Journal of
Marine Science and Engineering

MDPI

Article

Human Error Analysis and Fatality Prediction in Maritime Accidents

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Abstract: The main objective of this paper is to underscore the significance of human error as a dominant cause of maritime accidents. The research is based on a comprehensive analysis of 247 maritime accidents, with the aim being to identify human failures occurring during onboard and port activities, as well as during the supervision process. The first step of the analysis was facilitating the Human Factor Analysis and Classification System (HFACS) as an advanced analytical tool for the identification and categorisation of human factors. Based on coding process, the most critical areas of human error are identified, based on the process of risk evaluation and assessment. Furthermore, a prediction model was developed for predicting the probability of fatality in a maritime accident. This model was constructed using logistic regression, considering the predominant causal factors and their interplay. Lastly, a set of preventive measures aimed at enhancing the efficiency and safety of maritime transport is provided.

Keywords: maritime safety; human error; linear regression; HFACS; maritime accident; risk assessment

Citation: 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. https://doi.org/10.3390/jmse11122287

Academic Editors: Carlos Guedes Soares, Mihalis Golias and Spyros Hirdaris

Received: 13 October 2023
Revised: 24 November 2023
Accepted: 30 November 2023
Published: 1 December 2023

1. Introduction

Maritime safety is a critical concern because shipping is responsible for transporting about 90% of the world's trade in goods [1]. The shipping industry recently faced several challenges—the COVID-19 pandemic, a war in Ukraine and climate change. Geopolitical tensions have caused chaos in maritime transport and logistics, resulting in port congestion, the closure of certain ports, route reconfigurations, extended delays, and escalating shipping costs.

The war in Ukraine has disrupted maritime transport by affecting trade routes and increasing geopolitical tensions around key waterways like the Black Sea. Despite these challenges, the maritime industry remains a strong player and continues to be the backbone of international trade and economy. Even though recognising its importance and crucial role is essential, the vulnerabilities revealed by recent crises emphasise the necessity for the maritime industry to strengthen its resilience to future challenges.

To ensure the integrity and efficiency of maritime transport, it is crucial to prioritise safety. Shipping accidents and their potential consequences point to the shared responsibility of various stakeholders, including shipping companies, captains, crew members, and onshore authorities such as ports and supervisory bodies. The International Maritime Organisation has already implemented regulations and guidelines aimed at enhancing safety standards, covering aspects such as ship construction, stability, propulsion, and equipment. Despite the implementation of safety measures, the establishment of protocols, and inspections, the frequency of maritime accidents remains unacceptably high [2].

This study aims to identify the causal factors behind maritime accidents. Based on the findings of the European Maritime Safety Agency (EMSA) [3], maritime accidents are rarely caused by a single factor. Humans play a pivotal role in accidents, and directly or indirectly contribute to over 70–80% of maritime accidents [3,4]. In this context, various methods exist for hazard identification in various areas, systems, and industries. For maritime accidents research, the Human Factor Analysis and Classification System (HFACS) is a typical tool used for hazard identification, primarily for analysing and classifying human failure [5]. Furthermore, we identify the primary causal factors contributing to fatalities in maritime accidents by applying a linear regression model.

Our objective extends to the identification of critical areas of failure and the clarification of methods for identifying, assessing, and mitigating human failures. By prioritising safety and implementing the preventive measures proposed in this paper, the maritime industry can ensure the uninterrupted flow of global trade while minimising risks to human life, property, and the environment.

In view of the above, it becomes clear that human factors have a substantial influence on maritime traffic accidents. This research aims to underscore the importance of this influence, thus emphasizing the essential need for the study.

2. Materials and Methods

2.1. Overview of Accident Causation Models

According to the principle of direct causality—"if we know the cause, it is possible to look for the effect" and "if we see the effect, then it is possible to determine the cause" [6]—there is an evident need for the development of accident causation models. These models are used as techniques for assessing risk within a system and for analysing past accidents to uncover the causes of their occurrence. Models can be divided into sequential, epidemiological, and systemic models. Sequential models aim to eliminate or restrict the causes of safety failures, epidemiological models create stronger defences and barriers against the negative consequences of risks, and systemic models monitor and control the performances of humans or the system itself[1]. Currently, a wide range of methods is utilised for researching the human factor, depending on the size of the system or organisation and the negative factors with the potential to compromise system safety.

Systematic examination of the causes of maritime accidents began in the early 20th century with development the first scientific approach to accident prevention, known as the Simple Linear Model [6]. The Domino Model offers a systematic approach to understanding the causes of accidents. It envisions accidents as a sequence of events, represented by five key elements:

1. Social environment;
2. Human error (negligence);
3. Unsafe acts or mechanical and physical conditions;
4. Accidents;
5. Injuries.

Mitigating or addressing any of these five key elements can contribute to accident prevention or, in the case of "injuries", reduce the severity of injuries that may result from accidents. This model has influenced various accident investigation methods and forms the basis for models like Failure Modes and Effects Analysis (FMEA), Fault Tree Analysis (FTA), Cause–Consequence Analysis (CCA), ad Cause & Effect diagrams.

Reason's model (or the "Swiss Cheese" model) is a general method of human error analysis with a hierarchical structure of classified causes [7]. Reason (1990) systematically described the accident process using the example of Swiss cheese, defining four levels of possible failure:

1. Unsafe acts;

2. Preconditions for unsafe acts;
3. Unsafe supervision;
4. Organisational influences.

These levels represent layers of Swiss cheese, each offering protection against potential threats. Holes in layers signify system deficiencies or risks leading to accidents. Accidents occur when the layers align, allowing threats to penetrate [7].

Reason defines two types of failures:

- Latent failures—Hidden threats stemming from organisational issues, like misaligned priorities, culture, or procedures. These can exist in the system for a long time before the accident, representing unforeseen hazards;
- Active failures—Errors in judgment or decision-making by operators, which are easier to identify and are often the primary cause of accidents [7].

The SHELL model was first developed by Edwards (1972) to represent human–machine interactions. SHELL is a tool for analysing system components and properties and their possible interactions with people. The SHELL model uses a systems perspective, which suggests that humans are rarely the sole cause of an accident [8]. SHELL consists of components:

- Software (S)—processes, training, support, etc.;
- Hardware (H)—equipment, devices, technical equipment, etc.;
- Environment (E)—operating environment in which other components must work;
- Liveware (L)—people in the work environment (human performance, communication, interpersonal relations, etc.).

At the centre of the analysis of the SHELL model is the liveware component (L)—that is, the person who is in the "first line" of the operation. It is important to realise that a person and their behaviour are the least predictable of all the components of the system, and the most susceptible to internal (hunger, fatigue, motivation, etc.) and external influences (temperature, noise, light, etc.). Despite the fact that people are highly adaptable, they are often subject to performance fluctuations [8].

People are not standardised to the same extent as hardware (H). Therefore, they are represented in the SHELL diagram of the model as a block that does not have regular straight edges. It is necessary to be aware of the existing imperfections in the interactions between the individual components of SHELL model and its centre, i.e., man. The uneven edges of the components represent their imperfect interconnection, or interaction [8].

The Cognitive Reliability and Error Analysis Model (CREAM) was developed based on the principles of cognitive systems engineering. This system model is used for accident analysis and is based on modelling cognitive aspects of human performance to assess the impact of human error on system safety [9]. Two versions of CREAM have been developed for accident modelling:

- DREAM (Driver Reliability and Error Analysis Method) for traffic accident analysis;
- BREAM (Board Reliability and Error Analysis Method) for use in marine casualty analysis [10].

The Functional Resonance Analysis Method (FRAM) was introduced by Hollnagel (2012) as an accident analysis and risk assessment method based on non-linear accident modelling. It posits that unforeseen combinations of normal performance variability (resonance) lead to accidents. Controlling and preventing accidents involves managing variability among system functions and anticipating future incidents [11]. FRAM also helps us understand how systems maintain safety during dynamic operational situations. Hollnagel (2012) [11] identified four principles of the FRAM method:

- Equivalence of successes and failures—Failures and successes share the same origin, occurring for similar reasons;
- Principle of approximate adjustments—Socio-technical systems are complex, often underspecified, and subject to daily adjustments to match system conditions;

- Principle of emergence—Normal performance variability alone is generally insufficient to cause accidents or malfunctions, but when multiple functions' variability combines unexpectedly, non-linear effects can occur;
- Functional resonance—Variability in a group of functions can resonate, leading to an excessive amount of variability that the system cannot manage, potentially resulting in an accident.

System-Theoretic Process Model (STAMP) considers technical, human and organisational factors in complex socio-technical systems [12]. In the STAMP model, accidents in complex systems do not simply occur due to the failure of independent components. They likely occur because of external disturbances or dysfunctional interactions between them when the system components are not adequately controlled. Accidents are therefore not caused by a series of events, but by the inappropriate management or enforcement of safety constraints in system development, design and operation [12]. Analysis according to the STAMP model can be performed in two stages:

1. Development of a hierarchical control structure that includes identification of interactions between system components and identification of security requirements and constraints;
2. Classification and analysis of mismanagement, which includes classification of causal factors followed by reasons for mismanagement and dysfunctional interactions.

The hierarchical model of socio-technical systems was introduced by Rasmussen (1997) [13] as a system-oriented model emphasizing the complexity and rapid technological advancements in high-risk socio-technical systems. These systems are influenced by organisations operating under dynamic conditions like market competition, economic and political pressures, legislation, and increased safety awareness. Rasmussen (1997) suggests that these factors have transformed the dynamic nature of modern society, continually shaping work procedures and human behaviour in complex systems [13].

