is the most critical condition to ensure that the results are consistent, reliable, and effective. A commonly used partial validation approach in the literature for BN validation, based on three axioms, is frequently preferred [11,44]. This study also employs this three-axiom-based method to validate the accident network. Three axioms provided by the network are presented below. These axioms have been tested for the presented case study as well and confirmed that the presented network meets the requirements of the axioms.

Axiom 1: Any slight increase or decrease in the probabilities of each parent node should result in a corresponding relative increase or decrease in the final probabilities of the child node.

Axiom 2: The impact of changes in the subjective probability distributions of each parent node on the child nodes should be continuous and consistent. In other words, for a parent node that positively influences a child node, an increase in the parent node's value will result in an increase in the child node's value, and a decrease in the parent node's value will result in a corresponding decrease in the child node's value. However, in cases where a parent node negatively influences a child node, an increase in the parent node's value will result in a decrease in the child node's value, and vice versa. This behavior reflects the logical dependencies encoded in the Bayesian Network, where causal relationships can either amplify or diminish the probabilities in the child nodes, depending on the nature of the influence (positive or negative). For example, if "poor visibility" (parent node) has a negative influence on "safe navigation" (child node), an increase in poor visibility will decrease the probability of "safe navigation", while a decrease in "poor visibility" will increase the likelihood of "safe navigation".

Axiom 3: The combined effect magnitudes of probability variations originating from any set of attributes "x" (evidence) should always be greater than those from "$x - y$" (where ($x \in y$)). In other words, the total effect magnitude of probability variations should always be greater than the impact of a single attribute (the individual effects of parent nodes).

Following the validation of the network, the accident network was presented to the consulted experts, who reviewed it through dynamic change analyses to ensure its functionality. As a result of this step, an accident network was developed that outlines the probabilities of collision, contact, grounding, and sinking for a vessel navigating through the Istanbul Strait, depending on existing conditions. This accident network can be used to support basic operational decisions by key decision-makers such as ship masters, marine traffic operators, and coastal safety personnel.

5. Results and Discussion

In the Istanbul Strait, 130 different nonconformities influencing the occurrence of 240 accidents have been identified, categorized into Operational Conditions (20) and Human and Organizational Factors (110). The total observed frequency (f) of these nonconformities is 3875. Among these, 2370 contributed to collisions, 644 to contact, 707 to groundings, and 154 to sinking incidents. When all accidents in the Istanbul Strait are evaluated, organizational influences (26.6%), unsafe acts (26.5%), and operational conditions (21.9%) were identified as the most frequently observed prevalent main tiers (categories) of HFACS-PV. When examining the first-level subcategories, violations (18.6%), substandard bridge team members (16.4%), external operational conditions (16.2%), and insufficient resource management (15.4%) are the most influential subcategories in accidents occurring in the Istanbul Strait (Table 5).

Table 5. Classification of nonconformities contributing to accident occurrence in the Istanbul Strait under the HFACS-PV framework.

Tier 1	Tier 2	Tier 3	Nonconformities	Collision	Contact	Grounding	Sinking
Organizational Influences	Resource Management	Human	Electronic navigation devices (ECDIS, RADAR, etc.)	1	0	3	0
			Vessel maneuvering characteristics	0	4	1	0
			Cargo operations (loading, stability, lashing, etc.)	0	0	0	3
			Steering control system	0	1	1	0
			Anchoring maneuver	96	15	8	2
			Anchor heaving up maneuver	8	1	2	0
			Supply at anchorage (Ship-to-Ship)	1	0	0	0
			Bridge Resource Management applications (navigation)	23	20	23	2
			Bridge Resource Management applications (at anchor)	74	10	4	1
			COLREG rules and application	31	3	0	1
			Emergency management (emergency actions, etc.)	3	10	10	1
			Emergency management (dragging anchor)	39	6	4	1
			Bridge team members unfamiliar with navigation area	0	3	4	0
			Master unfamiliar with navigation area	0	6	10	0
			Minimum safe manning levels	1	0	0	1
			Inappropriate crew assignment (incompetency, etc.)	1	0	0	0
		Equipment and Facility	Inadequate anchorage area capacity	114	16	13	4
			Fixed or floating navigation aids in port	1	0	0	0
			Bridge navigation devices (ECDIS, RADAR, etc.)	0	1	1	2
			Bridge ergonomic design (blind sectors)	1	0	0	0
			Bridge navigation equipment layout (ECDIS, etc.)	2	0	1	0
	Organizational Climate	Structure	Lack of communication and coordination	0	0	0	0
			Deficiencies in command chain	0	0	0	0
			Shortcomings in authority distribution	0	0	0	0
		Policies	Promotion and advancement	0	0	0	0
			Shortcomings in drug and alcohol policy	0	0	0	0
		Culture	Weak safety culture among crew members	1	1	0	0
			Time pressure imposed by shipping company	2	1	1	0
			Management and oversight deficiencies by shipping company	0	0	0	0

Table 5. *Cont.*

Tier 1	Tier 2	Tier 3	Nonconformities	Collision	Contact	Grounding	Sinking
Organizational Influences	Organizational Process	Operation Management	Improper maneuvering management—anchorage	110	17	11	3
			Improper voyage management—ship	27	17	21	2
			Improper maneuvering management—port	1	0	1	0
		Legal Shortcomings	Watchkeeping system and schedule	5	0	0	0
			Anchor watch	4	0	0	0
			Planned maintenance rules	0	0	0	0
		Oversight	Pre-voyage risk assessment	5	0	0	1
			Risk assessment prior to narrow channel passage	19	18	16	1
			Risk assessment prior to anchoring	92	15	11	2
			Risk assessment prior to anchor heaving up maneuver	14	1	2	0
			Arrival risk assessment (port)	3	3	0	0
			Insufficient pre-maneuver navigation equipment checks	1	0	0	0
			Neglect of weather forecasts	0	1	1	5
Unsafe Supervision		Insufficient Supervision	Tests and controls—bridge navigation devices	1	4	5	1
			Tests and controls—main engine control panel	1	4	5	0
			Internal audit deficiency—voyage plan	5	1	3	6
			Internal audit deficiency—competency of watchkeeping officer	1	0	0	0
			Internal audit deficiency—pilot maneuver commands	1	5	4	0
			External audit deficiency—company audits	0	1	0	4
			Bridge alarm panel	0	0	1	0
			Routine maintenance of main engine	1	4	5	0
		Planned Inappropriate Operations	Voyage plan	30	18	19	7
			Watchkeeping—navigation watch	28	6	9	2
			Watchkeeping—restricted visibility	1	0	0	0
			Strait passage—without pilot	1	0	0	0
			Berthing maneuver	0	2	0	0
			Anchoring operation	94	16	11	2
			Anchorage area change	1	0	0	0
			Heaving up anchorage	18	1	2	0
		Failure to Correct a Known Problem	Uncharted shallow area	0	0	1	0

Table 5. *Cont.*

Tier 1	Tier 2	Tier 3	Nonconformities	Collision	Contact	Grounding	Sinking
Preconditions for Unsafe Acts	Substandard Team Members	Substandard Conditions of Team Members	Situational awareness deficiency—bridge team members	28	6	4	1
			Situational awareness deficiency—master	1	1	8	0
			Overconfidence—bridge team members	3	0	3	1
			Overconfidence—master	0	0	1	0
			Lack of Attention	29	6	10	1
			Physical fatigue	0	0	0	0
			Excessive workload	0	0	0	0
			Watchkeeping during night shift	84	23	23	3
		Substandard Practices of Team Members	Lack of bridge resource management	107	13	21	3
			Emergency management failure—engine failure	1	4	5	0
			Emergency management failure—emergency steering	1	4	5	1
			Ship-to-ship communication failure	17	2	0	0
			Ship-to-ship (language barrier issue)	0	0	0	1
			Ship-to-port control (communication not established)	134	32	35	4
			Ship-to-port control (language barrier issue)	3	0	2	0
			Master-pilot coordination	0	0	3	0
	Technology and Interface Malfunctions	Malfunctions in Electronic Navigation Aids	Bridge electronic navigation devices (ECDIS, RADAR, etc.)	0	0	0	0
		Interface Malfunctions	Coordinate system (GPS, ECDIS, etc.)	0	0	0	0
			Connection issues among navigation devices	0	0	0	0
			Erroneous data (GPS, ECDIS, RADAR, etc.)	0	0	0	0
Unsafe Acts	Errors	Skill Based	Ineffective use of electronic navigation aids	4	0	0	0
			Incorrect loading and stability calculation	0	0	0	1
			Insufficient lashing	0	0	0	2
		Decision Based	Improper maneuver—master (emergency anchoring)	1	3	4	0
			Improper maneuver—master	23	13	18	2
			Improper maneuver—officer	1	0	0	0
			Improper maneuver—pilot	1	5	4	0
			Delayed maneuver—master	6	0	0	0
			Inadequate maneuvering (rudder angle, deceleration, etc.)	12	3	0	1
			Improper route selection	0	0	1	0
			Improper anchoring maneuver (anchor drop)	50	11	8	1

