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Assessing Fatality Risks in Maritime Accidents: The Influence of Key Contributing Factors

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Abstract: This paper investigates the factors influencing the probability of fatality in various types of maritime accidents, including grounding, capsizing, sinking, man overboard incidents, and fatal falls, with a focus on several contributing factors—alcohol consumption, meteorological conditions, and visibility. Through comprehensive analysis, the alcohol consumption was examined in order to show how it impairs judgment and physical abilities, significantly increasing the risk of fatal outcomes in these accidents. The paper explores the interplay between alcohol consumption and other contributing factors, such as time of day (daytime/night) and weather conditions, providing a comprehensive understanding of how these variables collectively influence fatality rates in EU maritime transportation. The findings underscore the critical need for stringent alcohol regulations and enhanced safety protocols to mitigate the heightened risks associated with alcohol-impaired maritime operations.

Keywords: maritime; alcohol; safety; accident; fatality; prediction model

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Citation: Maternová, A.; Svabova, L. Assessing Fatality Risks in Maritime Accidents: The Influence of Key Contributing Factors. *Appl. Sci.* **2024**, *14*, 9153. https://doi.org/10.3390/app14199153

Academic Editor: Tomasz Figlus

Received: 10 September 2024
Revised: 7 October 2024
Accepted: 8 October 2024
Published: 9 October 2024

1. Introduction

Alcohol consumption is a critical issue in maritime transportation, significantly impacting the safety and wellbeing of seafarers and passengers alike. Alcohol as a major contributor to human error is a critical risk factor that needs to be managed. The maritime environment, characterised by long hours, social isolation, and high stress levels, makes seafarers particularly vulnerable to alcohol dependence. This dependence not only endangers the individuals but also poses severe risks to the overall safety of maritime operations.

The International Maritime Organisation considers alcohol consumption to be a significant contributing factor in maritime accidents, responsible for 15–20% of maritime accidents globally. This critical factor impairs visual functions, psychological stability, and cognitive abilities, which can have catastrophic consequences. Despite the implementation of international and national regulations, and strict alcohol policies, alcohol-related accidents continue to persist in maritime transport.

In light of these challenges, this paper aims to identify the effects of alcohol consumption on board maritime vessels, examining the alcohol levels in the circle of individuals influencing the occurrence of accidents. Additional influential factors during the accidents (darkness and meteorological factors) were taken into consideration.

It is important to note that the issue extends beyond crew members to passengers, especially on cruise ships where alcohol consumption is common because of beverage packages. In recent years, several accidents have involved alcohol-affected passengers. For example, in a 2015 accident near Toronto, a passenger fell overboard and subsequently lost his life with a blood alcohol content of 190 mg/100 mL [1]. Additional factors contributed to his death, including darkness, but it remains uncertain whether he would have survived without the influence of alcohol. In 2020, a fatal accident in Norway involving a pilot and a passenger occurred. Their recreational craft crashed into the shore at 36 knots, resulting in critical injuries and their deaths later that day. The AIBN stated that alcohol impairment, high speed, and nighttime conditions were contributing factors. Alcohol likely impaired attention and decision making, with fatigue and poor night vision potentially contributing as well [2].

In cases of accidents where alcohol is the primary contributing factor, crew members under the influence are responsible in 90% of instances. A notable example is the grounding of the M/V Wakashio off the southeast coast of Mauritius, which resulted in significant hull damage and a fuel oil spill that contaminated the coastline. The accident was likely caused by the master and chief officer navigating without detailed charts and altering the passage plan to receive a smartphone signal, reflecting a lack of awareness regarding safe navigation practices. Alcohol was identified as a contributing factor, impairing the crew's decision making and risk assessment, which led to the grounding [3]. Another alcohol-related accident occurred in December 2021, when the UK-registered cargo ship Scot Carrier collided with the Danish vessel Karin Høj in Sweden, causing the Karin Høj to capsize, which tragically resulted in the loss of two crew members. The investigation revealed that the second officer on the Scot Carrier had consumed alcohol and was influenced by alcohol, resulting in fatigue; moreover, he was distracted by a tablet during his watch, which contributed to the accident [4]. Thus, this paper aims to identify the effects of alcohol consumption on board maritime vessels by examining alcohol levels among individuals involved in accidents. Additional factors, such as darkness/visibility and meteorological conditions, were also considered. Based on data collected from almost 40 maritime accidents where alcohol was a contributing factor, a prediction model using real data is presented to assess the probability of fatality.

2. Literature Overview

This section provides an overview of scientific literature regarding the effects of alcohol on maritime accidents. The literature reviewed in this section reveals the significant impact of alcohol on maritime safety.

Komulainen's (2024) [5] analysis of maritime accidents in the Baltic Sea highlights the significant impact of alcohol on safety and security on board passenger vessels. The findings reveal that alcohol consumption is a major contributing factor to many maritime accidents, pointing out the need for stringent alcohol regulations and effective monitoring to ensure the safety of maritime operations.

Gug et al. (2022) [6] investigated the effects of alcohol on the navigational and decision-making abilities of ship navigators. The paper shows that even low levels of alcohol consumption can impair cognitive functions and motor skills, leading to decreased performance in ship manoeuvring and an increased risk of accidents.

Hasanspahić et al. (2021) [7] examined the role of the human factor in marine accidents. The paper categorised causal factors and discovered the ones that were the most common. The findings showed that the causes of maritime accidents were primarily dependent on two main human factor categories and confirmed that by influencing these two categories, the number of accidents could be reduced.

Wang et al. (2021) [8] explored the relationship between the severity of maritime accidents and influencing factors. The obtained results show that the marine accident severity is positively associated with sinking accidents, strong wind, heavy sea, strong current, and/or good visibility. With respect to ship types, fishing vessels, yachts and sailing vessels, and other ship types are the ship types most involved in accidents of higher severity. The severity level is higher for ships having incomplete or invalid seafarers' certificates, inadequate ship manning, incomplete or invalid ship certificates, and/or an age of over 30 years.