Rasmussen's model offers a system-oriented approach based on management concepts, providing a framework to model organisational, control, and operational structures linked to accidents. Rasmussen defined levels of failure:

- Government—activities of government, controlling safety practices in society through legislation;
- Regulators—activities of regulators, industrial associations and unions that are responsible for legislation implementation in various sectors;
- Company—activities of a particular company;
- Management—activities of the management body in a particular company that lead, manage and control the performance of employees;
- Staff member—individuals' activities interacting directly with technology or processes being controlled;
- Engineering disciplines—design of potentially risky equipment and operating procedures for process control.

Rasmussen's framework (1983) posits that decisions and actions across all levels interact and impact system performance [13]. Safety and accidents result from the decisions of all stakeholders, not just individual workers. Accidents stem from multiple factors, not just a single poor decision or action.

Considering the model's conditions, it is clear that decisions and actions from higher governance, regulatory, and management levels should cascade down and influence decisions and actions at lower levels for safe and effective performance. Conversely, information about the system's status from lower levels should flow up in the hierarchy to inform higher-level decisions and actions. This concept is termed "vertical integration" and is a vital component of a safe system.

AcciMap is a technique based on Rasmussen's framework [13]. It involves the construction of a multi-layer causal diagram in which the various causes of an accident are arranged according to their causal distance from the outcome. AcciMap identifies critical factors during routine activities that can influence the occurrence of an accident. This technique focuses on individuals in the system who can make decisions to enhance risk management and improve system safety.

The Technique for Human Error Rate Prediction (THERP) is a taxonomy-based technique of Human Reliability Assessment (HRA) used to assess the likelihood of human error during specific tasks, leading to improving overall safety. HRA has three primary purposes: error identification, quantification, and reduction. HRA can be categorised into two types: first-generation techniques and second-generation techniques. THERP is a first-generation HRA method. Second-generation techniques rely more on theory for assessing and quantifying errors. THERP is based on a taxonomy of errors (omission, timing, sequencing, action-based, etc.). TERP uses an event tree modelling system dealing with cognitive errors. Its goal is to bring more contemporary cognitive approaches into the process of identifying human errors, i.e., Rasmussen's and Reason's taxonomy. This move has led to a "hybrid" THERP taxonomy with terms such as skill-based errors, rule-based errors, and knowledge-based errors. Subsequently, a tree of cognitive events is created [14].

The Technique for the Retrospective and Predictive Analysis of Cognitive Errors (TRACEr) is another significant approach to human error identification. This method was initially designed with a focus on air traffic control. TRACEr serves as both a retrospective incident analysis tool and a predictive human error identification technique. The basis of the TRACEr's approach is its emphasis on the human–machine interface (HMI), arguing that accidents often result from cognitive and psychological processes influencing an operator's performance.

To extend TRACEr's use into the maritime context, an adaptation, TRACEr-MAR, was developed. This adaptation aims to highlight areas where improvements to the HMI could be beneficial [15]. The TRACEr could be combined with some other approaches, developed and used in the maritime sector for evaluating accidents. The European research project "CASMET" (Casualty Analysis Methodology for Maritime Operations) has developed a methodology for investigation and a taxonomy of maritime accidents. The CASMET approach has become one of the pillars of the European Marine Casualty Information Platform (EMCIP) developed by the European Maritime Safety Agency (EMSA), which is a platform providing support documents and information [16]. The use of the TRACEr technique combined with the CASMET approach could improve the applicability of the methodology of the analysis of maritime accidents.

2.2. Research Method: Human Factor Analysis and Classification System

The Human Factor Analysis and Classification System (HFACS) is a method based on Reason's Swiss Cheese model. HFACS was developed by American scientists Wiegmann and Shappell [17]. Their works [17,18] established four areas of human failure based on Reason's model. HFACS is a tool for categorising and assessing human error affecting accident occurrences [19]. Originally designed as an evaluation framework for human factor investigations within the aviation industry, HFACS has been adopted by other sectors, including marine, mining, and rail transport [20]. By using HFACS, potential errors can be identified across all categories.

The structure of the HFACS method aligns with Reason's model [7], consisting of four levels: unsafe acts, unsafe supervision, unsafe acts assumptions, and organisational influences. Specific causal categories have been developed within each level to identify active or latent failures [21]. The HFACS system enables the systematic identification and classification of failures and errors. It is important to note that the primary objective of HFACS is not to assign blame, but rather to comprehend the causal factors that contribute to accidents and to mitigate unsafe behaviour to enhance safety [19].

It is essential to choose an appropriate method of human error investigation [22]. In order to validate our selection of the HFACS method over other tools used for human error identification and assessment, we present several relevant scientific studies that support our assertions. For instance, Hulme et al. (2019a) [23] used the HFACS, AcciMap, FRAM and STAMP methods to examine 73 studies between 1990 and 2018. The authors made specific recommendations concerning the necessity of the development of accident reporting systems and innovative accident analysis approaches. It underscores that the HFACS method stands out as one of the most widely adopted and reliable techniques for human factor analysis. Furthermore, in another study by Hulme et al. (2019b et al.) [24], 43 studies were examined, using the HFACS tool across various domains. The findings revealed that the HFACS method is extensively applied within the realms of aviation, the maritime sector, and rail transportation. Based on Hsieh et al., 2018, and Illankoon et al., 2019 [25,26], it is evident that HFACS stands as a comprehensive and reliable approach in the domain of accident analysis. This methodology facilitates a profound examination of accidents, uncovering the causal factors at each level. Consequently, HFACS has gained considerable prominence in accident investigations over the past decade (Omole and Walker, 2015; Liu et al., 2019) [27,28]. Furthermore, Chauvin et al. (2013) [29] conducted a comprehensive study using HFACS for the analysis and categorisation of human and organisational factors in maritime accidents, employing the same databases as used in the present study.

As the literature overview related to the human error issue shows, HFACS has become relevant for research on human errors in the maritime sector. The complex and dynamic nature of maritime operations underscore the significance of addressing human error as a significant concern. As mentioned, HFACS has been successfully applied in research on failures in similar high-risk industries, making it a suitable choice for maritime safety research. A crucial aspect of any widely recognised human error identification technique lies in its ability to offer a taxonomy that adequately describes various error modes. This is significant because a robust error taxonomy can effectively store valuable information in databases, contributing to safety enhancements and facilitating the creation of advanced risk models tailored to specific accidental scenarios [30].

Researchers have effectively employed the HFACS method due to its compatibility with various techniques, enabling both qualitative and quantitative analyses, and providing detailed insights into accidents. In our study, the critical aspects of human failure identified by HFACS could be evaluated using the risk matrix method, which combines the assessment of probability and the severity of consequences. Additionally, we were able to quantify the likelihood of specific human errors contributing to fatal accidents based on a linear regression probability model.

2.3. Risk Matrix

The name "risk matrix method" implies that it is intended for the identification, evaluation, and assessment of risks. In this context, risk is defined as the chance of a loss or injury, measured in terms of severity and probability, the chance that something is going to happen, and the consequences if it does.

A risk matrix, one of the semi-quantitative risk assessment tools, represents a combination of severity and probability. The matrix allows a clear and simple visual comparison of different risks. Severity refers to the negative consequences that may arise, such as fire, explosion, the release of dangerous substances, the impact of natural hazards, environmental damage, damage to or loss of property, injuries, or fatalities. A severity scale ranges consequences from negligible to catastrophic. Usually, risk matrices consist of four to six levels of severity and probability. It is important to note that there is no universally adopted set of descriptions for these levels, but still, the selection of descriptors should be logical and aligned with the specific purpose. The risk matrix represents a mathematical expression of risk—a combination of the probability and severity of the consequences of the risk [31]. Probability expresses how likely the risk is to occur. It is expressed in five degrees, with the value indicated for each option (see Table 1).

Table 1. Probability and frequency of occurrence.

Probability	Probability and Frequency of Occurrence	Value
Frequent	Likely to occur many times (has occurred frequently) Probability: 1×10^{-3} Frequency: more often than once a month	5
Occasional	Likely to occur sometimes (has occurred infrequently) Probability: 1×10^{-5}–1×10^{-3} Frequency: more often than once in 1 year but not more often than once in 1 month	4
Remote	Unlikely, but possible to occur (has occurred rarely) Probability: 1×10^{-7}–1×10^{-5} Frequency: more often than once in 5 years but not more often than once in 1 year	3
Improbable	Very unlikely to occur (not known to have occurred) Probability: 1×10^{-9}–1×10^{-7} Frequency: more often than once in 5 years but not more often than once in 20 years	2
Extremely improbable	Almost inconceivable that the event will occur Probability: less than 1×10^{-9} Frequency: never (during lifetime of given system)	1

The severity of the consequences expresses the possible consequences of the risk based on the worst-case scenario. Table 2 shows examples of risks for the water transport sector at each scale of severity of consequences.

Table 2. The severity of consequences with examples.