Table 5. *Cont.*

Tier 1	Tier 2	Tier 3	Nonconformities	Collision	Contact	Grounding	Sinking
Unsafe Acts	Errors	Decision Based	Improper weighing anchor maneuver	14	1	1	0
			Navigation in storm conditions	3	0	0	0
			Operating beyond vessel design limits	0	1	1	5
			Cargo shifting or improper stability	0	0	0	2
			Master notifies port control late (drifting)	0	0	1	0
			Improper anchor site selection (dragging anchor)	42	5	5	1
		Perceptual Based	Failure to detect collision risk	25	1	0	1
			Failure to detect grounding risk	0	2	14	0
			Delayed detection of water ingress (sinking risk)	0	1	0	1
			Misinterpretation of depth data (unawareness shallow area)	0	1	0	0
			Auditory lookout—VHF	3	0	3	0
	Violations	Regulation	COLREG Rule 2 (Responsibility in Collision Risk)	8	0	0	0
			COLREG Rule 5 (Lookout)	44	9	15	2
			COLREG Rule 6 (Safe Speed)	0	1	3	0
			COLREG Rule 8 (Collision Avoidance Maneuver)	39	4	1	2
			COLREG Rule 10 (Traffic Separation Scheme)	23	4	1	1
			COLREG Rule 15 (Crossing Situations)	1	0	0	0
			COLREG Rule 19 (Vessels in Restricted Visibility)	1	0	0	0
			COLREG Rule 22 (Visibility of Lights)	4	0	0	1
			COLREG Rule 34 (Maneuver and Warning Signals)	2	0	0	0
			COLREG Rule 35 (Sound Signals in Restricted Visibility)	1	0	0	0
			Anchor watch (STCW)	63	12	6	2
			Navigation watch (STCW)	14	8	8	0
			Unmanned bridge (STCW)	4	0	0	1
			Local legislation (Turkish Straits Traffic Arrangement)	1	0	0	0
		Procedure	Company procedures—routine position checks	136	34	38	4
			Company procedures—routine mooring line checks	0	1	0	0
			Company procedures—safe anchoring (SMS)	102	16	12	2
			Company procedures—heaving up anchor in rough sea	5	0	1	0
			Company procedures—safe passage in narrow waterways	23	18	16	6
			Steering control system—emergency steering	1	5	4	1
		Abuse of Authority	Ignoring port control warnings	0	0	0	0
			Incorrect/incomplete information—pilot	0	0	0	0
			Incorrect/incomplete information—port control	0	0	1	1
			Alarm deactivation—ECDIS, Echo Sounder	0	0	2	0
			Volume reduction—VHF Radio	3	0	2	0

Table 5. *Cont.*

Tier 1	Tier 2	Tier 3	Nonconformities	Collision	Contact	Grounding	Sinking
Operational Conditions	External Conditions	Weather Conditions	Nighttime	95	24	28	5
			Sun reflection (sea surface)	0	0	0	0
			Strong currents	7	4	7	0
			Rough sea conditions	33	5	9	6
			Strong winds	4	1	1	0
		Local Restrictions	Port	3	5	0	0
			Coastal waters	0	0	0	1
			Anchorage area (crowded)	114	17	16	4
			Narrow waterway/channel	27	21	26	5
			Heavy traffic	15	12	11	1
			Shallow area	0	4	42	1
			Sharp turn	3	10	9	1
			Restricted maneuvering space	17	16	14	1
	Internal Conditions	Nonconformities and Failures	Engine malfunction	1	4	5	0
			Steering malfunction	1	4	5	1
			Power loss	2	2	2	0
			Rope cutting	0	1	0	0
		Vessel Structure	Inland vessel (river type)	0	0	1	9
			Old vessel (age $\geq$ 20)	117	31	27	8
			Worn hull structure	0	1	0	2

To illustrate how each HFACS-PV level affects different types of accidents in the Istanbul Strait and how these levels interact with one another, the HFACS-PV nonconformities and their observed frequencies, derived from accident report analyses, are presented in Table 5. Nonconformities with an observed frequency of zero are included in the tables to serve as a reference for future HFACS-PV practitioners.

In this study, as the second phase of validation, a total of 19 pilots, ship masters, and VTS operators working in the Istanbul Strait were asked to evaluate and comment on the effect of each operational condition identified in the study on accidents. Based on the experts' comments, the Operational Conditions affecting accidents in narrow waterways are presented in Table 6. The table indicates the number of interviewed experts who considered each operational condition a contributing factor to accidents in the Istanbul Strait.

After categorizing the nonconformities leading to accidents under the HFACS-PV framework for each type of accident, the overall structure of the network and its underlying nodes are explained below according to the HFACS-PV levels.

5.1. Nodes Under the Level of Organizational Influences and Their Relationship to Accidents

Nonconformities under the level of Organizational Influences encompass failures in high-level managerial activities. Deficiencies and shortcomings at the organizational level directly impact the emergence of nonconformities at the Unsafe Supervision level. These are often inadequacies that are not readily detectable in accidents, requiring in-depth analysis and interpretation. Within the BN structure, nodes under the Organizational Influences level include Familiarity with the Vessel, Familiarity with the Navigation Area, Personal

Education and Training, Safety Culture, Quality of Equipment and Facilities, Availability of Equipment and Facilities, Ergonomic Design, Company's Manning Strategy, Personnel Assignment, Procedures and Regulations, Review and Control, Port and Company Pressure, and Equipment and Facility Resources (Figure 3, Table 7). The nonconformities under each node and their relationships with other nodes are presented below.

Table 6. Experts' opinions on the study findings.

Operational Conditions	Expert Opinions (N = 19)		
	Effect	No Opinion	Not Effect
Ship's age	17	0	2
Ship's length	16	0	3
Ship's type	15	1	3
Status of the day	17	0	2
Ship's speed	19	0	0
Ship's draught	14	2	3
Wind direction	19	0	0
Wind speed	19	0	0
Current's set	19	0	0
Current's drift	19	0	0
Master's number of passage transits	10	0	9
Narrowest part of the channel	7	3	9
Sharpest turn along the channel	10	2	7
Local traffic	19	0	0
Existence of shore lights	16	0	3
Anchorage area capacity	6	5	8

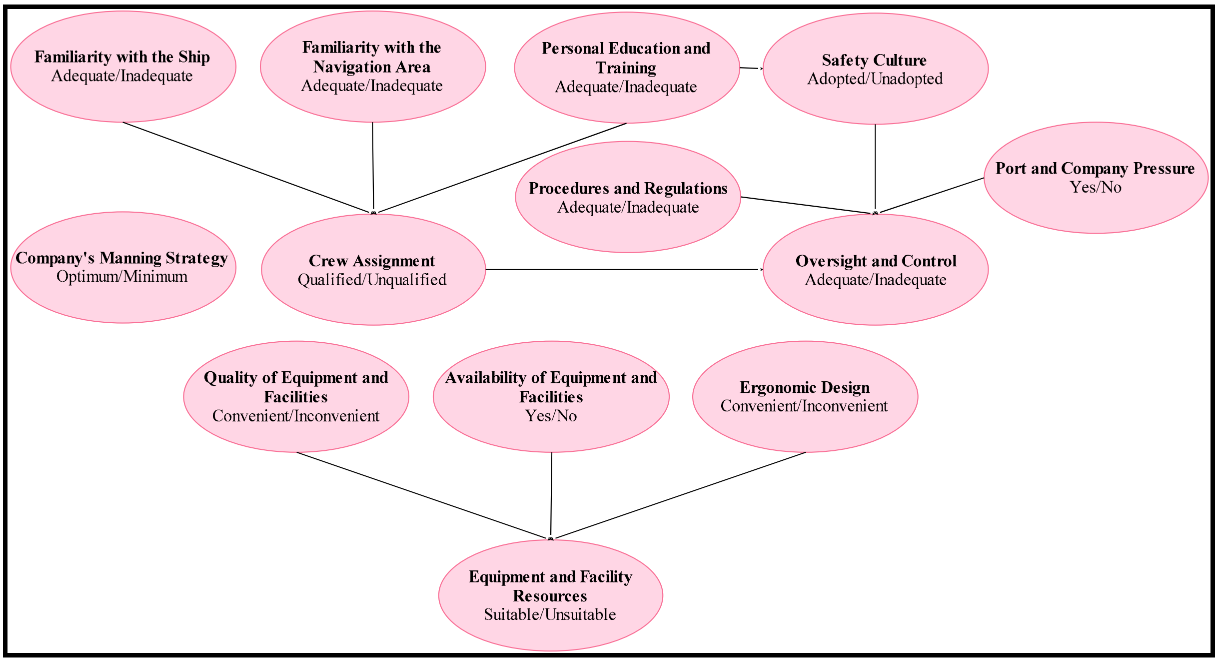

Figure 3. Bayesian Network structure at the Organizational Influences level.

Table 7. Nodes at the Organizational Influences level, their abbreviations, and parent nodes.

Node (Abbreviation)	Nonconformities Under the Node	Negative State	Parent
Familiarity with the Ship (FS)	Electronic navigation devices (ECDIS, Radar, GPS, Autopilot, Gyroscope, etc.), Ship's maneuvering characteristics, Steering control system, Cargo operations, Propeller type, Engine personnel's familiarity with engine room equipment	Inadequate	No
Familiarity with the Navigation Area (FNA)	Master, bridge team members and pilot unfamiliar with navigation area	Inadequate	No
Personal Education and Training (PET)	Anchoring maneuvers, Bridge resource management practices (At anchor, Underway), Emergency management (Anchor dragging, Emergency actions, steering lock, engine failure, power loss, etc.), COLREGs and their implementation, Mooring maneuvers, Resupplying at anchor (Ship-to-Ship)	Inadequate	No
Safety Culture (SC)	Weak safety culture among ship personnel/Company, Inadequate environment for effective use of bridge navigation equipment, Irregular watchkeeping system	Unadopted	PET
Quality of Equipment and Facilities (QEF)	Fixed or floating navigational aids in port, Bridge navigation devices (ECDIS, Radar, Depth sounder, Steering control system, etc.), Visual and auditory systems (Screens and sound devices), Maneuvering equipment (Backup rope, etc.)	Inadequate	No
Availability of Equipment and Facilities (AEF)	Anchorage area capacity (insufficient), Pilotage Service, Bridge publications (charts, books, etc.), Bridge navigation equipment (ECDIS, Radar, AIS, Depth sounder, etc.), Vessel Traffic Services equipment, Fixed or floating navigational aids in port	No	No
Ergonomic Design (ED)	Layout of bridge navigation equipment (ECDIS, Radar, AIS, Depth sounder, etc.), Bridge Ergonomic Design (Blind sectors, Overall, sound insulation, etc.)	Inadequate	No
Company's Manning Strategy (CMS)	Company's minimum manning policy, Suboptimal manning relative to ship and voyage intensity	Minimum	No
Crew Assignment (PA)	Minimum safe manning levels, Inappropriate personnel assignment	Unqualified	FS, FNA, PET
Procedures and Regulations (PR)	Watchkeeping system, Logging of anchor watches, Shift handovers, User manuals (Bridge maneuvering console), Navigation safety (restricted waters, cell phone use, etc.), Bridge introduction and familiarity procedures (For new joiners), Action instructions for emergencies, Voyage planning instructions, Fatigue management, User manuals (Navigation devices on the bridge), Maneuvering instructions, Risk assessment procedures, Standardization (Master's night/day orders, operational doctrines, etc.), Certification, Flag State's manning standards, Rules related to planned maintenance	Inadequate	No
Oversight and Control (OC)	Risk assessment before anchoring, Risk assessment before navigating narrow channels, Risk assessment before mooring maneuvers, Risk assessment before voyage, Risk assessment upon arrival (Port), Inadequate checking of navigation equipment before maneuvers, Risk assessment upon departure (Port), Ignoring weather forecasts, Ignoring navigation safety bulletins	Inadequate	SC, PR, CA, PCP