Shi et al. (2021) [9] reviewed the development of research on maritime accidents involving human factors by using a structured analytic technique. The authors identified research gaps: inadequate fundamental exploration of nonlinear interaction and intervening mechanisms, lack of application-based conceptualisation of maritime-specific analytical frameworks, and methodological limitations regarding data collection and quantitative analysis.

Lee (2020) [10] examines the specific context of Korea to understand how alcohol affects maritime safety. Lee's research highlights several significant accidents attributed to alcohol consumption, discussing both the immediate and long-term impacts on maritime operations and safety culture. The study also assesses the effectiveness of Korean regulations and enforcement practices.

Nævestad et al. (2018) [11] examined the safety culture in maritime transport in Norway and Greece, focusing on unsafe behaviours, such as working under the influence of alcohol. The study finds a strong correlation between alcohol consumption and unsafe maritime behaviours, including increased accident rates. The authors suggest that enhancing safety culture and addressing alcohol abuse can significantly reduce the incidence of maritime accidents.

Oluseye and Ogunseye (2016) [12] investigated the human factor issues responsible for maritime accidents in Nigeria. The authors examined nine human-related factors that are major causes of maritime accidents, namely poor crew interaction, crew fatigue, drugs and alcoholism, unsafe vessel speed, commercial pressure from management, complicated work processes, gaps in working knowledge, faulty crew judgment, and deliberate unruly behaviour; five of them—crew fatigue, drugs and alcohol, unsafe vessel speed, faulty crew judgment, and wilful behaviour of crew members—were significantly related to safety performance.

Chauvin et al. (2013) [13] analysed maritime collisions and identified decision errors as the primary cause. They highlighted several factors contributing to accidents, including poor visibility, misuse of instruments, loss of situational awareness, and inter-ship communication failures. The paper also emphasised the role of leadership in planning inappropriate operations and non-compliance with the Safety Management System (SMS). Additionally, the analysis categorised accidents into three classes, with a particular focus on collisions in restricted waters, poor visibility in open sea, and overall deficiencies in the socio-technical system.

Österman (2012) [14] identified several performance-influencing factors in maritime operations, with a particular focus on the impact of alcohol. The paper demonstrates that alcohol consumption significantly affects decision-making processes and physical coordination, increasing the likelihood of accidents. The paper emphasises the need for strict alcohol policies and continuous monitoring to ensure maritime safety.

Helander et al. (2009) [15] addressed the reliability issues of alcohol testing in maritime safety programs. The paper identifies failures in current testing procedures and suggests improvements to ensure accurate and reliable results.

Kim et al. (2007) [16] conducted experiments using ship handling simulators to study the effects of alcohol on navigational performance. Their findings indicate that alcohol consumption significantly impacts various aspects of ship handling, including coordination, reaction times, and decision-making abilities.

Ritze-Timme et al. (2006) [17] examined the performance of 21 captains navigating a container vessel. Their performance was assessed before and after alcohol consumption. The paper concluded that none of the participants, under the influence of alcohol, was capable of operating the simulated ship adequately.

Psaraftis (2002) [18] emphasises the importance of proactive safety measures in the maritime industry. The author argues that reactive approaches, which respond to accidents after they occur, are insufficient for ensuring long-term safety. He highlights that proactive strategies, such as stringent regulations, monitoring, and effective training programs, are crucial. While the paper broadly addresses maritime safety, it underscores the need for preventive measures against factors like alcohol consumption, which can impair judgment and lead to accidents.

Howland et al. (2001) [19] explored the effects of low-dose alcohol exposure on maritime cadets' ship handling abilities. The paper reveals that even low levels of alcohol can significantly impair performance, suggesting that zero-tolerance policies might be necessary to ensure safety in maritime operations.

3. Problem Background

Alcohol damages numerous physical and mental functions that are crucial for safe operations on board maritime vessels. The occurrence of on-board alcohol consumption is significantly high and contributes to a high number of fatalities in both commercial and recreational maritime shipping [14]. It is crucial to understand the effects of alcohol, its metabolism, and the consequences of its consumption, as well as the identification of alcohol on board as a risk factor contributing to fatalities on maritime vessels.

3.1. Effects of Alcohol

Alcohol consumption significantly impacts various aspects of human physiology and cognitive function. Even a small amount of alcohol can have notable effects on attention, memory, and overall performance, highlighting the increased risks to safety and operational efficiency at sea. By examining the health consequences of alcohol use, we underscore the importance of stringent regulations and awareness in mitigating alcohol-related maritime accidents. Alcohol consumption, especially excessive consumption, poses numerous health risks, affecting the wellbeing of individuals. The liver, which is mainly responsible for metabolizing alcohol, can suffer from fatty liver, hepatitis, and cirrhosis (a condition characterised by irreversible scarring and liver failure). The pancreas is also vulnerable, with chronic alcohol use leading to pancreatitis (an inflammation disrupting digestion and blood sugar regulation). Another common consequence of heavy drinking is higher blood pressure, which increases the risk of heart disease, stroke, and other cardiovascular issues [14,19].

Cognitive functions, which are critical for crew members and seafarers, involve the ability to perceive and react, processing and understanding, decision-making processes, and the production of appropriate responses to the environment [20].

Alcohol can result in the impaired performance of seafarers due to impaired physical and mental functions, which are crucial for the safe and efficient operation of a vessel (As mentioned, in study [17] the performance of more than 20 captains was examined. Their performance was assessed before and after alcohol consumption. The findings point to the fact that none of captains under the influence of alcohol was capable of operating the simulated ship adequately.). Such impaired performance was demonstrated in many maritime accidents with alcohol as a contributing factor. For example, in December 2021, the collision between the general cargo vessel Scot Carrier and the split hopper barge Karin Høj resulted in the capsize of the barge with two fatalities in Sweden. As mentioned, the subsequent investigation of the accident revealed that one of the main causes of the accident was that the watchkeeper was impaired from the use of alcohol and was also distracted by the use of a tablet during his watch [4].