Severity of Consequences	Examples of Maritime Transport	Value
Catastrophic	• multiple (more than 2) fatalities • irreparable losses [1]—for example stoppage of world trade • environmental disaster at sea [2], massive oil spills or chemical disasters involving the release of highly toxic substances resulting in extensive environmental contamination and ecosystem damage • destruction of the vessel—total loss of vessel • complete destruction of major ports, terminals, or critical maritime infrastructure • extensive legal liabilities, substantial fines, or penalties for shipowners, operators, or other parties	A
Hazardous	• fatality or severe injuries leading to death (even 1 person) • vessel capsizing or sinking • extensive ship damage (result in in vessel unseaworthy); • general reparation of ship required • massive oil spills covering large areas of water, coastlines, or sensitive ecosystems and requiring extensive cleanup efforts • chemical fires or explosions • catastrophic damage to infrastructure (port facilities, bridges, critical maritime infrastructure) • large financial losses (damage to cargo, disruption of trade routes, and substantial cleanup and recovery costs of EUR 100,000–500,000) • leakage of dangerous substances of large quantities requiring prolonged cleanup efforts with no long-term effects • prolonged delivery times (more than 72 h in port; more than 24 h on significant shipping route or hub) • public health concerns resulting from contamination of drinking water sources or food supplies • fines or penalties for shipowners, operators, or other parties	B

Table 2. *Cont.*

Severity of Consequences	Examples of Maritime Transport	Value
Major	• serious injuries without endangering life (even 1 person) • damage to ship or cargo (max. EUR 100,000) • financial losses (substantial repair costs, cargo losses, and loss of revenue for shipping companies, ports, and other stakeholders) • fines or penalties for shipowners, operators, or other parties • environmental pollution and costs of environmental remediation and restoration • public health concerns resulting from the contamination of drinking water sources or food supplies • prolonged delivery times, prolonged disruptions to shipping schedules, port operations, or supply chains (more than 24 h–less than 72 h in port; less than 24 h on significant shipping route or hub)	C
Minor	• minor injuries such as cuts, bruises, or minor sprains (even 1 person) • transportation restrictions • small property damage (on vessel—moderate damage requiring repair but not posing a significant risk to buoyancy, on cargo—damage of small value of cargo less than 2% of total value) • costs resulting from repatriation • very small or no environmental impact (spills of small quantities that can be promptly contained and cleaned up without any impact) • limited economic impact: minor repair costs; prolonged delivery times (more than 1 h–less than 24 h in port)	D
Negligible	• no injuries • close quarters • no environmental impact • no financial losses (on ship, infrastructure or cargo) • no disruption	E

[1] An example of irrepable losses is the case of the container ship Ever Given, which grounded in the Suez Canal in March 2021, obstructing this critical shipping route for six days. Approximately 12% of global trade flows through the Suez Canal, and the stranding of the vessel resulted in the suspension of over $9 billion worth of goods in transit each day. Subsequently, the Suez Canal Authority reached a financial settlement of $550 million with the ship's Japanese owner, Shoei Kisen Kaisha Ltd., and their insurers (Ramos, K., et al., 2021). [2] Significant and widespread release of dangerous substances or pollutants into the marine environment that causes severe and long-lasting harm to ecosystems, wildlife, and human health. the threshold for what constitutes an environmental disaster at sea can vary depending on several factors, including the type of substance, the sensitivity of the affected area, the extent of contamination, and the economic and ecological impact. For example, some substances are highly toxic or persistent in the environment even in small quantities. A relatively small release of certain hazardous substances (oil or chemical) can have devastating effects. For this reason, it is not appropriate to assess the extent of the environmental disaster based on the quantity of the leaked substance.

After assigning values of probability and the severity of consequences to each of the risks, they can be classified into three areas (see Table 3):

1. Acceptable (green) area;
2. Acceptable area (under certain circumstances; yellow and orange area—yellow risks are closer to the acceptable area, orange risks are closer to the unacceptable area);
3. Unacceptable (red) area.

If the risk falls within the unacceptable level (in the red area), it is crucial to implement preventive measures for risk reduction. These measures may involve reducing the probability of risk occurrence or mitigating the severity of its consequences.

Table 3. Combination of severity and probability. Adapted from [31].

Probability	Severity				
	Catastrophic A	**Hazardous B**	**Major C**	**Minor D**	**Negligible E**
Frequent 5	5A	5B	5C	5D	5E
Occasional 4	4A	4B	4C	4D	4E
Remote 3	3A	3B	3C	3D	3E
Improbable 2	2A	2B	2C	2D	2E
Extremely improbable 1	1A	1B	1C	1D	1E

In cases where the risk is tolerable based on the combination of consequence severity and the probability of danger occurrence at a particular level, it should not be assumed that safety measures can be relaxed. Rather, efforts should still be made to identify risks and implement measures to reduce the risk to an acceptable level [32,33].

The system is still exposed to risk when the risk is considered acceptable. However, in such instances, the risk is not a significant concern as it is improbable, and the severity of consequences is low. While the risk is acceptable, the responsible authorities may still find possibilities for further risk reduction within the available resources.

2.4. Logistic Regression

In this study, a prediction model for predicting the probability of fatalities in maritime accidents was created. The model was constructed using logistic regression, the output of which is the probability of fatality in an accident with specific causal factors. As the target variable in the logistic regression model, we used the indicator variable fatality (denoted by Y) with the value $Y = 0$ for those accidents where no fatality occurred, and $Y = 1$ for those accidents where at least one fatality occurred. This target variable is then modelled as a function of predictor variables using a logistic function that transforms a linear combination of predictor variables to a probability between 0 and 1.

The principle of binary logistic regression is as follows [34]. Let Y be a binary dependent variable that takes the value 1 (fatality occurred) with probability p and the value 0 (fatality did not occur) with probability $1 - p$. Let $X_1, \ldots, X_k$ be independent variables—predictor variables. The logistic regression model will be as follows:

$$log\frac{p}{1-p} = \beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k \quad (1)$$

$\beta_0, \beta_1, \ldots, \beta_k$ are unknown parameters to be estimated. Their estimates are denoted as $b_0, b_1, \ldots, b_k$. The previous function expresses the log odds of the target variable, which is then transform into a probability using the following function:

$$p = 1/(1 + exp(-\beta_0 - \beta_1 X_1 - \ldots - \beta_k X_k)) \quad (2)$$

The search for unknown parameters of logistic regression is most commonly carried out using the maximum likelihood method, which is given by the equation:

$$L(\beta_0, \beta_1, \ldots, \beta_k) = \prod {p_i}^{y_i} \cdot (1 - p_i)^{1-y_i} \quad (3)$$

or after taking the logarithm:

$$\ln L(\beta_0, \beta_1, \beta_2, \ldots, \beta_m) = \sum (y_i \ln p_i + (1 - y_i) \ln(1 - pi)) \quad (4)$$

while the product (sum) is realised over all observations y_i, where y_i is the realisation of the dependent variable Y in observation (accident) i and p_i is the probability of fatality in accident i.

The estimated probability obtained from the created model is used for the classification of accidents into two groups: accidents with fatalities (where $Y = 1$) and those without fatalities (where $Y = 0$). The mode quality is evaluated using a confidence matrix that provides the absolute and relative frequencies of correctly and incorrectly predicted cases. A case is considered correctly classified when:

- Using the created model, we predict the occurrence of a fatality, and in reality, a fatality did occur—true positive rate;
- Conversely, using the created model, we predict that no fatalities will occur, and in reality, no fatalities occurred—true negative rate.

Incorrect classification is considered when:

- Predicting a fatality during accident where no fatality occurred in reality—false positive rate;
- Conversely, predicting an accident without fatalities where, in reality, a fatality did occur—false negative rate [35].

The confidence table (see Table 4) for verifying the functioning of the model has the following structure:

Table 4. Confidence table. Adopted from [34].

		Prediction	
		0	**1**
Actual	0	True Negative (TN)	False Positive (FP)
	1	False Negative (FN)	True Positive (TP)

The quality of the model is expressed by its evaluation characteristics:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \tag{5}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{7}$$

Accuracy is the percentage of all correctly predicted accidents. It represents the ratio of accidents in which fatality prediction occurred, and fatality indeed occurred in real accidents, relative to the total number of all accidents. This indicator reflects the overall percentage of the model's correct classification and is often used to express the model's classification ability. Sensitivity expresses the percentage of true positive rates. It represents the percentage of accidents in which fatalities occurred and were correctly classified by the model. Precision is the column-based percentage of true positive rates. It is the percentage representation of how many accidents for which fatalities were predicted actually resulted in fatalities [36].

Since we consider the mentioned error of incorrect negative classification (FN) to be more severe, our goal will be to minimise the false negative rate as much as possible when creating the model, even at the cost of increasing the false positive rate. This step was taken because it is a more significant error to incorrectly predict that under the given circumstances there will be no fatality in the accident than to unnecessarily predict the risk of fatality that did not actually occur. In order to reduce the false negative rate, the default setting of probability threshold was lowered to 40%. Therefore, if the predicted probability obtained from the logistic regression model is higher than 0.40, the accident could be classified as a probable fatal accident. Conversely, if the probability is lower than 0.40, the accident will be classified into the category of non-fatal accidents. This value can be adjusted, and the analysis can be repeated with a different threshold level. In addition, the model quality will be evaluated using the ROC curve, which shows the relationship between sensitivity and false positive rate for various threshold values. The quality of the model can then be quantified as the area under the ROC curve (Area Under the Curve—AUC). The closer this value is to 1, the better the model is as a classifier [34]. All calculations are performed using IBM SPSS Modeler software, version 18.

Data Description

For the logistic regression model, all available variables from the database were used as explanatory variables, including interactions between selected variables. All predictor variables were set as indicator variables. These indicator variables took the value 1 if a specific causal factor contributed to accident. If the causal factor was not present, its indicator variable had a value of 0. The value 0 was chosen as the reference category in each case for the better interpretation of the coefficients of the created model [34].

In addition to the mentioned variables, some interaction variables were also included in the model. Specifically, the combination of human factors and the most common causal factors (in fatal accidents) was considered:

- Meteorological factor—waves/current;
- Technical—ship construction/devices for navigation/communication.

These variables were also included in the model in the form of contrast indicators and expressed the influence of the interaction of factors on the probability of fatality.

The dependent variable indicates the occurrence of an accident. Specifically, in 87 accidents (37.5%), there was a fatality, and in 145 cases (62.5%), there was no fatality. Due to this unbalanced ratio of accidents, the balancing was set through boosting. Individual groups were weighted to achieve approximately equal representation in the entire sample. After boosting, the sample contained a total of 296 accident cases, with 145 (50.35%) being accidents without fatalities and 143 (49.65%) being accidents with fatalities.