Table 7. *Cont.*

Node (Abbreviation)	Nonconformities Under the Node	Negative State	Parent
Port and Company Pressure (PCP)	Company's time pressure on the fleet, Port's departure pressure on ships	Yes	No
Equipment and Facility Resources (EFR)	Inadequacies related to the availability, quality, and design of equipment and facilities on board or in port	Unsuitable	QEF, AEF, ED

5.2. Nodes Under the Level of Unsafe Supervision and Their Relationship to Accidents

The role of any regulatory authority is to provide operational-level professionals with the opportunity to succeed. Unfortunately, this is not always possible. In a successful organization, professional guidance and supervision mechanisms are essential to achieve this. The Unsafe Supervision level in the BN structure includes the nodes of Voyage Planning, Watch Planning, Hours of Work and Rest, Maneuver and Operation Planning, Planned Maintenance, Monitoring of Seafarers' Performance and Quality Standards, Tests and Monitoring, Internal and External Audits, and Correcting a Known Problem. The nonconformities under each node and their relationships with other nodes are presented below (Figure 4, Table 8).

Table 8. Nodes at the Unsafe Supervision level, their abbreviations, and parent nodes.

Node (Abbreviation)	Nonconformities Under the Node	Negative State	Parent
Voyage Planning (VP)	Inadequate voyage planning, lack of plan, inappropriate strait passage without pilot assistance	Unsafe	CA, PR, OC
Watch Planning (WP)	Lookout—Navigation watch/restricted visibility, inappropriate assignment of bridge team members according to type of navigation	Unsafe	CMS, OC
Hours of Work and Rest (HWR)	Noncompliant working and rest hours	Inconvenient	CMS, PCP
Maneuver and Operation Planning (MOP)	Anchorage operations, departure from anchor, berthing maneuvers, refueling at anchor, inadequate pilot, tug, or VTS support, maneuver without tug, departure maneuver, ballast operations, towing operations	Unsafe	EFR, CA, OC
Planned Maintenance (PM)	Main engine, main engine control panel, bridge navigation devices (ECDIS, radar, depth gauge, steering control system, etc.)	Inadequate	OC, CA, EFR, IEA
Monitoring of Seafarers' Performance and Quality Standards (MSPQ)	Lack of monitoring of the competency of navigation officers on watch, lack of monitoring of competency of bridge team members on watch	Inadequate	CA, OC, IEA
Tests and Monitoring (TM)	Bridge navigation devices (ECDIS, radar, depth gauge, steering control system, etc.), main engine control panel, bridge alarm panel, engine alarm panel	Inadequate	CA, PR, OC
Correcting a Known Problem (CKP)	Uncharted shoals, unmarked buoy system changes on charts, unlit beacons/buoys in navigation area, incorrect harbor depth markers, incorrect troubleshooting of failures	Unsuccessful	EFR, IEA
Internal and External Audits (IEA)	Lack of internal audits—voyage planning, lack of external audits—company audits, lack of external audits—port/flag state inspections, etc.	Inadequate	CA, OC

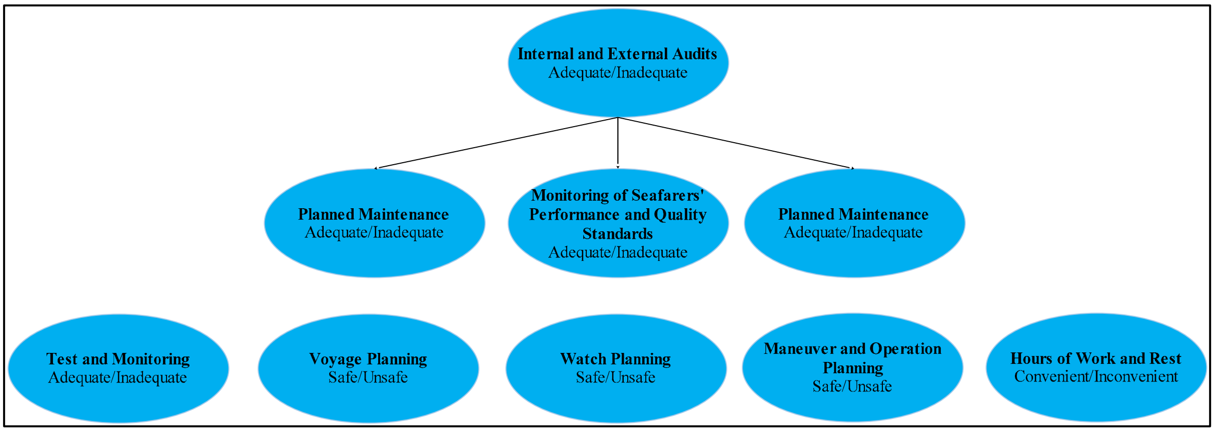

Figure 4. Bayesian Network structure at the Unsafe Supervision level.

5.3. Nodes Under the Level of Preconditions for Unsafe Acts and Their Relationship to Accidents

The nodes under the level of Preconditions for Unsafe Acts create a foundation for the occurrence of unsafe acts. The significance of this structure in accident causation has been highlighted by many researchers [34,64,65]. In the BN structure, the Preconditions for Unsafe Acts level includes nodes such as Confidence in Devices and Self, Situational Awareness, Fatigue, Stress, Engagement in Other Tasks, Workload, Drug, Alcohol and Medication Effect, Management, Leadership and Guidance, Communication and Coordination, and Technology and Interface Failures. The nonconformities under each node and their relationships with other nodes are presented in Figure 5 and Table 9.

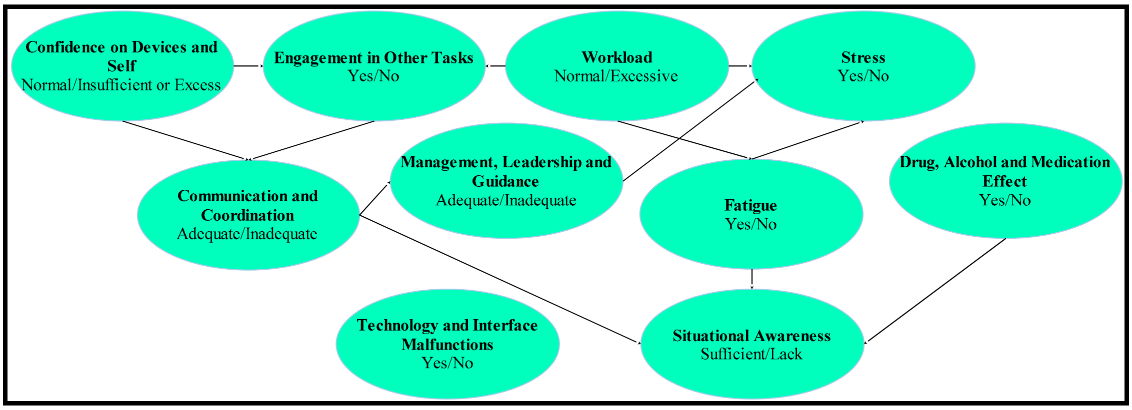

Figure 5. Bayesian Network structure at the Preconditions for Unsafe Acts level.

5.4. Nodes Under the Level of Unsafe Acts and Their Relationship to Accidents

The nodes under the level of Unsafe Acts are the active errors made by bridge and engine room team members that result in accidents. They arise from the accumulation of latent errors from the previous three levels (Organizational Influences, Unsafe Supervision, and Preconditions for Unsafe Acts) in an orderly manner. These actions may directly lead to an accident or cause it indirectly through the interaction of various factors. They encompass inappropriate and erroneous behaviors performed by team members. Since they are clearly observable in accident causation, maritime accident reports published by most organizations contain detailed information on Unsafe Acts.

Table 9. Nodes at the Preconditions for Unsafe Acts level, their abbreviations, and parent nodes.

Node (Abbreviation)	Nonconformities Under the Node	Negative State	Parent
Confidence on Devices and Self (CDS)	Overconfidence—Bridge team members, Master, Navigation officer; Lack of self-confidence—Master, Navigation officer; Overconfidence in electronic navigation equipment	Insufficient/Excessive	VP, MSPQ, MOP
Situational Awareness (SA)	Lack of attention; Lack of situational awareness—Bridge team members; Lack of situational awareness—Engine room team members; Lack of situational awareness—VTS operator; Lookout on night watch	Lack	F, S, DAME, CC
Fatigue (F)	Physical fatigue—Master, Navigation officer, Pilot; Sleep deprivation—Bridge team members	Present	WL, ÇDS
Stress (S)	Working under stress	Present	WL, MLG
Engagement in Other Tasks (EOT)	Navigation officer engaged with mobile phone, laptop, etc.	Present	WL, CKG, MSPQ
Workload (WL)	Excessive workload—Master, Navigation officer, Pilot; Excessive workload—VTS operator	Excessive	VP, MOP, HWR, WL
Drug, Alcohol, and Medication Effect (DAME)	Vessel operated under the influence of drugs/medication—Master, Navigation officer; Vessel operated under alcohol influence—Master, Navigation officer; Medical illness	Present	MSPQ, IEA
Management, Leadership, and Guidance (MLG)	Lack of bridge resource management; Failure in emergency management—Main engine/rudder failure, Power loss; Lack of Master's authority; Misguidance—Vessel Traffic Services; Misguidance—Pilot/Master's management inadequacy; Inadequate pre-voyage briefing	Insufficient	VP, CC, MSPQ, CKP
Communication and Coordination (CC)	Ship—VTS; Master—Pilot; Ship—Ship; Bridge—Engine room; Among bridge team members; Master—Navigation officer; Navigation officer—Lookout; Pilot—Tugboat	Absent	CDS, EOT
Technology and Interface Malfunctions (TIM)	Bridge electronic navigation devices (ECDIS, Radar, AIS, etc.); VHF radio; Navtex; Coordinate system (GPS, ECDIS, etc.); Inter-device connectivity issues (GPS, ECDIS, Radar, etc.); Erroneous data (GPS, ECDIS, Radar, etc.)	Present	TM

In the BN structure, the Unsafe Acts level includes the nodes of Skill Based Errors, Perceptual Errors, Decision Based Errors, Violations, and Triggering Unsafe Acts (Figure 6, Table 10). Skill Based Errors include mistakes made due to the inadequacy of individuals' cognitive, emotional, and psychomotor skills. While Skill Based Errors can directly lead to accidents, they often provide a foundation for the occurrence of perceptual errors. Perceptual errors play an active role in maritime accident causation by causing mistakes in the decision-making process of vessel operators.