Alcohol also impairs attention and the ability to concentrate on specific tasks. This is critical for crew members who must maintain high vigilance for extended periods. Impaired attention can lead to missed signals or delayed reactions, increasing the risk of accidents [21].

The ability to react immediately in the case of danger is crucial. To stop a large merchant vessel requires long distances and time for course changes. Moreover, many vessels must maintain a minimum speed to stay manoeuvrable. The advanced technical and electronic devices on board require high levels of capability and concentration. The complex process of acquiring information and providing appropriate manoeuvres in water traffic demands targeting foresight, attention, concentration, and a sense of responsibility. All of these important characteristics can be impaired even by low blood alcohol concentrations.

Both short- and long-term memory can be impaired and affected by alcohol. In the case of impairment of short-term memory, it is difficult to retain the information necessary for immediate tasks, leading to errors in everyday activities. For example, crew members might struggle to remember navigational data or operational procedures, which can impair the safety of the vessel and crew. On the other hand, long-term memory impairment affects the ability to recall past experiences and learn from them. This can result in an inability to learn from past mistakes or experiences, which is crucial for improving performance and safety practices [22].

Executive functions include the processes of planning, decision making, and problem solving. Alcohol disrupts these cognitive processes, leading to poor judgment, failures in decision making, and improper problem solving. Such impairment can result in emergencies at sea, where quick decision making is crucial for the safe operation of the vessel. For example, if the officer is under the influence of alcohol, he/she might misjudge weather conditions or fail to navigate through challenging waters, increasing the risk of collisions or groundings. Alcohol can also have an impact on social interactions and leadership abilities, which are essential for crew management and coordination during operations [23].

Alcohol consumption often affects psychomotor functions, such as coordination, balance, and reaction time. These impairments can decrease the ability to operate devices and machinery, navigate the vessel, and perform other tasks that require precise motor skills. For example, an intoxicated individual might struggle with maintaining balance on a moving vessel or operating complex machinery accurately, leading to operational failures.

Chronic alcohol consumption can lead to significant impairments in motor skills, making recovery and rehabilitation more challenging. Long-term consumption can cause permanent damage to the nervous system [24].

3.2. Alcohol Content and Its Effects

Blood alcohol content (BAC) represents the concentration of alcohol in the blood, measured as "weight by volume". BAC can be measured as milligrams of ethanol per millilitre of blood (mg/mL), which is equivalent to grams per litre (g/L). Sometimes, BAC can be measured as percentage by volume. For example, 0.05 g/100 mL = 0.05% = 0.5 mg/mL = 0.5 g/L.

On the other hand, breath alcohol concentration (BrAC) represents the concentration of alcohol in the breath. For the purposes of this paper, while investigating the alcohol content of seafarers on board maritime vessels, BAC was selected as the primary variable. Consequently, it was necessary to convert BrAC to BAC for consistency. BrAC measurements are typically reported in investigation reports where the individuals involved were alive, while BAC values are obtained from deceased seafarers.

Alcohol inhibits the central nervous system, and as the blood alcohol concentration (BAC) increases, its effects intensify, leading to various physical and mental changes. The metabolization of alcohol varies based on individual body constitution, consumption circumstances (including food and drink intake), and daily physical condition changes. Drunkenness is an acute intoxication symptom caused by alcohol ingestion, affecting the central nervous system. This intoxication results in ataxia (e.g., staggering and slurring), autonomic symptoms (e.g., facial flushing and sweating), and a general decline in central nervous system functions (e.g., impaired attention and judgment). As BAC increases, significant consciousness disturbances occur [19].

Table 1 outlines the amounts of alcohol consumed, BAC levels, and states of general intoxication.

Table 1. Amounts of alcohol consumed (BAC) and its effects.

Stage (BAC %)	State of Intoxication
Euphoria (0.02–0.05)	feeling of invigoration, reddening skin, cheerfulness, minor impairment of judgment and coordination
Slight intoxication (0.05–0.10)	slight tipsiness, active hand movements, without inhibition, higher body temperature/rapid heartbeat, increased impairment of judgment, memory and coordination

Table 1. *Cont.*

Stage (BAC %)	State of Intoxication
Early drunkenness (0.10–0.15)	generosity, quickness to anger, louder voice, wobbliness when standing, possible slurred speech, reduced reaction time
Drunkenness (0.15–0.30)	major loss of coordination/staggering, rapid breathing, repetition when speaking, nausea/vomiting, severe impairment of motor skills and judgment, blurred vision, confusion and dizziness, blackouts
Stupor (0.30–0.40)	inability to stand properly, confusion, incoherent speech, significant risk of loss of consciousness, danger of respiratory depression (slow and shallow breathing), possible risk of coma
Coma (0.40–0.50)	unresponsiveness even when shaken, incontinence (urination and bowels), deep and slow breathing, coma, respiratory arrest, potential failure of the central nervous system, death

Source: Authors, based on [14,23].

While the fundamental process of metabolizing alcohol is the same for everyone, genetic, biological, and environmental factors can influence how quickly this process occurs.

Factors influencing the metabolization of alcohol differ, from genetic differences to environmental and cultural factors:

- Genetic differences—These are the primary enzymes responsible for metabolizing alcohol—alcohol dehydrogenase (ADH) and aldehyde dehydrogenase (ALDH). Genetic variations in these enzymes can affect how quickly alcohol is metabolized [5].
- Cultural and environmental factors—cultural norms on drinking can influence tolerance and the adaptation of the body to alcohol. Populations may have developed a higher tolerance for alcohol during the years of consumption.
- Diet and lifestyle can also impact how alcohol is processed, based on different types of diets [25].
- Body composition—generally, individuals with more body mass have a lower BAC after consuming the same amount of alcohol than those with less body mass [26].
- Gender—the effects of alcohol consumption differ significantly between men and women, largely due to biological and metabolic variations. For instance, women tend to reach higher blood alcohol concentrations (BAC) than men after consuming the same amount of alcohol, due to lower body water content and hormonal differences. Additionally, women may experience more severe alcohol-related health consequences, such as liver damage, at lower consumption levels [27].
- Regular consumption—people who consume alcohol regularly may develop a higher tolerance; so, they may have lower BAC levels than occasional drinkers after consuming the same amount of alcohol [19].