3. Application

The initial research phase involved the selection of appropriate databases that compile investigation reports on maritime accidents. Then, relevant reports on shipping accidents between 2015 and 2022 were selected. The next step of the research was a comprehensive analysis of maritime investigation reports, focusing on identifying all causal factors that influenced the occurrence of accidents. These factors included meteorological conditions, technical issues, human errors, and other relevant elements. After the analysis, the Human Factor Analysis and Classification System (HFACS) was used to classify human failures on operational and management levels. Lastly, during the final phase of the research, the most critical areas involving the most frequently occurring failures were identified. A risk assessment matrix was applied for risk assessment. This process enabled the highlighting of high-risk areas that required attention and potential interventions.

3.1. Causal Factors Identification

Shipping accidents can be caused by various factors, including technical failures, human failures, meteorological conditions, vis major (superior force), and other unpredictable factors.

The technical condition of a ship often plays a significant role in accident occurrence. Insufficient maintenance and inspections, inappropriate design, and the vessel's age contribute to its inadequate technical and operational condition. Equipment and mechanical failures, such as issues with anchoring, mooring, propulsion, navigation, and communication, also fall within technical failures. In the HFACS method, accidents caused by human negligence in equipment checks and maintenance can be classified separately as "technical environment" incidents.

Meteorological factors include adverse weather and hydrological conditions. These include the influence of wind, currents, tides, atmospheric precipitation, and fog, significantly impacting safe navigation.

As mentioned, the human factor is the predominant factor causing most maritime accidents. Human failure can be divided into intentional and unintentional. Failures can occur during onboard activities ("operational level"), but also can occur due to the failure of supervisory authorities or due to incorrect organisational decisions ("management level"). For safe navigation, it is important to ensure that processes are carried out correctly, with the monitoring and observance of rest periods and implementing regular training.

In addition, other elements can impact safe navigation. "Vis-major" or force majeure refers to unpredictable natural phenomena that can cause severe damage and are often impossible to prevent. This non-man-made factor can have adverse effects on both health and the environment. Additionally, "other factors" include dangers associated with the nature of cargo, especially when transporting hazardous materials with dangerous physical and chemical properties. Knowledge of regulations and proper procedures for handling such cargo is essential for onboard and port safety. Man-made threats, such as crises, inflation, cultural shifts, globalisation, strikes, conflicts, and wars, indirectly influence safe ship operations.

There is a wide range of databases containing maritime investigation reports. In the context of EU maritime accidents data, The European Marine Casualty Information Platform (EMCIP) serves as a repository for data and information on maritime accidents and incidents involving various types of ships. It facilitates the generation of statistics and analysis concerning technical, human, environmental, and organisational factors associated with maritime accidents [3]. The EMSA has developed an approach for the analysis of findings from EMCIP investigation reports with focus on potential safety issues. EMCIP contains reports on all maritime occurrences for each of the EU countries, using the national databases.

For the deeper investigation of a specific factor—human error—two databases that collect accident investigation reports were used: the Marine Accident Investigation Branch (MAIB) and the Transportation Safety Board of Canada (TSB). The MAIB and the TSB databases include several commercial vessels, such as containers, tankers, bulk carriers, RO-RO (roll-on/roll-off) vessels, passenger ships, and small vessels. The investigations conducted by these agencies covered a range of accident types, including grounding, man overboard incidents, collisions, fires, explosions, capsizing or sinking, as well as other specific types of accidents. The databases were used because they contain reports providing full explanations of causes contributing to maritime accident. Such reports were used for the research on human errors in the maritime domain.

3.1.1. Maritime Accidents Based on MAIB Reports

The Marine Accident Investigation Branch (MAIB) was established in 1989 as a response to the RO-RO ferry MS Herald of Free Enterprise accident, which resulted in the loss of 193 lives [37]. The MAIB is an official organisation of the UK government, investigating maritime accidents that occur in UK waters and accidents involving ships registered under the UK flag worldwide. The primary objective of these investigations is to determine the causes of accidents, which helps to raise awareness of risks and develop preventive measures to enhance safety.

In the UK, it is mandatory for all commercially operated vessels in UK waters and all UK-registered vessels worldwide to report accidents. The MAIB receives approximately 1200 accident reports annually, of which 25 to 30 present detailed investigations and have their findings published [37].

Within the selected interval 2015–2022, 135 maritime accidents were selected for research. The analysis revealed 277 causal factors in these accidents—human failure occurred 211 times, the meteorological factor occurred only 26 times, and 40 technical failures also contributed to accidents. In addition to the mentioned factors, when analysing a maritime accident, a situation may also occur when it is not possible to determine the cause with certainty. In most cases, no witness (crew member, captain) survived, so relevant information on accident causes could not be provided. Data on the causal factors of selected maritime accidents are presented in Table 5.

Table 5. Causal factors of analysed maritime accidents. Data from [37].

Years	Number of Accidents	Causal Factors ∑	Factors			
			Human	Meteorological	Technical	Other
2015	27	54	42	3	9	2 unknowns
2016	29	62	45	8	9	2 unknowns
2017	19	36	27	2	7	1 unknown
2018	20	41	30	6	5	1 unknown
2019	19	35	28	2	5	3 unknowns
2020	12	27	23	3	1	1 vis major
2021	6	18	14	1	3	1 unknown
2022	3	12	10	1	1	-
∑	**135**	**295**	**219**	**26**	**40**	**11**

3.1.2. Maritime Accidents Based on TSB Reports

The Transportation Safety Board of Canada (TSB) is an independent agency of the Canadian government responsible for improving transportation safety. It investigates accidents and provides safety recommendations for various transportation sectors, including air, rail, sea, and pipeline [38]. The TSB was established in response to several notable accidents that highlighted the need for an independent agency capable of investigating transportation accidents.

Since its establishment, the TSB has investigated several significant accidents, such as the train crash of Lac-Mégantic, the Air France Flight 358 crash, and the sinking of the Costa Concordia [38].

From 2015 to 2022, 112 maritime accidents were chosen for the researching of causal factors. Through the analysis of these accidents, 160 causal factors were identified. Among these factors, human failure was responsible for 95 occurrences, meteorological conditions contributed to 23 incidents, and 42 accidents were attributed to technical failures. A situation where unknown factors were at fault (no witnesses of ongoing investigation) occurred in 30 instances (see Table 6).

Tables 5 and 6 show the numbers of accidents within each year, provided by both databases. It is noticeable that the numbers of causal factors significantly exceed the counts of accidents. This is primarily due to the fact that, in most cases, multiple causal factors contribute to a single accident. In the case of human errors, the predominant contributors are individuals lacking appropriate training and engaging in improper practices, which can be categorised into various domains within the HFACS method (refer to the practical application of HFACS, Table 7). After examining 247 maritime investigation reports from both databases, it was determined that between 2015 and 2022, the human factor accounted for approximately 70% of cases. Technical factors contributed to about 20%, while adverse meteorological or hydrological conditions accounted for only 10% of all factors influencing accident occurrence.

Table 6. Causal factors of analysed maritime accidents. Data from [38].

Years	Number of Accidents	Causal Factors ∑	Factors			
			Human	**Meteorological**	**Technical**	**Other**
2015	11	21	11	6	6	1 unknown
2016	15	21	14	3	4	1 vis major
2017	19	31	20	1	10	1 unknown
2018	22	38	20	6	12	2 unknowns
2019	14	24	16	3	5	4 unknowns
2020	13	20	13	3	4	4 unknowns
2021	8 [1]	8	5	2	1	unknown (6 [2])
2022	11	-	-	-	-	ongoing investigation (11)
∑	**112**	**160**	**99**	**23**	**42**	**30**

[1] In the accident "*Collision between an aircraft de Havilland DHC-2 MK. I, Tofino Air (Beaver), C-FMXR and Eagle Adventures Water Taxi C12997BC (Rocky Pass), British Columbia, 18 October 2021*", only causal factors on the side of the skipper, not the pilot, were investigated. However, a technical factor that contributed to the accident (broken wing) was taken into account. [2] 5 cases are still under ongoing investigations, in one case ("*Sinking and subsequent loss of life, fishing vessel Island Lady Labrador Sea involved, Newfoundland 17 September 2021*") the investigation could not determine with certainty the cause of the disappearance of the vessel. However, it is likely that the vessel sank and that both crew members entered the water unexpectedly, without life-saving equipment, and without being able to successfully make a distress call.

Although human error emerged as the predominant causal factor, it is important to note that not all accidents involved human failure specifically. Some accidents were only caused by technical or meteorological factors. However, certain accidents were caused by multiple levels of human failure, for instance: inadequate communication, fatigue, and stress combined with the routine violation of rules. This combination of factors intensified the occurrence of accidents. Table 6 provides a comprehensive overview of the human errors in the analysed maritime accidents.

3.2. Application of HFACS

Example of Coding Process

This chapter provides a comprehensive analysis of causal factors contributing to maritime accidents. Based on the HFACS, this is called a coding process. The authors specifically chose an accident wherein multiple causative factors, including the human factor, were at play. This coding process was systematically applied to analyse the causal factors across all 247 investigated maritime accidents.

For the practical application of the coding process, the accident of the Norway general cargo vessel was chosen, which occurred on 18 February 2015 while on passage from Belfast to Skogn. The ship ran aground near Kilchoan, West Scotland. The general cargo vessel remained aground for about 2 days and, due to adverse weather, was heavily pounded onto the rocky foreshore. This caused heavy damage to its hull and the breaking of the double bottom, resulting in 25 tonnes of marine gas oil spilling into the water. After its salvage, the vessel was towed to dry dock where it was surveyed, declared a constructive total loss and scrapped [37].