5.5. Nodes Under the Level of Operational Conditions and Their Relationship to Accidents

The nodes under the level of Operational Conditions include environmental conditions that play a complementary role for the unsafe acts of bridge and engine room team members to result in accidents. When Operational Conditions combine with triggering unsafe acts, an accident becomes difficult to avoid. These are divided into Internal Conditions and External Conditions. By considering these factors in their decision-making process, team members can prevent accidents.

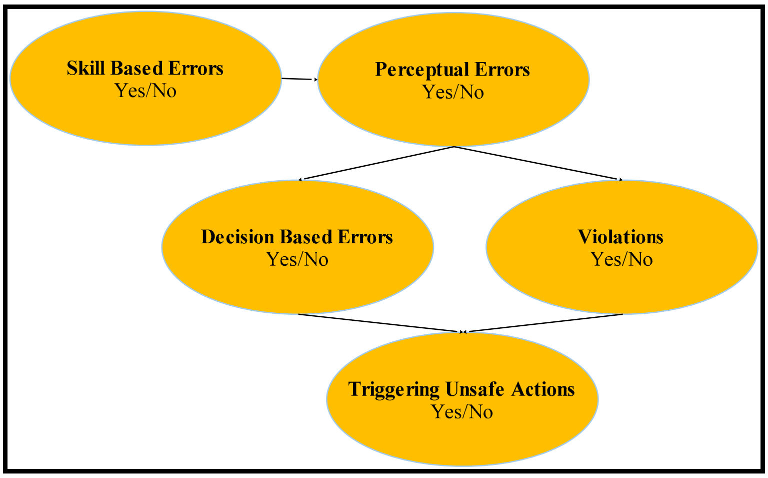

Figure 6. Bayesian Network structure at the Unsafe Acts level.

Table 10. Nodes at the Unsafe Acts level, their abbreviations, and parent nodes.

Node (Abbreviation)	Nonconformities Under the Node	Negative State	Parent
Skill Based Errors (SBE)	Inability of bridge team members to effectively use electronic navigation aids (GPS, ECDIS, Radar, AIS, etc.); Inadequate lashing; Incorrect loading and stability calculations; Inability to effectively use the engine control panel (Master); Failure to follow course; Inability of bridge team members to effectively use maneuvering consoles (main engine, bow thruster, propeller, rudder control system, etc.); Inability to use synchronized mode for propellers (Master); Ineffective use of rudder modes (tracked, untracked) (Watch Officer); Incorrect tide calculation by bridge team members; Incorrect use of ballast system	Present	SA, MLG
Perceptual Errors (PE)	Failure to detect risk of collision; Auditory lookout—VHF; Failure to detect risk of grounding; Late detection of water ingress in vessel (sinking risk); Misinterpretation of depth data (unawareness of shallow areas); Inability to understand intentions of target vessel; Inability to assess effects of wind and current; Misinterpretation of navigation data (ECDIS, AIS, GPS, Radar, etc.); Failure to notice or delayed detection of issues (ECDIS, AIS, GPS, Radar, etc.); Position (ECDIS, AIS, GPS, Radar, etc.); Distance measurement—inter-vessel distance; Course and rudder angle—rudder control system; Navigation warnings—Navtex	Present	TIM, CC, SA, SBE
Decision Based Errors (DBE)	Inappropriate anchoring maneuver (dropping anchor); Selection of unsuitable anchorage area (dragging); Incorrect maneuver—Master, Pilot, Officer; Improper anchor retrieval maneuver (weighing anchor); Insufficient maneuvering (rudder angle, speed reduction, speed increase, etc.); Delayed maneuver—Master, Pilot, Officer; Operating the vessel beyond design limits; Inappropriate course selection; Cargo shift or improper stability; Delayed maneuver—Pilot; Deviating from planned route; Departure from port in adverse weather and sea conditions; Ignoring pilot recommendations by Master	Present	MLG, SA, PE

Table 10. *Cont.*

Node (Abbreviation)	Nonconformities Under the Node	Negative State	Parent
Violations (V)	COLREG Rules; Navigation and anchor watch (STCW); Local regulations (passage regulations and codes); Watch handover (STCW); Working and rest hours (ILO); Company procedures—Routine checks on vessel position; Company procedures—Safe anchorage (SMS); Company procedures—Safe passage through narrow waterways (SMS); Company procedures—Anchor retrieval in heavy sea conditions; Company policy—Alcohol; Master's standing orders; Unused devices (ECDIS, AIS, Radar, BNWAS, Depth sounder, etc.); Volume reduction—VHF radio; Incorrect/missing information—VTS, Pilot; Alarm deactivation—ECDIS, Depth sounder, Radar, Rudder control; Ignoring VTS warning; Deviation from safe route for demonstration purposes	Present	MLG, PE
Triggering Unsafe Act (TUA)	Decision errors, perceptual errors, skill errors, and violations committed by individuals	Present	DBE, V

In the BN structure, the Operational Conditions level includes the nodes of Nonconformities and Failures Preventing Ship's Motion, Ship's Age, Visibility, External Conditions Effecting Ship's Motion, Day Status, Weather, Sea and Visibility, Locational Restrictions, Type of Navigation, Ship's Type, Ship's Length, VTS Sector, Traffic Density, Local Traffic, Transit Traffic, and Port Traffic (Figure 7 and Table 11).

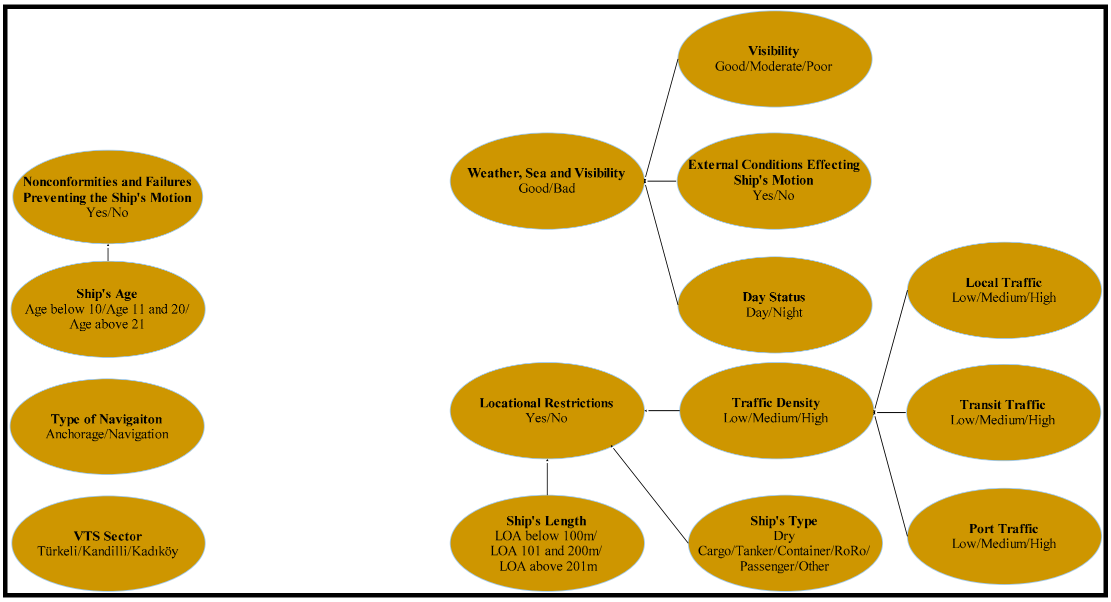

Figure 7. Bayesian Network structure at the Operational Conditions level.

5.6. *Accident Types Nodes*

This level includes the nodes of Collision, Contact, Grounding, and Sinking that occur as a result of nonconformities in HFACS-PV. This is not a level within HFACS-PV, and no nonconformities are listed under these nodes (Figure 8 and Table 12).

Table 11. Nodes at the Operational Conditions level, their abbreviations, and parent nodes.