The rate at which alcohol is metabolized by the liver (about 0.015 BAC per hour) remains relatively consistent for all people [28]. The initial BAC after drinking and the subjective effects of alcohol can vary widely among individuals due to the factors mentioned above.

3.3. Statistics on Alcohol-Influenced Maritime Accidents

In recent years, the prevalence of alcohol-related maritime accidents has raised significant concerns within the maritime industry and regulatory bodies. The statistics indicate that a substantial portion of marine incidents involve crew members or operators under the influence of alcohol, which contributes to navigational errors, collisions, and fatalities at sea.

Figure 1 shows the impact of alcohol consumption on accidents in the maritime sector over the period from 2019 to 2023. It illustrates both the total number of reported accidents (accidents in chosen regions, incidents not involved) and those specifically related to alcohol consumption. The data reveal a steady increase in both categories, reflecting the growing concern about alcohol consumption as a critical factor in maritime incidents. In 2019, there were 850 reported accidents in total, with 140 of them being alcohol-related. By 2023, these numbers had risen to 1027 total accidents and 185 alcohol-related cases, showing an upward trend.

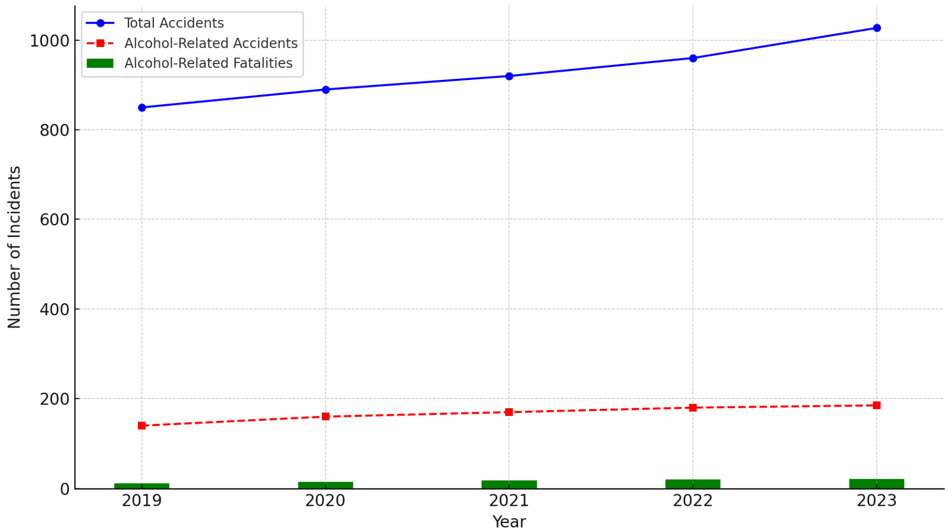

Figure 1. Impact of alcohol consumption on maritime accidents and fatalities (2019–2023).

Moreover, the chart also includes the number of fatalities linked to alcohol-related accidents, with a marked increase over the years, from 12 alcohol-related fatalities in 2019 to 22 in 2023; the data underscore the growing probability of fatal outcomes in incidents where alcohol is involved. These findings reflect global patterns reported by sources such as the EASA, U.S. Coast Guard, and maritime safety organisations [29–31]. The chart visually supports the argument that alcohol consumption in the maritime sector significantly raises the risk of both accidents and fatalities, highlighting the need for stricter regulations and prevention measures in this industry.

3.4. Legal Framework and Policies

The legal framework for alcohol limits on board maritime vessels is generally standardised as all crew members and shipping companies are required to comply with the International Convention on Standards of Training, Certification and Watchkeeping for Seafarers (STCW, 1978) [32]. This convention sets the minimum qualification standards for masters, officers, and watch personnel on maritime merchant ships. The STCW was adopted in 1978 by the International Maritime Organisation (IMO). Initially, the STCW Convention only recommended alcohol limits as a maximum of 80 milligrams of alcohol per 100 millilitres of blood for the watchkeepers on duty. As it was not possible to enforce these recommendations, it led to inconsistent application across member states [32].

In 2010, the Manila Conference introduced the Manila Amendments to the STCW Convention, setting mandatory alcohol consumption limits for seafarers, replacing the original recommendations. These limits aimed to enhance maritime safety by addressing the risks of alcohol impairment and aligning with those for drivers in many European countries, simplifying compliance for international shipping companies. The limits were set at:

- 25 micrograms of alcohol per 100 mL of breath;
- 50 mg per 100 mL of blood;

- 67 mg per 100 mL of urine [33].

National regulations may set stricter limits than those prescribed by the STCW Convention. Furthermore, seafarers must adhere to the drug and alcohol policies established by the shipping companies they work for. This section provides an overview of the international regulations and shipping company approaches regarding BAC limits on board maritime vessels. For example, in the EU, each country can implement stricter regulations, but they must comply with the minimum standards set by the IMO. For example:

France has a more stringent limit—0.02% BAC for seafarers.

Norway is not an EU member but is closely aligned with the EU through the European Economic Area (EEA) and sets the limit of BAC for professional seafarers at 0.02% [34].

In the United States, a BAC limit is set by the USCG of 0.04% for individuals operating a commercial vessel. For recreational ships, the limit is less strict—0.08 BAC, which is similar to the limit for operating an automobile on land [35].

Regulations in Asia can differ in various countries, but each country must follow the guidelines set by the IMO. While the majority of countries follow the STCW Convention on the alcohol limits in blood or breath, India, as well as Singapore, set stricter rules regarding BAC limits at 0.04% [36].