Findings based on the investigation report:

- The vessel grounded when the Officer of the Watch lost situational awareness as a result of being under the influence of alcohol;
- The effective administration of the owner's zero alcohol policy might have prevented the development of a culture in which the chief officer considered it acceptable to consume alcohol before his watch;

- Had a lookout been on the bridge, he would have been well placed to prevent the accident by alerting the master to the chief officer's condition and that navigational waypoints had been missed;
- Had the BNWAS been switched on it is probable that the OOW would have realised at an earlier stage that a navigation waypoint had been missed;
- Had the passage plan been appropriately entered into the ECS, the available safety features would have been available, and the alarms could have alerted the OOW to potential dangers at an early stage;
- Had an appropriate and detailed passage plan been prepared and implemented in a professional and precautionary manner, it is unlikely that the voyage would have ended with the vessel hard aground;
- The abuse of alcohol was a symptom of systemic non-compliance with the SMS on Lysblink Seaways, which had gone unchallenged despite regular audits [37].

Notes from authors:

- Change of voyage because of adverse weather;
- The chief officer made a private telephone call that caused him anxiety, after which he consumed about 0.5 litre of rum (off duty);
- At midnight the chief officer took over as OOW, then sat in a chair located to starboard of the central manoeuvring station, from where he monitored the systems, but was sleepy and turned off the audio;
- The vessel's steering was in autopilot mode;
- Deviation from planned route until grounding (vessel passes wrong route because of wind and alarms turned off);
- No lookout was posted during the hours of darkness;
- The emergency checklist for grounding was not consulted;
- The master advised that the vessel was not damage and that there was no pollution or injuries, but the vessel's hull had been breached and its steering gear was damaged;
- Poor navigational practices, and defences/control measures for the Officer of the Watch becoming incapacitated were being ignored;
- Delay in contacting the coastal state;
- Neither the master nor the chief officer had received training in the use of the ECS and available safety features.
- The only alarm that had been enabled was for cross-track error, but this had been inappropriately set up and the audio alarm had been silenced.

The table below illustrates the coding process, providing examples of human failures correctly classified within each category, all derived from this particular accident (see Table 7).

Table 7. Example of coding process.

UNSAFE ACTS	
Decision errors	
Skill-based errors	
Perceptual errors	
Routine violations	
Exceptional violations	The audible alarm for cross track deviation had been silenced BNWAS switched off

Table 7. *Cont.*

PRECONDITIONS FOR UNSAFE ACTS	
Physical environment	Darkness Adverse weather (wind)
Technological environment	Cross-track error of alarm (not set)
Adverse mental state	Loss of situational awareness as a result of being under the influence of alcohol
Adverse physiological state	
Physical/mental limitations	
Crew resource management	
Personal readiness	Influence of alcohol
	UNSAFE SUPERVISION
Inadequate supervision	Chief officer considered it acceptable to consume alcohol before the watch. Master and chief officer did not received training in the use of the ECS and available safety features
Planned inappropriate operations	No lookout on the bridge to prevent the accident by alerting the master to the chief officer's condition and that navigational waypoints had been missed Unprepared and unimplemented appropriate and detailed passage plan Passage plan not entered into the ECS
Failed to correct problem	
Supervisory violations	Systemic non-compliance with the SMS on Lysblink Seaways
ORGANISATIONAL INFLUENCES	
Resource management	
Organisational climate	
Organisational process	

3.3. Summary

Based on the HFACS coding process, it is possible to determine with accuracy not only all human factors that caused the accident, but also other factors (technical and meteorological). In this case, the failure of a technical factor represents a cross-track error within an alarm system that was improperly configured and failed to function as intended. Additionally, meteorological conditions played a role in the accident. Strong winds and high waves necessitated a change in the planned course of the voyage. It is essential to note, however, that the meteorological factor alone did not directly cause the boating accident. The primary catalyst for the incident was a series of human errors.

However, the meteorological factor significantly contributed to the total destruction of the vessel.

The shipping accident occurred as a result of a chain of human failures. This chain ranged from a loss of situational awareness due to alcohol consumption and consciously shutting the volume of alarms down, which could have alerted people to impending danger, to lapses within supervisory authorities due to non-compliance with the no-alcohol policy.

4. Results

4.1. Coding Process Results

The coding process involves the systematic classification of human failures into HFACS categories. This method allows for identifying and analysing critical areas of human failure at the "operational level" or the "management level". This analysis uses investigation reports from the Transportation Safety Board (TSB) and the Marine Accident Investigation Branch (MAIB) databases.

The coding process aims to highlight and prioritise the most frequent errors that repeatedly occur during the onboard operations or at the level of the supervision/organisation. These errors are particularly important and are highlighted by different shades of red. The intensity of the red corresponds to the frequency of failures, with darker shades indicating more frequent occurrences (see Table 8).

Table 8. Human failure classification.

Category of Failure	Subcategories	MAIB	TSB	∑	% [1]
Unsafe acts	Decision Errors	31	14	45	14.2%
	Skill-Based Errors	8	5	13	4.1%
	Perceptual Errors	6	2	8	2.5%
	Routine Violations	30	12	42	13.2%
	Exceptional Violations	11	2	13	4.1%
Preconditions for unsafe acts	Physical Environment	7	2	9	2.8%
	Technological Environment	14	6	20	6.3%
	Adverse Mental State	9	2	11	3.5%
	Adverse Physiological State	4	3	7	2.2%
	Physical/Mental Limitations	6	1	7	2.2%
	Crew Resource Management	12	11	23	7.2%
	Personal Readiness	10	5	15	4.7%
Unsafe supervision	Inadequate Supervision	23	14	37	11.6%
	Planned Inappropriate Operations	7	5	12	3.8%
	Failed to Correct a Known Problem	7	4	11	3.5%
	Supervisory Violation	6	5	11	3.5%
Organisational influences	Resource Management	7	1	8	2.5%
	Organisational Climate	2	0	2	0.6%
	Organisational Process	19	5	24	7.5%
∑		**219**	**99**	**318**	**100.0%**

[1] The percentage of each subcategory on the total number of human failures, for both databases (MAIB + TSB).

The research shows that the most frequent category of human failure is "Unsafe acts", accounting for 38% of all failures. This category consists of two types of human failure: errors (unintentional behaviours leading to failure) and violations, which involve the conscious violation of rules. Within the "Unsafe acts" category, the most common failures are related to decision-making errors, accounting for 45 occurrences. These errors were caused by inappropriate human behaviour, such as incorrect procedures, inadequate reactions to dangerous situations, failure of critical thinking, and working in hazardous areas. Skill-based errors, which result from automatic and unconscious behaviour during routine activities, accounted for 13 occurrences. These errors include missing procedure steps, improper equipment usage, and distractions. Perceptual errors occurring in limited sensory conditions were identified in eight occurrences. Examples include mishearing or misinterpreting instructions and misjudging distances.

The category of Unsafe acts also includes violations. Routine violations, including 42 occurrences, involve knowingly disregarding safety regulations, not wearing protective equipment, and intentionally disabling alarms. Exceptional violations, occurring 13 times, represent more serious deviations from rules and regulations, such as leaving the workplace while on duty, engaging in extremely dangerous manoeuvres, or maintaining dangerous vessel speeds.

The second category, "Preconditions for unsafe acts", accounts for 29% of human failure. It encompasses three areas of failure: environmental factors, personnel factors, and the operator's condition. Environmental factors, with 29 occurrences, consider the effects of the physical and technological environment, including inappropriate ship construction and operating conditions affecting people, such as poor lighting or vibrations. Personnel factors consist of crew management factors (failure in communication, lack of teamwork—23 occurrences) and failure of personal readiness (persons cannot perform a duty—influence of alcohol, non-observance of mandatory rest periods—14 occurrences). The operator's condition includes an adverse mental state (mental fatigue, distraction, stress—11 occurrences); adverse physiological conditions (physical fatigue, health problems, use of drugs and narcotics to improve health—7 occurrences); and physical or psychological limitations—7 occurrences.

The third category, "Unsafe Supervision", classifies failures at the management level. It primarily examines the shortcomings of supervisory bodies responsible for providing adequate leadership, supervision, training, and guidance. Within the investigated accidents, 71 occurrences (23% of the total human errors) were attributed to failures in this category. The subcategory inadequate supervision accounts for the highest number of failures within this category, with 37 occurrences, including insufficient training, failure to monitor work performance, and inadequate rest for crew members. Planned inappropriate operations include 12 occurrences, with inappropriate transshipment processes (undeclared or incorrectly declared cargo, inappropriate or missing "cargo manifest", pressure to complete processes). Failure to correct a known problem is a category in which failures occur because a known problem has not been corrected and a dangerous situation has persisted (tolerating an alcoholic at work, not reporting a dangerous crew member—11 occurrences). Supervisory violations represent a situation where individuals in leadership positions intentionally do not follow existing instructions, rules, and regulations—11 occurrences.

The last category, "Organisational influences", accounted for 10% of human errors. Faulty decisions at the management level within the organisational structure directly affected the procedures of supervisory authorities and the safe practices of captains and crew members. This category is divided into three areas: resource management, which encompasses failures in top management decisions regarding financial allocation, facility maintenance, human resources, and equipment (8 occurrences); the organisational climate, consisting of failures in orders, delegation, responsibility, or shipping company policies (2 occurrences); and organisational process, involving errors in time constraints, schedules, work pace, risk management, and safety program development within the organisation (23 occurrences).

4.2. Evaluation of Critical Areas

In this section, the critical areas of human failure are evaluated (see Table 9). The assessment combines two factors: the probability of an accident occurring within a specific area of failure (frequency of failure in a particular category) and the severity of the consequences most commonly observed in those areas.

A better understanding of the overall risk associated with each critical area can be given by considering the frequency and severity of failures. For instance, if violations of regulations occur frequently and are associated with more severe consequences, they would be considered higher-risk areas. This evaluation helps prioritise efforts made to address the most crucial areas of human failure and mitigate the associated risks.

Based on the research on critical areas of human failure, it can be concluded that the most frequent human factor failures occurred in the following categories:

- Decision errors (14.2%);
- Routine violations (13.3%);
- Inadequate supervision (11.7%);
- Crew resource management (7.3%);
- Organisational process (7.3%).