Node (Abbreviation)	Nonconformities Under the Node	Negative State	Parent
Nonconformities and Failures Preventing Ship's Motion (NFPSM)	Power loss, Engine failure, Rudder failure, Rope cutting, Controllable pitch propeller failure, Bow-Stern thruster failure	Yes	ShA, PM
Ship's Age (ShA)	Aged ship (age $\geq$ 21), Worn hull structure	-	No
Visibility (Vsb)	Conditions affecting visibility such as night, fog, rain, sun glare (sea surface)	Poor	No
External Conditions Effecting Ship's Motion (ECESM)	Severe sea conditions, Strong current, High wind, Icing, Tides (Current)	Yes	No
Day Status (DS)	Negative conditions due to shore lighting and other vessel lights at night	Night	No
Weather, Sea, and Visibility (WSV)	Negative conditions due to weather and sea conditions	Bad	Vsb, ECESM, DS
Locational Restrictions (LR)	Conditions depending on the navigation type and the VTS Sector	Present	TD, ST, SL
Type of Navigation (TN)	Anchorage area (crowded), Narrow waterway channel, Port, Coastal waters, Open sea	-	No
VTS Sector (VTSS)	Negative conditions within the VTS Sector due to restricted maneuvering areas, heavy traffic, sharp turns, and shallow areas	-	No
Ship's Type (ST)	Dry cargo, Tanker, Container, RoRo, Passenger, Other, Inland ship (river type ship)	-	No
Ship's Length (SL)	Negative conditions due to long and wide ship and narrow channel width	-	No
Traffic Density (TD)	High general traffic density due to local traffic, transit traffic, and port traffic	High	LT, TT, PT
Local Traffic (LT)	High local traffic density in the area	High	No
Transit Traffic (TT)	High transit traffic density in the area	High	No
Port Traffic (PT)	High port traffic density in the area	High	No

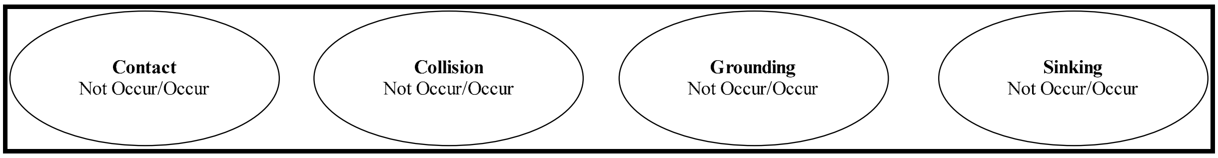

Figure 8. Bayesian Network structure of accident types.

Table 12. Nodes at the accident types level, their abbreviations, and parent nodes.

Node (Abbreviation)	Nonconformities Under the Node	Negative State	Parent
Contact (Cnt)	Contact accident	Occurred	TUA, VTSS, TN, NFPSM, LR, WSV
Collision (Cll)	Collision accident	Occurred	TUA, VTSS, TN, NFPSM, LR, WSV
Grounding (Grd)	Grounding accident	Occurred	TUA, VTSS, TN, NFPSM, LR, WSV
Sinking (Snk)	Sinking accident	Occurred	TUA, VTSS, TN, NFPSM, LR, WSV

6. Dynamic Network Model Predicting Accidents in Istanbul Strait

The network developed in this study systematically maps the underlying causes and influences on maritime safety through the HFACS-PV framework and fuzzy-Bayesian Network, encompassing 56 nodes distributed across five main tiers: Organizational Influences, Unsafe Supervision, Preconditions for Unsafe Acts, Unsafe Acts, and Operational Conditions. This network helps the users make predictions and accurate decisions. Each tier is carefully coded by color, providing a structured and visually accessible representation of the factors that contribute to maritime incidents (Figure 9).

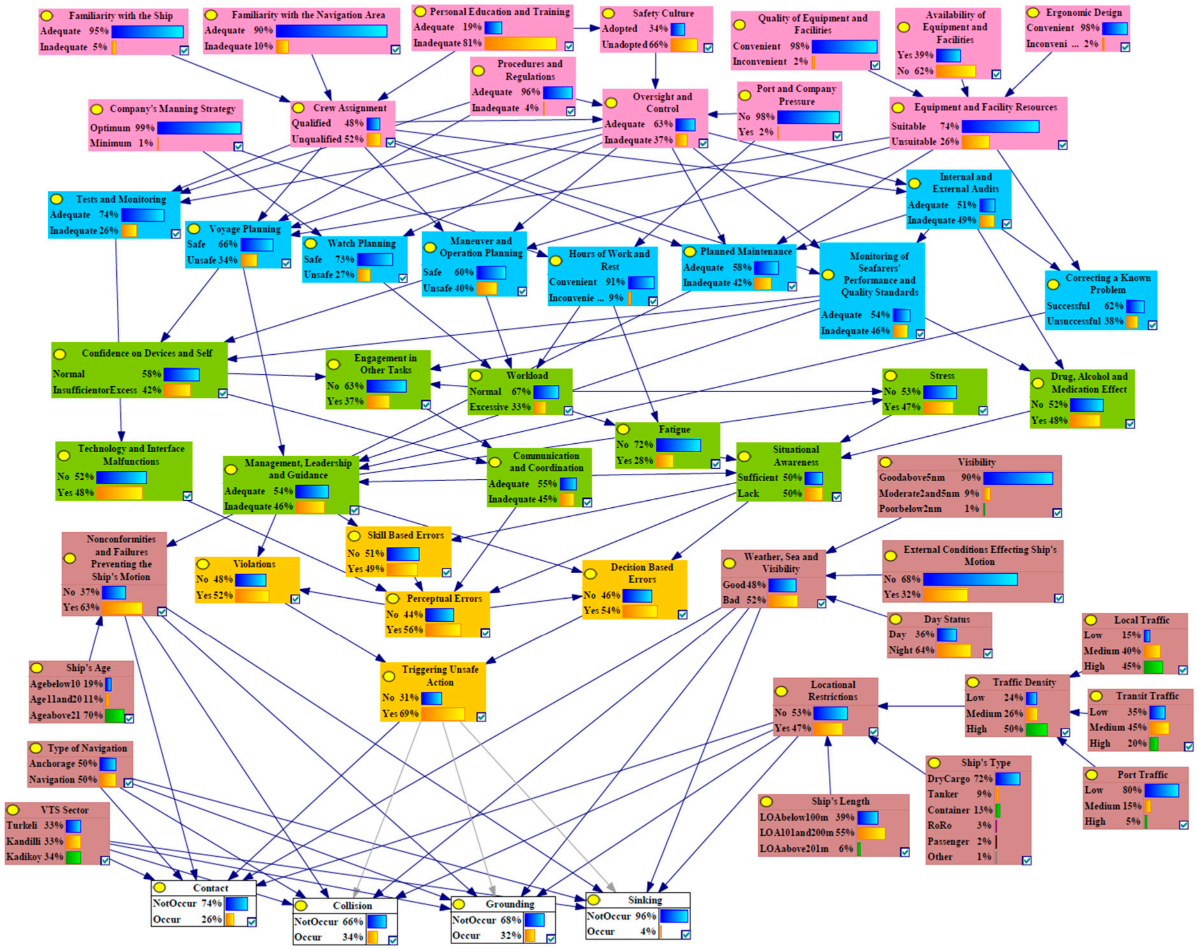

Figure 9. Istanbul Strait Dynamic Bayesian Network.

The Organizational Influences tier (Pink), comprising 13 nodes, includes elements related to company policies, crew management strategies, ergonomic design, and equipment quality. This layer highlights how organizational decisions shape the overall safety culture and operational environment.

The Unsafe Supervision tier (Blue) includes nine nodes focusing on aspects of supervisory oversight, such as voyage and watch planning, monitoring, and corrective actions. These supervisory actions are crucial as they bridge organizational intentions and on-the-ground operations.

Preconditions for Unsafe Acts is the most extensive tier (Green), with 10 nodes that address situational and human factors, including management and leadership activities, technology and interface malfunctions, workload, fatigue, and conditions impacting crew performance. This tier emphasizes the personal and situational preconditions that set the stage for potential safety risks.

The Unsafe Acts tier (Yellow), with four nodes, pinpoints specific errors in actions and decisions made during operations. This category includes violations, decision-based errors, skill-based errors, and perceptual mistakes, directly addressing unsafe behaviors (triggering events) at the operational level.

Finally, the Operational Conditions tier (Brown) includes 15 nodes that outline external factors, such as weather, traffic density, and visibility, which significantly affect navigational safety and crew performance. Additionally, internal factors such as non-conformities and failures preventing ship's motion and ship's age are included in this tier which play an important role in accident occurrence patterns.

This network framework serves as a comprehensive tool for visualizing and analyzing the relationships between organizational influences and operational outcomes. By clearly delineating the causal pathways across these categories, the network provides an evidence-based foundation for understanding the root causes of maritime incidents and identifying critical areas for targeted intervention and safety enhancement in the maritime sector.

7. Application of Dynamic Accident Network Model on Case Studies

In the case study, an accident occurrence prediction was conducted for a dry cargo vessel planned to transit the Istanbul Strait. The Istanbul Strait consists of three sectors from south to north: Sector Kadikoy, Sector Kandilli, and Sector Turkeli (Figure 10). Vessels aiming to transit from the Sea of Marmara to the Black Sea complete their passage through these three sectors. This case study aims to identify the accident probabilities that the planned vessel may encounter during navigation and anchoring in the three sectors of the Istanbul Strait. Because the network was based solely on previous accidents that had already occurred, the initial network also produced high probabilities (30–40%). Consequently, the tested worst-case scenario understandably resulted in high probabilities. The narrow nature of the Istanbul Strait and the existence of hazardous environmental conditions are also effective on those high probabilities. In fact, in the presence of bad environmental conditions in the Istanbul Strait, old ships without pilots and tugboats sail with high accident risk. Many accidents and near-accidents occur every year. Mostly these incidents are prevented by coastal safety and ship rescue efforts. These interventions cause high costs for both coastal safety and the shipping company. Therefore, a probability value of 60% or higher has been defined as a high-risk transit.

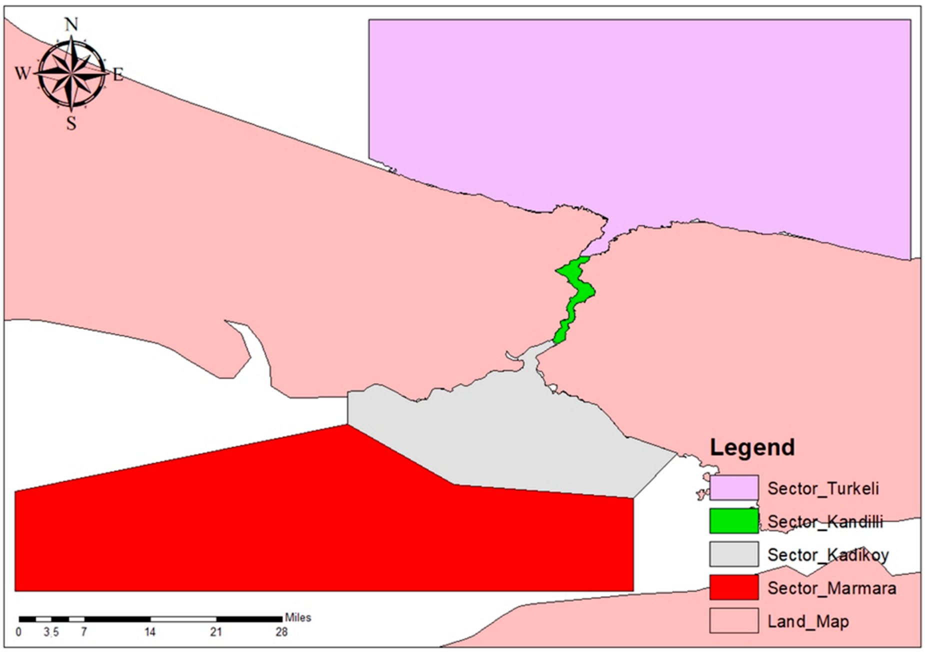

Figure 10. Map of Istanbul Strait and sectors.