Shipping companies may implement stricter alcohol policies, with various levels of BAC based on the type of cargo and vessel. Some companies permit a BAC of up to 0.04% during off-hours; on the other hand, others prefer a zero-alcohol policy. Companies like Maersk, Hapag-Lloyd, and COSCO enforce zero-alcohol policies, while MSC and ONE set a BAC limit of 40 mg per 100 mL. Captains and senior officers are responsible for enforcing these rules and often use on-board alcohol test meters to check the BAC of crew members. Seafarers who violate the policy face disciplinary actions, including dismissal.

4. Materials and Methods

4.1. Data Collection

For the research purposes, we compiled data from multiple maritime accident investigation reports, ensuring a representative selection of cases where alcohol was a confirmed contributing factor. Reports were sourced from various organisations investigating the maritime accidents:

- Marine Accident Investigation Branch (MAIB)—UK government organisation authorised to investigate marine accidents in UK waters and also accidents involving UK registered ships worldwide.
- Agencija za istraživanje nesreća u zračnom, pomorskom i željezničkom prometu (AIN)—Croatian agency for the investigation of accidents in air, sea, and railway traffic.
- Marine Accident and Incident Investigation Committee (MAIC)—responsible for the investigation of all types of marine accidents involving ships under the Cyprus flag, anywhere in the world; or maritime accidents that occur within Cyprus's territorial and internal waters.
- Danish Maritime Investigation Board (DMAIB)—an independent body under the Ministry of Industry, Business and Financial Affairs of Denmark. The DMAIB investigates accidents on Danish and Greenlandic ships and accidents on foreign ships in Danish and Greenlandic water.
- The Marine Casualty Investigation Board (MCIB)—the Irish government agency for investigating all types of marine casualties related to, or on board, Irish registered vessels worldwide and other vessels in Irish territorial waters and inland waterways.
- The Marine Safety Investigation Unit (MSIU)—an accident investigation body established to investigate maritime accidents involving Maltese-registered ships anywhere in the world and foreign-flagged ships operating in Maltese waters.
- The Hellenic Bureau for Marine Casualties Investigation (HBMCI)—competent for investigating maritime incidents and casualties and for conducting of reports for the vessels floating under the Hellenic (Greek) flag and other vessels within the Hellenic

territorial waters or within the Hellenic Search and Rescue region, provided that SAR services were delivered by Greek Authorities, as well as any casualty or incident that involves the substantial interests of Hellas.

- Państwowa Komisja Badania Wypadków Morskich (PKBWM)—an agency of the Polish government investigating maritime accidents.
- The Transportation Safety Board of Canada (TSB)—an independent agency investigating occurrences in the air, marine, pipeline, and rail modes of transportation.
- The National Transportation Safety Board (NTSB)—an independent federal agency investigating accidents and significant events in the US for each transportation mode.
- Japan Transport Safety Board (JTSB)—investigates maritime (and also rail and air) accidents and contributes to preventing them, mitigating the damage caused by the accidents in order to increase safety.
- Statens haverikommission (SHK)—the Swedish independent governmental authority under the Ministry of Defence that investigates all types of serious civil or military accidents and incidents to increase safety.
- United States Coast Guard (USCG)—body responsible for preparing and publishing investigation reports in accordance with the federal statutes and regulations of the US.

Each of these organisations specialises in the thorough investigation of maritime incidents and accidents. Within the databases, vessels of all types were selected (containers, tankers, bulk carriers, and RO-RO, as well as passenger and small vessels). Accidents of the following types were investigated:

- Collision;
- Crush incident;
- Fatal fall;
- Grounding;
- Man overboard;
- Sinking.

Only accidents where alcohol was a contributing factor, and those in which a breath or blood alcohol test was conducted, were included in the research. If the responsible person was under the influence of alcohol and had died, but no toxicology report was included in the autopsy, such a report was not a part of the research. For the analysis, 38 accident investigation reports were obtained from the period 2012–2024. In our paper, we analysed a total of 38 maritime accident investigation reports. While this sample may appear limited compared to broader studies, it is important to recognise the strict inclusion criteria we applied. Out of more than 1000 closed and complete investigative reports, only these 38 of these accidents explicitly identified alcohol as a major contributing factor and provided BAC or BrAC information, which was crucial for our research objectives. This selection, while reducing the overall number of reports, ensures that we are analysing the most relevant cases. The necessity of detailed alcohol-related data in maritime accident investigation reports further limited our inclusion of more cases. Therefore, our sample size reflects the rarity of well-documented alcohol-related incidents within the available databases from 2012 to 2024, across 13 different databases. (In our dataset, 97% of cases involved males, with the only female case being a fatal accident in July 2018, where the chief stewardess, with a blood alcohol concentration of 430 mg/100 mL, fell from her cabin and sustained fatal neck injuries.)

4.2. Methodology

In this paper, we focus on predicting fatalities in maritime accidents by creating a predictive model. The outcome variable in the predictive models is Y = fatalities, which takes the value $Y = 1$ if the accident was fatal and $Y = 0$ if not. We consider the occurrence of fatalities, i.e., the value $Y = 1$, as the target category (the so-called "hit") of the outcome variable, as it is more important for the practical use of the created models to correctly identify critical accidents with fatalities.

As explanatory variables in the predictive models, we used the variables listed in Table 2 where the distribution of values for these explanatory variables is described. For quantitative variables, we provide basic numerical characteristics of their central tendency, variability, and shape, while for categorical variables, we state the distribution of their frequencies. Along with the explanatory variables, the outcome variable is also included in Table 2.

Table 2. Variables used in prediction models.