Failures commonly happen during onboard activities, such as making wrong decisions, failing to assess critical situations, or lacking experience—violations, whether by crew members or management, are also common failures resulting from breaking regulations.

The worst situations in terms of accident severity involve death, injuries, damage to the vessel and its components, and the release of dangerous substances into the water. The most dangerous categories of human failure are:

- Exceptional violations;

- Crew resource management;
- Personal readiness;
- Planned inappropriate operations;
- Failure to correct the known problem;
- Supervisory violations.

Table 9. Assessing critical areas of human failure at sea.

Category of Failure	INHERENT RISK 1 = Low/Acceptable, 5 = High/Unacceptable		
	Probability (1–5)	Severity (E–A)	Risk (P × S)
Decision Errors	5	C	5C
Skill-Based Errors	3	C	3C
Perceptual Errors	2	C	2C
Routine Violations	5	D	5D
Exceptional Violations	3	B	3B
Physical Environment	2	C	2C
Technological Environment	3	C	3C
Adverse Mental State	2	D	2D
Adverse Physiological State	2	D	2D
Physical/Mental Limitations	2	C	2C
Crew Resource Management	4	B	4B
Personal Readiness	3	A	3A
Inadequate Supervision	5	C	5C
Planned Inappropriate Operations	2	A	2A
Failed to Correct a Known Problem	2	B	2B
Supervisory violations	2	B	2B
Resource Management	2	E	2E
Organisational Climate	1	D	1D
Organisational Process	4	C	4C

Research on human failures within these categories has shown that the most frequent deaths of passengers or crew members occur due to exceptional violations, such as not wearing life-saving equipment, making unauthorised modifications to the vessel's design, or disabling warning signals. Personal readiness failures often lead to deaths and injuries caused by fatigue or alcohol influence. The category of inappropriate planned operations is characterised by errors from the supervisory authority, including incorrect crew assembly and failure to define rest periods.

Failure to correct known problems refers to cases where the captain, despite warnings, sails in poor weather conditions, leading to failures. Supervision violations represent another dangerous category of human errors, with unqualified individuals often present on board and operational regulations not being followed, especially to expedite departure from the port. Failures in crew coordination mostly involve communication errors on board, where an uncoordinated crew member fails to perform their assigned activity, often not due to their own fault.

Fatalities most commonly occur when the vessel capsizes and sinks, accounting for 56 incidents. The second most frequent fatal accident is "man overboard", where a person drowns or dies from hypothermia, with 30 occurrences. Collisions rank third with 11 fatal accidents. Other types of accidents had fewer fatal occurrences, with the highest rate of injuries observed in fire and collision incidents. The largest volume of hazardous substances leaks happened during vessel capsizes, sinkings, and groundings.

4.3. Modeling the Prediction of the Probability of Fatality in a Maritime Accident

The analysis was conducted by creating a programming stream in the IBM SPSS Modeler. The process of creating the model is shown in Figure 1.

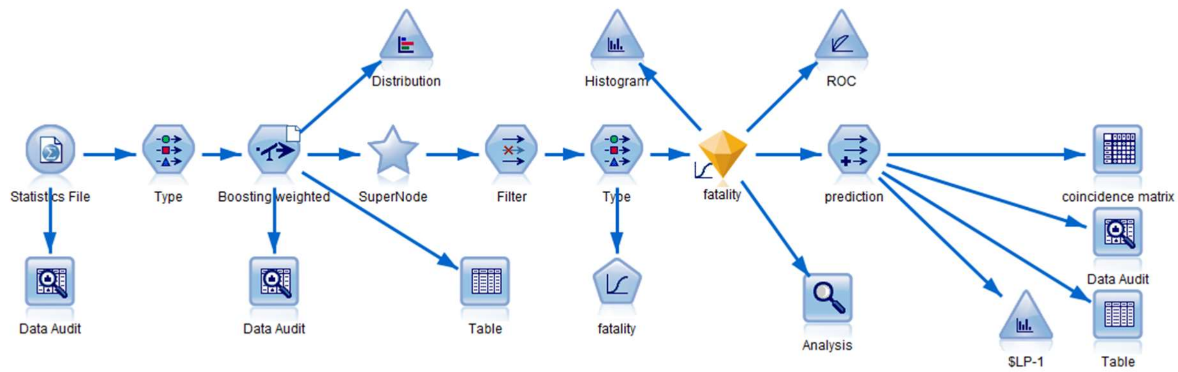

Figure 1. The process of creating the prediction model.

The complete logistic regression model is presented in the table below. Variables that were omitted from the model were excluded due to their low variability or strong interdependence. Table 10 shows data used for the logistic regression model.

Table 10. Logistic regression model.

Variable	B	S.E.	Wald	Sig.	Exp (B)
meteorological: ice	42.477	18,364.78	5.35×10^{-6}	0.998	2.80×10^{18}
meteorological: fog	1.456	0.725	4.026	0.045	4.29
meteorological: rain/precipitations	−1.016	0.858	1.403	0.236	0.36
meteorological: waves/current	21.644	12,791.1	2.86×10^{-6}	0.999	2.51×10^{9}
technical: propulsion	0.384	0.528	0.53	0.467	1.47
technical: ship construction	−0.437	2.035	0.046	0.830	0.65
technical: equipment	0.448	0.393	1.298	0.255	1.57
technical: devices for navigation/communication	2.538	1.422	3.184	0.074	12.65
human: category unsafe acts (HFACS)	0.219	0.318	0.475	0.491	1.24
human: category preconditions (HFACS)	0.368	0.323	1.3	0.254	1.44
human: category supervision (HFACS)	0.224	0.331	0.459	0.498	1.25
human: category organisation (HFACS)	0.375	0.387	0.943	0.332	1.45
other: vis major	0.356	1.048	0.115	0.734	1.43
other: unknown	−0.897	0.518	2.997	0.083	0.41
human: category Organisation (HFACS) + meteorological: waves/current	0.842	1.927	0.191	0.662	2.32
human: category Unsafe acts (HFACS) + technical: ship construction	1.051	2.007	0.274	0.601	2.86
human: category Organisation (HFACS) + technical: ship construction	1.006	1.825	0.304	0.581	2.73
human: category Preconditions (HFACS) + technical: ship construction	−2.151	1.853	1.348	0.246	0.12

Table 10. *Cont.*

Variable	B	S.E.	Wald	Sig.	Exp (B)
human: category Supervision (HFACS) + technical: devices	21.3	11,801.51	3.26×10^{-6}	0.999	1.78×10^{9}
human: category Unsafe acts (HFACS) + technical: devices	1.213	1.398	0.753	0.386	3.36
human: category Preconditions (HFACS) + technical: devices	2.77	1.416	3.828	0.05	15.96
constant	40.027	38,009.47	1.11×10^{-6}	0.999	2.42×10^{17}

The first column of the table presents the estimated coefficients of log odds. Their conversion into a relationship with the probability of fatality in an accident is found in the last column of the table. These coefficients can be interpreted as follows: when the coefficient B is positive, resulting in $Exp(B) > 1$, the respective factor contributes to an increased probability of a fatal an accident. If the estimated coefficient B is negative, leading to $Exp(B) < 1$, the factor decreases the probability of a fatal accident.

The Figure 2 illustrates the ranking of individual predictor variables in the created model based on their importance in predicting fatalities. The figure shows the top 10 most important factors.

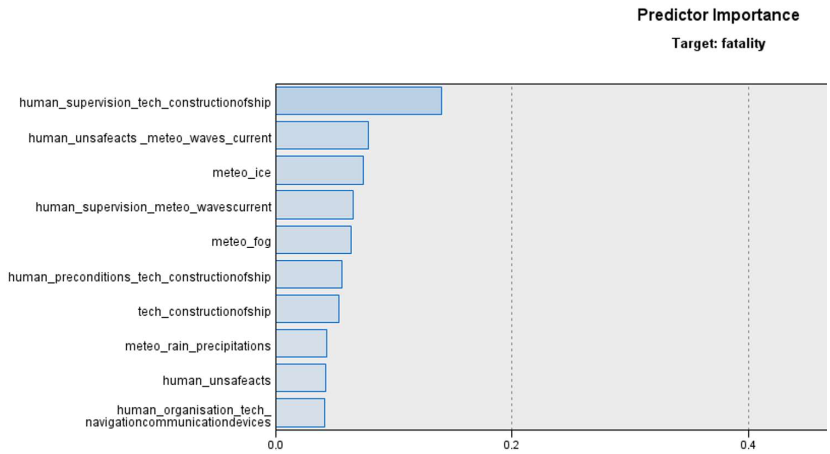

Figure 2. The ranking of predictor variables and their importance.

The most significant factor increasing the likelihood of fatalities is the human factor, specifically within the category of Unsafe Supervision (according to HFACS), together with the causal factor of inappropriate vessel construction. This represents a predominant combination of causal factors with the greatest impact on the probability of fatality occurrence. The second most critical combination involves the human factor (Unsafe acts) and the simultaneous influence of hydrological factors, such as waves or currents. In these cases, fatal accidents typically result from decision-making errors and skill-based errors during manoeuvring under adverse hydrological conditions. Various individual influencing factors also have a significant impacts on the probability of fatality onboard, such as:

- Meteorological/hydrological factors—ice, precipitation, fog;
- Technical failures—improper vessel construction;
- Human factors—unsafe acts (most commonly decision errors and skill-based errors).

Another combination with a significant impact on the probability of fatalities is human error (Unsafe Supervision) coupled with the influence of hydrological phenomena.

These fatalities often resulted from a lack of training, which would have helped captains manoeuvre under adverse navigational conditions.