Anchorage areas within the strait are available in Sector Turkeli and Sector Kadikoy. Vessels awaiting permission to transit may choose to anchor in these designated areas.

In the accident network, the probabilities for nodes related to human and organizational factors were obtained from accident data and expert opinions and were held constant across all scenarios. Information related to the transiting vessel and environmental conditions is provided below:

Ship's type: Dry cargo
Ship's length: 155 m
Ship's age: 22 years
Transit time: 18:30 (night)
Visibility: 6 miles
Wind and sea condition: Beaufort scale 4, Douglas scale 3
Current: Surface current from north to south with a maximum speed of 4 knots
Local traffic density: High
Transit traffic: Moderate
Port traffic: Low

In this section, accident probability predictions based on vessel characteristics and environmental conditions (operational conditions) are conducted for an example scenario in the Istanbul Strait using the dynamic accident network proposed in this study. Following the predictions, recommendations are provided regarding the actions necessary to ensure the vessel's safe passage. An analysis will be conducted on the accident probability that a dry cargo vessel with the above internal and external operational conditions may encounter during transit.

Initially, the scenario data were input into the accident network created based on maritime accident data for the Istanbul Strait. For this purpose, the Genie 4.1 software was utilized. Subsequently, changes in accident probability were analyzed for each sector in both navigation and anchoring conditions. Given the current scenario, where wind strength reaches Beaufort scale 4 and current speed reaches 4 knots, external conditions hindering vessel movement are assumed to be present.

All of the above conditions were applied in the Genie 4.1 software for each of the three sectors in the Istanbul Strait for both anchoring and navigation conditions (a total of six conditions). An example application for the Kadikoy Sector anchorage area is presented in Figure 11. The probability and conditional probability values of relevant nodes in the network for the scenario's current conditions are entered as 100%, with the scenario conditions represented by red nodes in the network. The accident probability results for each sector of the Istanbul Strait in the example scenario are presented in Table 13.

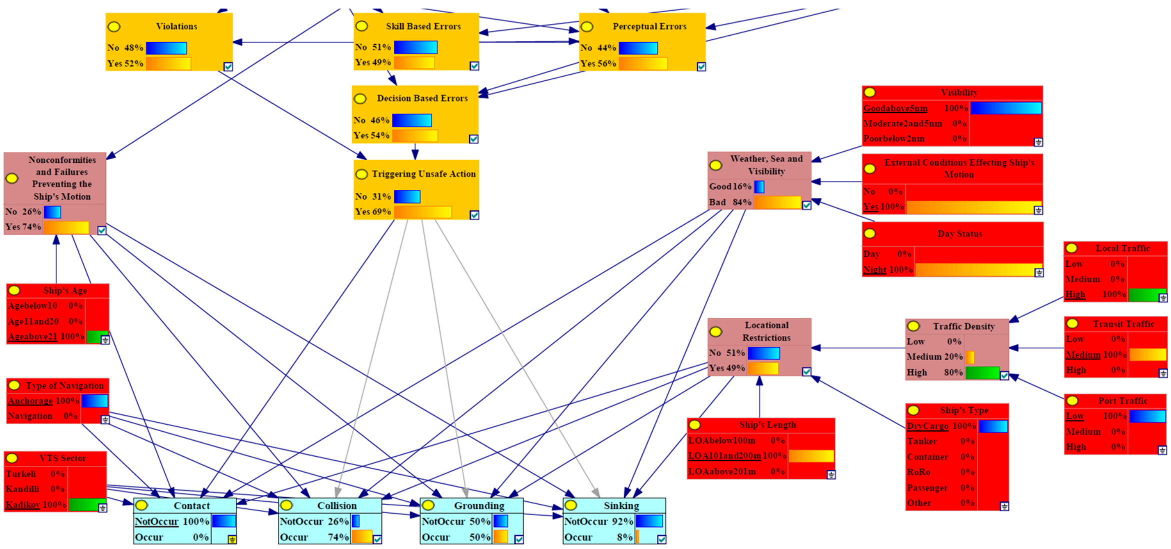

Figure 11. Nodes (red) set for the scenario and probabilities.

Table 13. Accident probabilities (%) and difference in probabilities (%).

Sector Name	Navigation Status	Accident Probabilities (%)/Change in Probabilities (%)							
		Collision		Contact		Grounding		Sinking	
		Original	Change	Original	Change	Original	Change	Original	Change
Initial Network Kadıköy	Anchorage	0	-	58	-	38	-	5	-
	Transit passage	47	-	54	-	47	-	4	-
Case Study Sector Kadıköy	Anchorage	0		74	+16	50	+12	8	+3
	Transit passage	56	+9	62	+8	61	+14	7	+3
Initial Network Kandilli	Anchorage	0	-	0	-	0	-	0	-
	Transit passage	62	-	33	-	58	-	2	-
Case Study Sector Kandilli	Anchorage	0	-	0	-	0	-	0	-
	Transit passage	75	+13	42	+9	69	+11	4	+2
Initial Network Sector Türkeli	Anchorage	0	-	33	-	22	-	5	-
	Transit passage	45	-	24	-	27	-	6	-
Case Study Sector Türkeli	Anchorage	0	-	45	+12	31	+9	10	+5
	Transit passage	52	+7	29	+5	35	+8	10	+4

When analyzing the scenario results (Table 13), it was observed that the vessel in question has a high accident probability (greater than 60%) during both anchoring maneuvers and transit passage within Sector Kadikoy, as well as during transit passage in Sector Kandilli. For the transit in Sector Turkeli, it was determined that the vessel does not pose a high accident probability for any of the four accident types. Probabilities and probability changes represented as 0% in the scenario indicate that the specific accident probability for that navigation type in that sector does not exist. For instance, the accident probability during anchoring maneuvers for a vessel transiting through Sector Kandilli was found to be 0%. This is because Sector Kandilli does not include an anchorage area. Thus, the probability of an accident event that can occur is naturally 0%, indicating that the network provides consistent results.

In Sector Kadikoy, the scenario results revealed that the vessel faces a high collision probability during anchoring maneuvers and a high probability for collision and grounding during transit passage. In Sector Kandilli, the vessel faces a high probability for contact and grounding during transit passage. To ensure safe passage, change analyses were conducted on the accident network. For example, the network was analyzed to examine how accident probabilities change if the passage was planned during the daytime instead of nighttime. For this analysis, the day status node was set to 100% daytime for the same scenario, and evaluations were conducted for six conditions across the three sectors.

The results indicate that planning the passage during the daytime reduced the accident probabilities for anchoring and navigation maneuvers in Sector Kadikoy to acceptable levels (below 60%) and eliminated high collision probabilities (Sector Kadikoy anchoring collision probability: 48%; Sector Kadikoy navigation collision probability: 52%; grounding probability: 44%). However, in Sector Kandilli, the high contact accident probability persisted (63%). This indicates that merely rescheduling the passage to daytime hours is not sufficient as a standalone preventive measure.

Given that the high accident probabilities are close to the threshold value, even minor preventive measures could reduce the probabilities to acceptable levels. The first preventive measure that comes to mind for a strait passage is the use of a pilot. Although the network does not include a specific node for pilots, the primary duty of pilots is to ensure the safe passage of vessels through the strait. Pilots are highly experienced professionals who possess extensive knowledge of the region and have conducted thousands of passages in the area. Considering this, it is believed that conducting the passage during daytime hours under the guidance of a pilot would eliminate the high accident probability. While the current accident network does not include a pilot application node, this aspect can be considered during the development of this network or in the creation of accident network structures for other narrow waterways.

When analyzing the scenario results, it becomes clear that the vessel planned for transit under the given scenario conditions should not be allowed to proceed without preventive measures. To validate the consistency of the study's findings, studies related to the Istanbul Strait in the literature were reviewed. The Turkish Straits System, which includes the Istanbul Strait, is among the narrowest and most challenging waterways for navigation in the world [4,66]. Tonoğlu et al. (2022), in their study, identified Sectors Kadikoy, Kandilli, and Turkeli as the most accident-prone sectors of the Istanbul Strait, in that order [67]. Similarly, Yildiz et al. (2021) found that Sectors Kadikoy and Kandilli are the sectors with the highest frequency of maritime accidents in the Istanbul Strait [68]. In Sector Kadikoy, the most common accidents are collisions, contacts, and groundings, while in Sector Kandilli, contacts and groundings are predominant [5].

Operational factors contributing to accidents in the Istanbul Strait include currents, sharp turns, vessel type, vessel length, traffic density, and aging hull structures [69,70]. Accidents in the Istanbul Strait occur significantly more often at night than during the day, with 64.2% of accidents happening at night [5]. Another critical factor in accident causation is machinery failure [71,72], which frequently occurs on older vessels. Seventy percent of accidents in the Istanbul Strait involve older vessels (21 years and above). Many vessels experiencing machinery failures have suffered groundings, contacts, and collisions in the strait [72].

The findings in the literature corroborate the results of this study. The accident network constructed in this study has been demonstrated to provide accurate predictions of high accident probabilities and to offer effective solutions to mitigate these risks. Consequently, the results of this study can serve as a decision-support system not only for VTS operators, ship masters, and company representatives but also for national and international stakeholders in the maritime industry, aiding in both accident probability prediction and the development of preventive measures.