Variable	Role	Description	Type of Variable	Values	Distribution
fatality	outcome variable	indicator of fatality in accident	qualitative nominal	$Y = 1$ for fatality	9 (23.7%)
				$Y = 0$ for non-fatality	29 (76.3%)
BAC	input variable	blood alcohol content of person under influence, who caused the accident/is responsible for the process	quantitative continuous	$\langle 0; \infty)$	min = 0.058 max = 0.690 mean = 0.254 median = 0.221 st. dev = 0.160 skewness = 1.322 kurtosis = 1.140
weather	input variable	weather during the accident	qualitative ordinal	$\{1, 2, \ldots, 10\}$ where $X = 1$ refers to 1 light air (wind 0.3–1.5 m/s) wave height 0–0.3 m and $X = 10$ refering to hurricane (wind $\geq$ 32.7 m/s) wave height over 14 m (values resulting from a combination of Beaufort 12-point scale for wind speed and Douglas 9-point scale for sea state)	$X = 1$: 7 times (18.4%) $X = 2$: 7 times (18.4%) $X = 3$: 10 times (26.3%) $X = 4$: 8 times (21.1%) $X = 5$: 0 times (0%) $X = 6$: 6 times (15.8%) $X = 7$: 0 times (0%) $X = 8$: 0 times (0%) $X = 9$: 0 times (0%) $X = 10$: 0 times (0%)
time of day	input variable	time of day when accident happened	qualitative nominal	$X = 1$ for night	24 times (63.2%)
				$X = 0$ for day	14 times (36.8%)

Source: Authors.

The models created are very simple, as they use only three explanatory variables; however, they achieve high accuracy in their predictions. We develop the predictive model using three methods and two different approaches, resulting in four models for predicting fatalities in maritime accidents:

- A simple logistic regression model using the three above-mentioned explanatory variables, which allows a prediction of the probability of a fatality in an accident.
- A simple classification tree using the CART method with the three mentioned explanatory variables; this is used to predict the occurrence of a fatality in an accident.
- A logistic regression model using the specified explanatory variables and all two-way and three-way interactions, enabling the prediction of the probability of a fatality in an accident.
- A classification tree using the CHAID method with the three specified explanatory variables and all two-way and three-way interactions; this is used to predict the occurrence of a fatality in an accident.

These four models were selected for their interpretability and high performance in predicting fatalities among several models created using machine learning methods. The first two mentioned models were developed as simple yet highly effective models for predicting fatalities in maritime accidents, considering three factors: alcohol content, weather, and time of day. The other two models also incorporate possible interactions between these factors, based on the hypothesis that, for example, a combination of higher alcohol content and nighttime could increase the likelihood of a fatality in an accident, whereas the interaction of daytime and good weather could reduce the likelihood of a fatality.

As shown in Table 2, non-fatal accidents and fatal accidents are represented in a ratio of approximately 1:3. Therefore, in all the models, we use the oversampling method to balance the samples of non-fatal and fatal accidents. This means that cases from the smaller group of non-fatal accidents are given more weight in the model creation process to roughly equalise the size of the non-fatal accident group with the fatal accident group. This approach enables the creation of models with higher predictive performance.

The performance of the models is evaluated using a classification table and the evaluation metrics calculated from it. The classification table is a four-field table that quantifies the absolute and relative numbers of correctly and incorrectly classified cases. An example of such a table is shown in Table 3.

Table 3. Classification table.

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

Source: [28].

- $Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$ represents the overall accuracy of the model, i.e., the proportion of all correctly classified accidents, both fatal and non-fatal.
- $Sensitivity = \frac{TP}{TP+FN}$ is the proportion of correctly classified fatal accidents among all actual fatal accidents.
- $Precision = \frac{TP}{TP+FP}$ is the proportion of correctly classified fatal accidents among those accidents predicted as fatal.

Moreover, for all the models, we determine the value of AUC (area under the curve), which represents the size of the area under the ROC curve that shows the dependence of sensitivity on the false positive rate for different threshold values. The closer this value is to 1, the better the model is as a classifier [37].

When describing the methods used to create the prediction models, three methods were used in total: logistic regression and two decision tree methods, CART and CHAID. These methods were chosen from various machine learning methods due to the interpretability of their results. Compared to methods such as neural networks or the k-nearest neighbours method, the chosen methods allow us to assess the significance of variables and interpret the obtained model coefficients, as the goal of this paper is not only to create a powerful simple model for predicting fatal accidents but also to interpret the obtained results. For this reason, we also present a graph showing the ranking of variable importance in the model for each method.

4.2.1. Logistic Regression

Logistic regression is a statistical method used to analyse the relationship between a binary or multinomial dependent outcome variable and one or more independent input variables. This technique models the outcome variable as a function of the input variables through the logistic function, which converts the linear combination of predictors into a probability value ranging from 0 to 1. If the outcome variable Y is binary and holds the values $Y \in \{0, 1\}$, the probability is calculated for the hit category, which is usually denoted by the value $Y = 1$ [38,39].

Let Y be a binary outcome variable, which takes the value $Y = 1$ with probability p and $Y = 0$ with probability $1 - p$. Let $X_1, X_2, \ldots, X_m$ be the input explanatory variables.

The logistic regression model relates the log odds of Y being 1 to a linear combination of the predictor variables:

$$log\frac{p}{1-p} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_m X_m \quad (1)$$

Here, β_0, β_1, β_2, ..., β_m are the parameters to be estimated, denoted by b_0, b_1, b_2, ..., b_m upon estimation. The logistic function is used to convert the linear combination of input variables into a probability p of the hit value $Y = 1$:

$$p = \frac{1}{(1 + exp(-\beta_0 - \beta_1 X_1 - \beta_2 X_2 - \ldots - \beta_m X_m))} \quad (2)$$

where the product is over all observations i; y_i is the observed value of the outcome variable (0 for non-fatal accident or 1 for fatal accident) for the i-th observation; and p_i is the predicted probability of $Y = 1$, i.e., the probability that the i-th accident is fatal.

The parameters of the logistic regression are estimated by the maximum likelihood method, i.e., by maximising the log-likelihood function, given by:

$$\ln L(\beta_0, \beta_1, \beta_2, \ldots, \beta_m) = \sum (y_i \ln p_i + (1-y_i)\ln(1-pi)) \quad (3)$$

The estimations of the parameters are often obtained using iterative methods, such as the Newton–Raphson or Fisher scoring algorithms [31].