Human error at the level of preconditions for unsafe acts, most frequently influenced by alcohol and fatigue, combined with poor vessel design, are factors of lower significance in the likelihood of death occurrence on board. Similarly, the combination of human factor failures at the organisational level and technical failures (failure of navigation and communication equipment) has a low impact on the probability of fatality occurrence. This is a very logical combination considering that if a company prioritizes profit over safety and does not invest in functional or new equipment, it creates space for accidents. The predicted probabilities estimated from this model are classified into two groups: accidents with a risk of fatality and accidents without fatality. Figure 3 shows the distribution of individual probabilities of fatality occurrence in maritime accidents, based on the actual outcomes (normalised by colour).

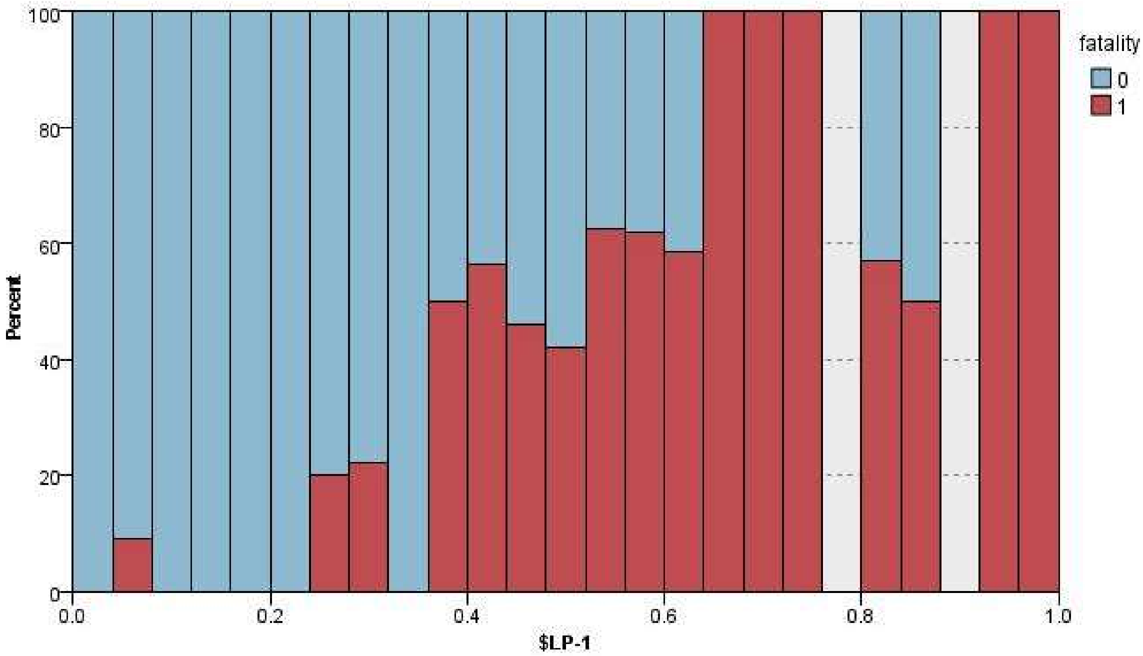

Figure 3. The distribution of probabilities of fatality occurrence.

In the left part of the chart, where the model predicted low probabilities of fatality occurrence, accidents without fatalities are indeed more frequent. Conversely, in the right part, where high probabilities of fatality occurrence are predicted, such accidents occur. However, in some instances, the model incorrectly predicts low or high probabilities of fatality occurrence. \$LP-1 represents the probability prediction of the value Y = 1 using the logistic regression model, i.e., \$LP-1 = $\hat{P}(Y = 1)$.

The classification table of the created model (Table 11) provides the absolute count of correctly and incorrectly classified accidents. For this classification of predicted fatality probabilities in accidents, the threshold of 0.40 was used.

Table 11. Classification table.

		Prediction	
		0	**1**
Fatality	0	52	93
	1	11	132

In Table 11, we show the calculated evaluation statistics that reflect the quality of the created model. The model demonstrates an overall accuracy of 64% in distinguishing between accidents with a risk of fatality and those without. The model's sensitivity is 92.2%, indicating the percentage of correctly predicted fatal accidents. It also attains a precision of 58.8%, indicating the percentage of cases in which fatality was predicted correctly. As mentioned, to provide proper balance between these two data subsets, we implemented sample balancing through boosting (from 232 to 288).

Based on these evaluation statistics, the model excels in identifying accidents with a risk of fatality. The error rate in predicting fatal accidents is only 7.7%, but at the cost of an increased error rate in accidents without fatalities. Figure 4 shows the ROC curve of the created model, providing another perspective on the model's quality.

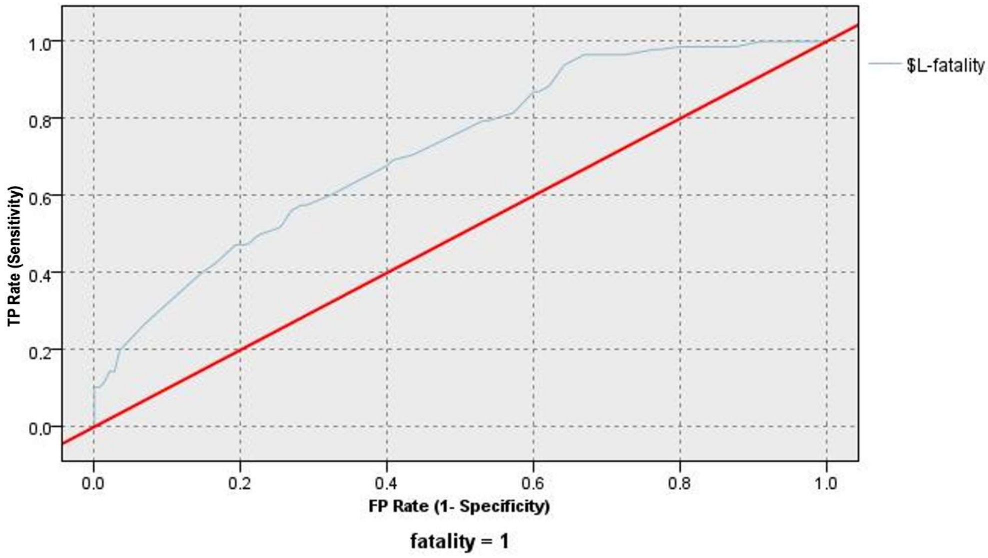

Figure 4. ROC curve representing the model's quality.

The area under this curve is AUC = 0.729. From this perspective, we consider the created model to be of sufficient quality to predict the risk of fatality in maritime accidents. Red diagonal line represents the random allocation model, i.e., fatality predicting. The resulting model is compared to this reference model. If the ROC curve closely aligns with the diagonal, it suggests a weaker model. The closer it approaches the upper-left corner, the stronger the model becomes.

5. Proposal of Measures for Critical Areas for Increasing Maritime Safety

Ensuring safety at sea strongly depends on the collaboration between supervisory authorities and organisations. However, when organisations prioritise operational aspects such as speed of processes, and meeting quotas, safety often takes a back seat. The International Maritime Organisation (IMO) regulates safety through regulations in the shipping industry. One of the most important is the ISM Code, which mandates that every shipping company must have a Safety Management System (SMS). This system should include:

- Safety and environmental protection policy;
- Instructions and procedures to ensure the ship's safe operation and environmental protection in compliance with international and flag state law;
- Clear delineation of authority levels and communication channels between shore authorities and crewmembers;
- Protocols for reporting accidents/incidents and non-compliance with the code's provisions;
- Procedures for emergency preparedness and response;

- Guidelines for international audits and management controls [39].

However, shipping companies often do not implement SMS systems (partially or completely). SMS systems should be implemented for each vessel individually to ensure efficiency and safety, as each vessel and its crew are unique. Therefore, the emergency standards, the number and type of training, and the responsible persons onboard should be individually determined.

The SMS and safety management systems on board marine vessels are only mandatory for vessels with a displacement of more than 500 GT[2]. However, research on maritime accidents has shown that approximately one-third of accidents involve vessels with a GT of up to five hundred tonnes. It is crucial to introduce SMS systems for smaller vessels, and the SMS system should also be implemented for vessels with a displacement of less than 500 GT (involving fishing vessels).

As mentioned, an improperly set organisational process and a lack of supervision represent a significant risk that needs to be reduced. In addition to introducing SMS systems even for minor rules, it is also necessary to formulate regulations on the organisation of work and a clear definition of the duties (and powers) of individual crew members. After implementing new measures and regulations, it is necessary to monitor them (risk monitoring after its reduction).

Furthermore, there is a need to establish a comprehensive supervision system that not only oversees crew members' compliance with regulations, but also identifies any hazards within the system during their daily tasks and activities. Additionally, monitoring the operating environment's impact is crucial to ensure safety and mitigate risks.

Moreover, a "secret safety checks" system should be provided in addition to regular safety checks. Checks within this system should occur so that the controller can be included as a new or a temporary crew member, liaising with staff and monitoring security risks throughout the vessel's operation. The limitation of this method is that the process controller must be trained to perform activities as a member of the vessel's crew.

A significant challenge identified is the insufficient training provided to crew members, including a lack of training on equipment usage and vessel-specific procedures. Furthermore, there is a need to address the issue of selecting suitable crew members who possess the necessary skills, experience, good health, and mental well-being. It is important to point out that the average age of managerial crew members and captains in the commercial maritime sector falls between 50 and 62 years [41], which presents some concerns. This age range reflects the requirement for more than adequate experience, sailing nautical miles, and the ability to handle various critical situations.

As modern technologies are increasingly integrated into maritime operations to improve safety and prevent accidents, onboard managers must understand technologies and ensure their correct usage. Regular training programs focusing on the operation of navigational instruments can enhance awareness and proficiency in handling advanced ship equipment.

Furthermore, safety can be enhanced through motivational measures implemented by management:

- Positive motivation involves financial rewards beyond regular salaries for performing safe navigation without incidents;
- Negative motivation can also increase safety by imposing sanctions for non-compliance with rest periods, consuming alcohol during duty, or neglecting training obligations.