8. Conclusions

Narrow waterways, such as straits and channels, represent maritime zones with the highest probability of accidents due to the inherent dangers vessels encounter in these constrained environments. Accidents frequently occur in these narrow passages, with the Turkish Straits System, particularly the Istanbul Strait, being among the world's most challenging waterways. This study develops a dynamic accident network aimed at predicting maritime accidents in narrow channels, with the Istanbul Strait serving as the case study area. The accident network, developed using historical data and insights from experts with extensive experience in the Istanbul Strait, has been evaluated collaboratively with these experts to ensure the reliability of the outcomes. This network can be utilized as a decision-support system by VTS operators and maritime authorities during the decision-making process. For example, local port authorities might recommend piloting services, tug assistance, or even suspend transit due to perceived risks.

The results of this study effectively address the research questions posed in Section 2. Specifically, the proposed HFACS-BN hybrid model demonstrates its ability to dynamically predict accident probabilities under varying operational and human organizational conditions. The model's application to the Istanbul Strait highlights its practical utility for VTS operators, enabling evidence-based decision-making to mitigate risks before vessel transits. Furthermore, this study contributes novel insights into how hybrid models can overcome the limitations of static and retrospective accident analysis approaches, thereby advancing the field of maritime safety modeling.

Beyond predicting accidents, the network also analyzes the effectiveness of preventive measures, providing guidance for operators. The operation of channel transit must be dynamically planned, specific to each vessel and narrow waterway, with meticulous risk analyses conducted for each transit. Critical decisions such as mandating pilotage, requiring tug escort, or suspending transit should be considered based on the quantitative outcomes of these analyses.

Solid scientific evidence supporting the effectiveness of this model opens new research directions, such as integrating real-time data inputs and expanding the framework for application to other high-risk maritime environments. The adaptability of the proposed network structure ensures its relevance for future studies, particularly when enhanced with artificial intelligence, wearable technology data, or integration into electronic navigation systems. Such advancements could further refine the predictive capabilities of the model, allowing for real-time data input under varying conditions and enabling dynamic, real-time predictions. Moreover, by incorporating artificial intelligence, the developed network can be transformed into software and integrated into electronic chart systems at VTS stations, significantly improving situational awareness and decision-making in maritime operations.

While this study has made several valuable contributions, its limitations can be outlined in three main points. First, the network is specific to a particular narrow waterway, hence not directly applicable to other waters. Second, the network currently does not include detailed considerations such as pilotage and tug assistance. Lastly, the network assumes static human factor inconsistencies based on historical maritime accident data, thus not reflecting real-time conditions. If real-time data inputs from wearable technologies monitoring stress, sleep deprivation, and attention deficit are incorporated, these factors could also be integrated into the decision-making process. Therefore, future research should aim to address these limitations by incorporating real-time data inputs (in combination with Fuzzy Logic and Artificial Intelligence), such as wearable technologies that monitor stress, sleep deprivation, and attention deficits, into the decision-making process. Additionally, expanding the model's scope to account for other waterways and operational scenarios will deepen its applicability and enhance its contributions to maritime safety.

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References

1. Zhang, W.Z.; Pan, J.; Sanchez, J.C.; Li, X.B.; Xu, M.C. Review on the protective technologies of bridge against vessel collision. *Thin-Walled Struct.* **2024**, *201*, 112013. [CrossRef]
2. Özkanlısoy, Ö.; Akkartal, E. The effect of Suez Canal blockage on supply chains. *Dokuz Eylül Üniversitesi Denizcilik Fakültesi Derg.* **2022**, *14*, 51–79. [CrossRef]
3. EMSA. *Annual Overview of Marine Casualties and Incidents 2023*; European Maritime Safety Agency: Lisbon, Portugal, 2023; pp. 1–66.
4. Yildiz, S.; Tonoğlu, F.; Uğurlu, Ö.; Loughney, S.; Wang, J. Spatial and statistical analysis of operational conditions contributing to marine accidents in the Singapore Strait. *J. Mar. Sci. Eng.* **2022**, *10*, 2001. [CrossRef]
5. Yildiz, S.; Uğurlu, Ö.; Loughney, S.; Wang, J.; Tonoğlu, F. Spatial and statistical analysis of operational conditions influencing accident formation in narrow waterways: A Case Study of Istanbul Strait and Dover Strait. *Ocean Eng.* **2022**, *265*, 112647. [CrossRef]

6. Wang, Y.F.; Roohi, S.F.; Hu, X.M.; Xie, M. A new methodology to integrate human factors analysis and classification system with Bayesian Network. In Proceedings of the IEEE International Conference on Industrial Engineering and Engineering Management, IEEM2010, Macao, China, 7–10 December 2010; pp. 1776–1780. [CrossRef]
7. Heij, C.; Bijwaard, G.E.; Knapp, S. Ship inspection strategies: Effects on maritime safety and environmental protection. *Transp. Res. Part D Transp. Environ.* **2011**, *16*, 42–48. [CrossRef]
8. Deng, J.; Liu, S.; Xie, C.; Liu, K. Risk coupling characteristics of maritime accidents in Chinese inland and coastal waters based on NK model. *J. Mar. Sci. Eng.* **2021**, *10*, 4. [CrossRef]
9. Felski, A.; Zwolak, K. The ocean-going autonomous ship—Challenges and threats. *J. Mar. Sci. Eng.* **2020**, *8*, 41. [CrossRef]
10. Akhtar, M.J.; Utne, I.B. Human fatigue's effect on the risk of maritime groundings—A Bayesian Network modeling approach. *Saf. Sci.* **2014**, *62*, 427–440. [CrossRef]
11. Uğurlu, Ö.; Yıldız, S.; Loughney, S.; Wang, J.; Kuntchulia, S.; Sharabidze, I. Analyzing Collision, Grounding, and Sinking Accidents Occurring in the Black Sea Utilizing HFACS and Bayesian Networks. *Risk Anal.* **2020**, *40*, 2610–2638. [CrossRef] [PubMed]
12. Adumene, S.; Afenyo, M.; Salehi, V.; William, P. An adaptive model for human factors assessment in maritime operations. *Int. J. Ind. Ergon.* **2022**, *89*, 103293. [CrossRef]
13. Yildiz, S.; Uğurlu, Ö.; Wang, J.; Loughney, S. Application of the HFACS-PV approach for identification of human and organizational factors (HOFs) influencing marine accidents. *Reliab. Eng. Syst. Saf.* **2021**, *208*, 107395. [CrossRef]
14. Antão, P.; Soares, C.G. Analysis of the influence of human errors on the occurrence of coastal ship accidents in different wave conditions using Bayesian Belief Networks. *Accid. Anal. Prev.* **2019**, *133*, 105262. [CrossRef] [PubMed]
15. Fan, S.; Blanco-Davis, E.; Yang, Z.; Zhang, J.; Yan, X. Incorporation of human factors into maritime accident analysis using a data-driven Bayesian network. *Reliab. Eng. Syst. Saf.* **2020**, *203*, 107070. [CrossRef]
16. Fedi, L.; Faury, O.; Etienne, L.; Cheaitou, A.; Rigot-Muller, P. Application of the IMO taxonomy on casualty investigation: Analysis of 20 years of marine accidents along the North-East Passage. *Mar. Policy* **2024**, *162*, 106061. [CrossRef]
17. Kaptan, M.; Sarıalioğlu, S.; Uğurlu, Ö.; Wang, J. The evolution of the HFACS method used in analysis of marine accidents: A review. *Int. J. Ind. Ergon.* **2021**, *86*, 103225. [CrossRef]
18. Ma, L.; Ma, X.; Wang, T.; Chen, L.; Lan, H. On the development and measurement of human factors complex network for maritime accidents: A case of ship groundings. *Ocean Coast. Manag.* **2024**, *248*, 106954. [CrossRef]
19. Zaib, A.; Yin, J.; Khan, R.U. Determining role of human factors in maritime transportation accidents by fuzzy fault tree analysis (FFTA). *J. Mar. Sci. Eng.* **2022**, *10*, 381. [CrossRef]
20. Sarıalioğlu, S.; Uğurlu, Ö.; Aydın, M.; Vardar, B.; Wang, J. A hybrid model for human-factor analysis of engine-room fires on ships: HFACS-PV&FFTA. *Ocean Eng.* **2020**, *217*, 107992. [CrossRef]
21. Hollnagel, E.; Goteman, O. The functional resonance accident model. In Proceedings of the Cognitive System Engineering in Process Plant, Sendai, Japan, 4–5 November 2004; pp. 155–161.
22. Underwood, P.; Waterson, P. *Accident Analysis Models and Methods: Guidance for Safety Professionals*; Loughborough University: Loughborough, UK, 2013. Available online: https://repository.lboro.ac.uk/articles/report/Accident_analysis_models_and_methods_guidance_for_safety_professionals/9354404?file=16964201 (accessed on 8 December 2024).
23. Hollnagel, E.; Woods, D.D.; Leveson, N. *Resilience Engineering: Concepts and Precepts*; Ashgate Publishing, Ltd.: London, UK, 2006.
24. Feng, Y.; Wang, H.; Xia, G.; Cao, W.; Li, T.; Wang, X.; Liu, Z. A machine learning-based data-driven method for risk analysis of marine accidents. *J. Mar. Eng. Technol.* **2024**, 1–12. [CrossRef]
25. Reason, J. *Human Error*; Cambridge University Press: New York, NY, USA, 1990.
26. Wiegmann, D.A.; Shappell, S.A. Human factors analysis of postaccident data: Applying theoretical taxonomies of human error. *Int. J. Aviat. Psychol.* **1997**, *7*, 67–81. [CrossRef]
27. Wiegmann, D.A.; Shappell, S.A. Human error analysis of commercial aviation accidents: Application of the Human Factors Analysis and Classification system (HFACS). *Aviat. Space Environ. Med.* **2001**, *72*, 1006–1016. [PubMed]
28. Reinach, S.; Viale, A. Application of a human error framework to conduct train accident/incident investigations. *Accid. Anal. Prev.* **2006**, *38*, 396–406. [CrossRef] [PubMed]
29. Tvaryanas, A.P.; Thompson, W.T. Recurrent error pathways in HFACS data: Analysis of 95 mishaps with remotely piloted aircraft. *Aviat. Space Environ. Med.* **2008**, *79*, 525–532. [CrossRef]
30. Chen, S.T.; Wall, A.; Davies, P.; Yang, Z.L.; Wang, J.; Chou, Y.H. A Human and Organisational Factors (HOFs) analysis method for marine casualties using HFACS-Maritime Accidents (HFACS-MA). *Saf. Sci.* **2013**, *60*, 105–114. [CrossRef]
31. Uğurlu, Ö.; Yıldız, S.; Loughney, S.; Wang, J. Modified human factor analysis and classification system for passenger vessel accidents (HFACS-PV). *Ocean Eng.* **2018**, *161*, 47–61. [CrossRef]
32. Aydin, M.; Uğurlu, Ö.; Boran, M. Assessment of human error contribution to maritime pilot transfer operation under HFACS-PV and SLIM approach. *Ocean Eng.* **2022**, *266*, 112830. [CrossRef]
33. Zhan, Q.; Zheng, W.; Zhao, B. A hybrid human and organizational analysis method for railway accidents based on HFACS-Railway Accidents (HFACS-RAs). *Saf. Sci.* **2017**, *91*, 232–250. [CrossRef]
34. Chauvin, C.; Lardjane, S.; Morel, G.; Clostermann, J.P.; Langard, B. Human and organisational factors in maritime accidents: Analysis of collisions at sea using the HFACS. *Accid. Anal. Prev.* **2013**, *59*, 26–37. [CrossRef]