4.2.2. Classification and Regression Tree (CART)

The classification and regression tree (CART) methodology is a popular machine learning technique that constructs decision trees for classification or regression tasks. This method splits the data into subsets based on the values of the predictor variables, creating a tree structure where each internal node represents a decision based on an input variable, each branch represents the outcome of that decision, and each leaf node represents a predicted class for the outcome variable [40,41].

In the context of classification, in the task of predicting fatality in maritime accidents, the goal of CART is to predict the class of an outcome variable (fatal or non-fatal accident) by creating a tree that recursively partitions the data. The algorithm starts with the complete dataset and identifies the variable along with its threshold, which optimally splits the data into two subsets, based on the impurity of the resulting subsets. Various metrics can be used to measure impurity, with the Gini index and entropy being the most commonly employed. The tree structure is formed by iteratively dividing the data into smaller subsets according to the values of the input variables. This process continues until a stopping criterion is satisfied, such as a minimum number of observations per leaf or a specified maximum tree depth. In this paper, we set the maximum tree depth to 5, with a minimum of 2% records in the parent node, 1% records in the child node, and a minimum change in impurity of 0.0001 as the stopping criteria [40].

The Gini index, which assesses the likelihood of incorrectly classifying a randomly selected data point from a node, is calculated as follows:

$$Gini\ Index = 1 - \sum {p_i}^2 \quad (4)$$

where p_i is the proportion of samples in class i at the node. The Gini index is minimised when all the samples at a node belong to the same class.

Entropy, another measure of impurity, quantifies the amount of information or uncertainty in a dataset and is computed as:

$$Entropy = -\sum p_i \cdot \log p_i \quad (5)$$

where p_i is the proportion of samples in class i at the node. Entropy reaches its minimum when all the samples at the node are of the same class.

The Gini index and entropy are the primary impurity measures used in the CART algorithm. Some research indicates that the Gini index often performs marginally better in classification tasks, whereas entropy may be more sensitive to variations in data distribution.

A key advantage of the CART method is its ability to handle both categorical and continuous input variables. CART models are robust against multicollinearity among input variables and outliers in the dataset. They can also manage missing data by employing surrogate variables for each predictor. However, one major drawback is the potential for overfitting, where the model becomes overly complex and captures noise rather than general patterns. To mitigate overfitting, CART models can be pruned. Pruning is a process that involves removing branches that do not significantly enhance the model's performance. In this paper, the CART tree was pruned to enhance generalisation and reduce overfitting [42].

4.2.3. Chi-Squared Automatic Interaction Detector (CHAID)

CHAID is a statistical technique used to create decision trees for classification and regression tasks. This method identifies the optimal splits of the data based on the chi-squared test of independence for categorical variables or the F-test for continuous variables [43,44].

The CHAID algorithm begins by identifying the input variable that has the strongest association with the outcome variable. For categorical predictors, the association is evaluated using the chi-squared test of independence, while for continuous predictors, the F-test is used. The steps involved are as follows. The dataset is initially split based on each predictor variable. For categorical variables, each category forms a potential split. For continuous variables, the data are divided into intervals. The next step is merging. For each predictor, pairs of categories or intervals are merged if their p-value from the chi-squared test (or F-test) exceeds a specified significance level. This merging process continues until no further merging is possible without exceeding the p-value significance level. The last step is selection. The predictor variable and corresponding split that result in the most significant association with the outcome variable (identified by the lowest p-value) are selected. This split maximises the difference between the resulting subsets with respect to the outcome variable [43,44].

The CHAID tree is constructed by recursively applying the splitting criterion to each subset until a stopping condition is met. The stopping conditions may include a minimum number of observations per node, a maximum tree depth, or a p-value threshold. In this paper, the CHAID tree was constructed using the following stopping criteria: maximum tree depth 5; minimum records in parent branch 2% and in child branch 1% of cases in training sample; minimum change in expected call frequencies for chi-squared test 0.001; maximum iterations for convergence 100 [40].

Unlike CART, CHAID incorporates an automatic pruning mechanism during the tree construction process. As the tree grows, nodes that do not contribute significantly to the overall model (based on the p-value threshold) are not split further, effectively controlling the complexity of the tree and reducing overfitting [45].

The CHAID method is advantageous due to its ability to handle both categorical and continuous variables, its robustness to missing values, and its straightforward interpretation of results. Moreover, CHAID is particularly effective for detecting interactions between variables. However, CHAID trees can be sensitive to outliers and may produce splits that are less intuitive than those from other tree methods. Additionally, the reliance on p-values means that the results can be influenced by the sample size, with larger samples potentially leading to more splits [46].

All calculations in this article were conducted using IBM SPSS Modeler, version 18.3. Data preparation was partially carried out using IBM SPSS Statistics, version 28. A significance level of 0.05 was used for all statistical tests.

5. Results

In the following section, the factors contributing to the investigated accidents are identified, categorised, analysed, and quantified in order to prepare the dataset for the models predicting fatalities in maritime accidents. Firstly, two simple models were used, based on the impact of three key factors—alcohol consumption, weather conditions, and time of day. Then, a logistic regression model was applied in order to estimate the probability of a fatality occurring in an accident. Beyond these basic models, we developed models incorporating interactions between variables for examination of the combined effects of these factors on fatal outcomes. The first of these more complex models was also a logistic regression model.

5.1. Contributing Factors Categorisation and Quantification

For our research on modelling and predicting the probability of fatalities in maritime accidents where alcohol was a contributing factor, we considered several key elements. Firstly, alcohol was identified as a contributing factor in each analysed accident. We then examined the meteorological conditions present during each accident, specifically assessing wind speed and sea state according to the Beaufort and Douglas scales. Additionally, we considered the type of accident and visibility conditions, noting whether the incidents occurred during daylight or nighttime hours. Detailed data for these factors are provided in Appendix A.

The dataset consists of variables such as type of accident, blood alcohol concentration (BAC) levels, number of fatalities, meteorological factors during the accident, and the visibility. These data were chosen for research due to their comprehensive nature, capturing key aspects of incidents at sea that can influence the severity and outcome of accidents. These data allow us to explore the potential correlations and causative factors that contribute to fatal accidents.