6. Discussion

Human failure plays a significant role in impacting maritime safety, as nearly 70% of accidents can be traced back to human errors. These errors often stem from issues related to cognitive, perceptual, and psycho-behavioural processes. It is noteworthy that even supervisory authorities and organisational structures may not be immune to these failures. In the wake of such accidents, a critical focus has been placed on identifying lessons learned and implementing key changes. These lessons have prompted revisions in safety protocols, training programs, and operational procedures, ultimately enhancing maritime safety. The main conclusions resulting from our research can be summarised as follows:

1. The research includes the analysis of 247 maritime accident investigation reports from MAIB and TSB databases in the period 2015–2022;
2. Determining causal factors involved categorisation into four groups—meteorological, technical, human, and other factors;
3. The HFACS method classified human errors and failures into four main categories: unsafe acts, preconditions for unsafe acts, unsafe supervision, and organisational influences;
4. By employing the coding process of the HFACS method, repetitive errors within each category were identified. This allowed for identifying specific areas requiring monitoring and implementing preventive measures to enhance maritime safety;
5. Risk assessment methods were used to analyse and evaluate critical areas in the context of improving maritime transport safety;
6. The most critical causal factors causing maritime accidents with fatalities are identified and assessed, based on the prediction model using linear regression;
7. Limitations of the study lie in two aspects—firstly, only full investigation reports on maritime accidents were used. The authors focused on these accidents because such reports offer a thorough understanding of the causes. In contrast, accidents with less severe consequences tend to have less detailed reports (if any), posing challenges in data acquisition. For this reason, the coding process and regression model were based on the 232 accidents instead of 247. The second limitation lies in the subjectivity of the HFACS method. The categorisation of unsafe events using HFACS is based on individual, subjective opinions of experts and/or researchers using it. However, this limitation can be greatly reduced when HFCAS analysis is carried out by an expert with experience in safety investigations;
8. By identifying the most significant threats, the paper has proposed preventive measures and the introduction of new safety processes. These initiatives aim to reduce the incentives for engaging in dangerous behaviour.

Currently, a reactive approach is used in maritime transport, whereby preventive measures are taken in response to past safety risks or accidents. For example, the accident with the Herald of Free Enterprise was the breaking point for the change of structural elements of RO-RO vessels [42] and for safe communication models [43]; evacuation procedures and exercises were changed after an accident with Costa Concordia in 2012 [44]. Thus, a reactive strategy works on the principle of reacting to safety events that have taken place in the past. In principle, it can be said that "something has to go wrong" (in the sense of safety) for it to be "improved". A reactive strategy is an important part of mature safety management; however, its effectiveness depends on the thorough investigation of the root causes of each event.

The International Maritime Organisation (IMO) adopts a similar reactive approach, as most of its conventions and regulations respond to major maritime accidents [45]. Examples include:

- The SOLAS convention (International Convention for the Safety of Life at Sea, 1974) developed in response to the Titanic accident [46]. The sinking of the Titanic in 1912 marked a crucial moment in maritime safety, leading to a shift from national attempts to regulating maritime safety independently [47];
- The main objective of the SOLAS convention is to specify minimum standards for the construction, equipment and operation of ships, compatible with their safety;
- The MARPOL convention (International Convention for the Prevention of Pollution from Ships, 1978), dealing with the prevention of pollution of the marine environment by ships from operational or accidental causes. The MARPOL Convention was adopted on 2 November 1973 at IMO. The Protocol of 1978 was adopted in response to a spate of tanker accidents in 1976–1977 [48];

- The ISM Code (International Safety Management Code, 1993) was adopted in response to the Herald of Free Enterprise incident. The ISM Code provides an international standard for the safe management and operation of ships and for pollution prevention [49].

The IMO's reactive approach has helped in creating a comprehensive regulatory framework aimed at preventing accidents on the one hand, and the minimisation of damages on the other hand, if an accident occurs despite all preventive measures [50].

Despite technological progress and an appropriately set legislative framework, the same pattern is repeated over and over again in shipping accidents—human failure. It is therefore obvious that the reactive approach will need to be supplemented with a proactive and predictive approach. The basic task of a proactive approach is the search for dangers and risks that are currently present during the operation of the organisation. Its basic principle is to identify hazards and risks present in the system and take steps to correct them before they become dangerous. A proactive approach is usually used for less serious security incidents, which are not harmful (if so, only minimally). The main task of the predictive approach is the active search for and identification of future security failures before they can appear and thus represent a potential danger [31]. As part of the predictive approach, it is possible to monitor maritime accident investigation data over a long period of time, investigate safety risks and uncover hidden dangers in the system. Considering the action of the human factor as the main cause of navigation accidents, it is necessary to focus on the identification of critical areas of human failure. The combination of a proactive and predictive approach to risks can help to increase the safety of maritime transport and safety procedures onboard.

7. Conclusions

Over the past fifty years, the shipping industry has focused on improving the reliability of ship systems and increasing the durability of the ship's structure. These steps were intended to reduce the number of fatal accidents and, at the same time, bring increased productivity and efficiency to the processes. Real improvements in hull design (inland vessels with double hulls and double bottoms; watertight bulkheads of RO-RO vessels and others), improvement of stabilisation and propulsion systems, and the development of navigation and signalling devices and their implementation onboard should guarantee a certain level of safety. Modern ship systems are technologically very advanced and highly reliable. Considering all these facts, the rate of maritime accidents is still high, and the risk of accidents has not significantly decreased, despite the implementation of regulations establishing safety limits and requirements for the operation of vessels (e.g., new IMO regulations on the mandatory introduction of the SMS system within shipping companies). The number of accidents is not decreasing primarily because ships' structures and system reliability are a small part of the safety equation.

The maritime system is human-based, and failures are crucial in these incidents; 70–85% of maritime accidents can be attributed, at least in part, to some form of human error.

To significantly enhance safety in the shipping industry, a crucial focus must be placed on addressing human errors, which are responsible for most maritime accidents. In recent years, two key issues have emerged: a lack of qualified workers at the operational level and the increasing level of automation. Even in highly automated processes, crew members and captains must not overlook their duties and responsibilities.

Their primary purpose is planning, control, supervision, and active engagement beyond critical situations. Flexibility in problem-solving, adequate knowledge, skills, experience, improvisation, and sometimes intuition are necessary during such critical moments.

Authorised authorities (ports, shipping companies, and supervisory authorities) should focus on providing quality training and education that guarantees the safety of onboard activities and port operations. Shipping companies should prioritise ongoing training for crew members, captains, and other personnel. The training programmes should emphasize the importance of their roles in safety, provide essential knowledge, and offer practical training in managing critical situations. Training should contain not only technical skills but also soft skills, such as teamwork and effective communication, which are crucial onboard maritime vessels. Well-trained individuals are less likely to make errors and can respond more effectively to critical situations.

Another recommendation for increasing maritime safety is to establish a mentorship programme to transfer knowledge from experienced captains and crew members to new, less qualified crew members. This will help bridge the gap between qualified workers and inexperienced recruits and improve teamwork.

Assessing safety risks is a crucial step towards increasing safety. Therefore, each shipping company, as well as ports and authorities, should develop risk assessment and management processes, drawing lessons from past failures and accidents to prevent similar incidents in the future. Even in automated processes, human judgment and quick decision-making remain crucial. Advancements in automation, artificial intelligence, and monitoring systems can complement human decision-making and reduce the likelihood of errors.

Based on the research findings, mitigating fatigue aboard maritime vessels is crucial for enhancing maritime safety. Recommendations include compliance with work hour regulations (maximum work hours and minimum rest hours are essential), effective sleep habits, a balanced diet, regular exercise, strategic drills, daytime task scheduling, task variety, and learning from past incidents. Implementing these measures is crucial for reducing fatigue-related incidents and enhancing maritime safety [51].

The paper's findings and recommendations highlight the most common failures attributed to the human factor in maritime transport. These proposals provide significant insights into the underlying causes of errors. By increasing awareness of safety risks, assessing and evaluating them, and proposing preventive measures, water transport safety can be significantly enhanced.

Author Contributions: Conceptualisation, A.M. and M.M.; methodology, A.M.; validation, L.Š. and A.M.; formal analysis, A.D. and A.M.; investigation, A.M. and M.M.; resources, A.M. and A.D. and L.Š.; data curation, L.Š. and A.M.; writing—original draft preparation, A.M.; writing—review and editing, M.M.; visualisation, M.M.; supervision, A.D. and A.T.; project administration, A.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was not applicable to this study as it did not involve specific individuals and does not contain any personal data. The research is based on publicly available data utilising no identifiable personal information of any kind. Therefore, the need for written informed consent for publication is not applicable.

Data Availability Statement: For access to the data presented in this study, reach out to the corresponding author upon request.

Acknowledgments: The paper was supported by the VEGA Agency by the Project 1/0798/21. "The Research on Measures to Introduce Carbon Neutrality in the Rail and Water Transport" that was run at the Faculty of Operation and Economics of Transport and Communications, University of Žilina.

Conflicts of Interest: The authors declare no conflict of interest.

Notes

1 Sequential models, which aim to eliminate the causes of accidents, work reliably for accidents caused by technical and physical component failures along with human failures in relatively simple systems. However, they are limited if they are to explain the cause of accidents in more complex systems. Epidemiological models (e.g., Reason's model) are used to investigate causal factors in more complex systems. Therefore, the Human Factor Analysis and Classification System (HFACS) method was chosen for research, which is based on Reason's model. The HFACS method is tool used for the evaluation of human failure and is directly applicable to the research needs of causal factors in maritime transport.

[2] A measure of a ship's overall internal volume and is determined by dividing by 100 the contents, in cubic feet, of the vessel's enclosed spaces [40].

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