35. Chen, S.T.; Chou, Y.H. Examining Human Factors for Marine Casualties using HFACS—Maritime Accidents (HFACS-MA). In Proceedings of the 2012 12th International Conference on Its Telecommunications (Itst-2012), Taipei, Taiwan, 5–8 November 2012; pp. 385–390.
36. Bayazit, O.; Kaptan, M. Dynamic risk analysis of allision in port areas using DBN based on HFACS-PV. *Ocean Eng.* **2024**, *298*, 117183. [CrossRef]
37. Maternová, A.; Materna, M.; Dávid, A.; Török, A.; Švábová, L. Human error analysis and fatality prediction in maritime accidents. *J. Mar. Sci. Eng.* **2023**, *11*, 2287. [CrossRef]
38. Uğurlu, F.; Yıldız, S.; Boran, M.; Uğurlu, Ö.; Wang, J. Analysis of fishing vessel accidents with Bayesian network and Chi-square methods. *Ocean Eng.* **2020**, *198*, 106956. [CrossRef]
39. Aydin, M.; Akyuz, E.; Boustras, G. A holistic safety assessment for cargo holds and decks fire & explosion risks under fuzzy Bayesian network approach. *Saf. Sci.* **2024**, *176*, 106555. [CrossRef]
40. Bayes, T. An essay towards solving a problem in the doctrine of chances. *Stud. Hist. Stat. Probab.* **1970**, *1*, 134–153. [CrossRef]
41. Howson, C.; Urbach, P. *Scientific Reasoning: The Bayesian Approach*; Open Court Publishing: Chicago, IL, USA, 2006.
42. Trucco, P.; Cagno, E.; Ruggeri, F.; Grande, O. A Bayesian Belief Network modelling of organisational factors in risk analysis: A case study in maritime transportation. *Reliab. Eng. Syst. Saf.* **2008**, *93*, 845–856. [CrossRef]
43. Animah, I. Application of bayesian network in the maritime industry: Comprehensive literature review. *Ocean Eng.* **2024**, *302*, 117610. [CrossRef]
44. Pristrom, S.; Yang, Z.; Wang, J.; Yan, X. A novel flexible model for piracy and robbery assessment of merchant ship operations. *Reliab. Eng. Syst. Saf.* **2016**, *155*, 196–211. [CrossRef]
45. Yazdi, M.; Kabir, S. A fuzzy Bayesian network approach for risk analysis in process industries. *Process Saf. Environ. Prot.* **2017**, *111*, 507–519. [CrossRef]
46. BayesFusion, L. *GeNIe Modeler*; BayesFusion, LLC: Pittsburgh, PA, USA, 2024.
47. Meng, X.; Li, H.; Zhang, W.; Zhou, X.Y.; Yang, X. Analyzing risk influencing factors of ship collision accidents: A data-driven Bayesian network model integrating physical knowledge. *Ocean Coast. Manag.* **2024**, *256*, 107311. [CrossRef]
48. Baksh, A.-A.; Abbassi, R.; Garaniya, V.; Khan, F. Marine transportation risk assessment using Bayesian Network: Application to Arctic waters. *Ocean Eng.* **2018**, *159*, 422–436. [CrossRef]
49. Eleye-Datubo, A.; Wall, A.; Saajedi, A.; Wang, J. Enabling a powerful marine and offshore decision-support solution through Bayesian network technique. *Risk Anal.* **2006**, *26*, 695–721. [CrossRef] [PubMed]
50. Li, M.; Zhang, R.; Liu, K. A new marine disaster assessment model combining bayesian network with information diffusion. *J. Mar. Sci. Eng.* **2021**, *9*, 640. [CrossRef]
51. Hänninen, M.; Kujala, P. Bayesian network modeling of Port State Control inspection findings and ship accident involvement. *Expert Syst. Appl.* **2014**, *41*, 1632–1646. [CrossRef]
52. John, A.; Yang, Z.; Riahi, R.; Wang, J. A risk assessment approach to improve the resilience of a seaport system using Bayesian networks. *Ocean Eng.* **2016**, *111*, 136–147. [CrossRef]
53. Afenyo, M.; Khan, F.; Veitch, B.; Yang, M. Arctic shipping accident scenario analysis using Bayesian Network approach. *Ocean Eng.* **2017**, *133*, 224–230. [CrossRef]
54. Fan, S.; Zhang, J.; Blanco-Davis, E.; Yang, Z.; Yan, X. Maritime accident prevention strategy formulation from a human factor perspective using Bayesian Networks and TOPSIS. *Ocean Eng.* **2020**, *210*, 107544. [CrossRef]
55. Lin, C.-T.; Wang, M.-J.J. Hybrid fault tree analysis using fuzzy sets. *Reliab. Eng. Syst. Saf.* **1997**, *58*, 205–213. [CrossRef]
56. Wang, W.-J. New similarity measures on fuzzy sets and on elements. *Fuzzy Sets Syst.* **1997**, *85*, 305–309. [CrossRef]
57. Hsu, H.; Chen, C. Fuzzy hierarchical weight analysis model for multicriteria decision problem. *J. Chin. Inst. Ind. Eng.* **1994**, *11*, 126–136.
58. Buckley, J.J. *Fuzzy Probability and Statistics*; Springer: Berlin/Heidelberg, Germany, 2006.
59. Kaushik, M.; Kumar, M. An integrated approach of intuitionistic fuzzy fault tree and Bayesian network analysis applicable to risk analysis of ship mooring operations. *Ocean Eng.* **2023**, *269*, 113411. [CrossRef]
60. Gudder, S. Fuzzy probability theory. *Demonstr. Math.* **1998**, *31*, 235–254. [CrossRef]
61. Arun, N.; Mohan, B. Modeling, stability analysis, and computational aspects of some simplest nonlinear fuzzy two-term controllers derived via center of area/gravity defuzzification. *ISA Trans.* **2017**, *70*, 16–29. [CrossRef]
62. Vahidnia, M.H.; Alesheikh, A.A.; Alimohammadi, A. Hospital site selection using fuzzy AHP and its derivatives. *J. Environ. Manag.* **2009**, *90*, 3048–3056. [CrossRef] [PubMed]
63. Zhao, R.; Govind, R. Defuzzification of fuzzy intervals. *Fuzzy Sets Syst.* **1991**, *43*, 45–55. [CrossRef]
64. Shappel, S.A.; Wiegmann, D.A. *The Human Factors Analysis and Classification System-HFACS*; US Federal Aviation Administration: Des Plaines, IL, USA, 2000; pp. 1–19.
65. Schröder-Hinrichs, J.U.; Baldauf, M.; Ghirxi, K.T. Accident investigation reporting deficiencies related to organizational factors in machinery space fires and explosions. *Accid. Anal. Prev.* **2011**, *43*, 1187–1196. [CrossRef]
66. Ceylan, B.O.; Elidolu, G.; Arslanoğlu, Y. A novel approach for the analysis of engineering complex system accidents: The casualty of the M/V Vitaspirit. *Ocean Eng.* **2023**, *276*, 114217. [CrossRef]
67. Tonoğlu, F.; Atalar, F.; Başkan, İ.B.; Yildiz, S.; Uğurlu, Ö.; Wang, J. A new hybrid approach for determining sector-specific risk factors in Turkish Straits: Fuzzy AHP-PRAT technique. *Ocean Eng.* **2022**, *253*, 111280. [CrossRef]

68. Yildiz, S.; Sönmez, V.Z.; Uğurlu, Ö.; Sivri, N.; Loughney, S.; Wang, J. Modelling of possible tanker accident oil spills in the Istanbul Strait in order to demonstrate the dispersion and toxic effects of oil pollution. *Environ. Monit. Assess.* **2021**, *193*, 538. [CrossRef] [PubMed]
69. Aydogdu, Y.V. A comparison of maritime risk perception and accident statistics in the Istanbul Straight. *J. Navig.* **2014**, *67*, 129–144. [CrossRef]
70. Erol, S.; Demir, M.; Çetisli, B.; Eyüboglu, E. Analysis of ship accidents in the Istanbul Strait using neuro-fuzzy and genetically optimised fuzzy classifiers. *J. Navig.* **2018**, *71*, 419. [CrossRef]
71. Aydogdu, Y.V.; Yurtoren, C.; Park, J.-S.; Park, Y.-S. A study on local traffic management to improve marine traffic safety in the Istanbul Strait. *J. Navig.* **2012**, *65*, 99–112. [CrossRef]
72. Demirci, S.E.; Elçiçek, H. Scientific awareness of marine accidents in Europe: A bibliometric and correspondence analysis. *Accid. Anal. Prev.* **2023**, *190*, 107166. [CrossRef] [PubMed]