Figure 2 shows the distribution of various types of maritime accidents. For our research, a varied range of accident types were included in order to ensure a representative sample. The analysis reveals that the 17 out of the 38 recorded accidents (approximately 45%) involved cases where the responsible person lost motor skills and coordination after consuming alcohol, leading to fatality. This includes 7 incidents of fatal falls and 10 incidents of "man overboard" situations. We can observe that in cases of high BAC levels, the accidents often resulted in fatalities (or severe consequences). For example, the BAC amount in fatal falls ranged from 110 to 430, and in "man overboard" incidents from 122 to 346. These results strongly suggest that impaired judgment and loss of physical control, stemming from alcohol consumption, are significant risk factors.

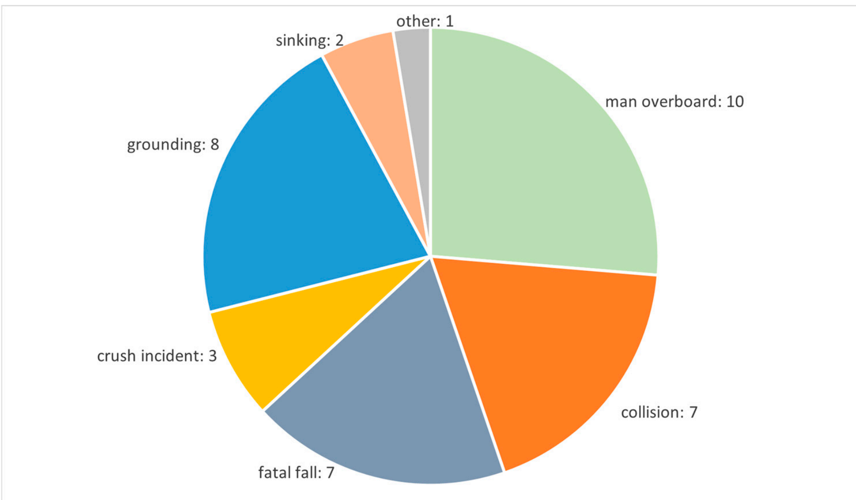

Figure 2. Types of maritime accidents examined.

5.2. Models Predicting Fatality in Maritime Accidents

In this section, the results of the models predicting fatality in maritime accidents are presented, and the obtained results are interpreted. First, we introduce two simple models based on the influence of three factors—alcohol, weather, and time of day—on the occurrence of fatalities in accidents.

The logistic regression model can be used to estimate the probability of a fatality occurring in an accident. The complete table of the model is shown in Table 4. The last category, weather = 6, was chosen as the reference category for the input variable weather, and the option night = 1 was chosen as the reference for the variable night. The reference category for the outcome variable is fatality = 0; therefore, the given model applies to the category outcome variable Y = 1 (fatality in an accident).

Table 4. Simple logistic regression model.

Variable	B	Std. Error	Wald	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
						Lower Bound	Upper Bound
Intercept	−3.07	1.18	6.77	0.009			
BAC	9.08	4.35	4.36	0.037	8777.90	1.74	4.42×10^7
Weather_1	21.58	8520.79	0.00	0.998	2.36×10^9	0.00	.
Weather_2	20.67	0.00	.	.	9.43×10^8	9.43×10^8	9.43×10^8
Weather_3	1.82	1.08	2.86	0.091	6.17	0.75	50.83
Weather_4	1.70	1.01	2.81	0.094	5.47	0.75	39.94
Timeofday_0	−0.74	0.88	0.69	0.405	0.48	0.09	2.71

Column B shows the estimated regression coefficient, while the values in the Exp(B) column can be used for interpretation. The BAC variable is statistically significant in the model at a significance level of 0.05, with a positive regression coefficient B. The Exp(B) value indicates that the higher the blood alcohol content, the higher the probability of a fatality in the accident. More specifically, with other conditions unchanged (i.e., weather and time of day), each additional unit of blood alcohol increases the probability of a fatality in an accident nearly 8.778 times. Regarding weather, all the weather types (labelled 1 to 4) have positive regression coefficients, indicating that compared to the reference weather category (labelled as 6), the probability of a fatality in an accident is several times higher with other conditions unchanged (i.e., BAC and time of day). However, given the significance of these variables in the model, only weather types 3 and 4 significantly differ from weather type 6 in their impact on the occurrence of a fatality at a significance level of 0.10. At this significance level, the occurrence of weather type 3 increases the probability of a fatality more than sixfold, and weather type 4 more than fivefold. Finally, if the accident occurred during the day, the probability of a fatality is almost half compared to an accident occurring at night with other conditions unchanged (i.e., BAC and weather). However, this effect is not statistically significant at the 0.05 level. The order of importance of predictors in the logistic regression model is shown in Figure 3.

In this model, the variable weather is considered the most important (importance = 0.55), followed by the variable BAC (importance = 0.35), and night is in third place (importance = 0.10).

To determine the appropriate threshold value for classifying a fatality in an accident, we created a histogram of the distribution of the predicted probabilities of a fatality, with colour differentiation of the actual outcome variable values (Figure 4). The histogram is normalised by colour for easier comparison of unevenly represented predicted probabilities.

As shown in Figure 4, it is clear that the threshold value should be set at 0.40. Therefore, for an estimated probability lower than 0.40, the accident will be classified as non-fatal, and otherwise, for an estimated probability of 0.40 or higher, it will be classified as fatal. This shift in the threshold value from the original level of 0.50, which is most commonly used, increases the proportion of true positive predictions and decreases the model error due to the number of false negative predictions. This increases the model's sensitivity to the identification of accidents where a fatality is likely. We made this threshold value adjustment because we consider the error of incorrectly predicting a fatal accident (false positive) as less serious if it does not occur, compared to predicting a non-fatal accident when a fatality actually occurs (false negative). In our view, a false negative error has less severe consequences. The classification table of the logistic regression model, along with the evaluation metrics, is presented in Table 5.

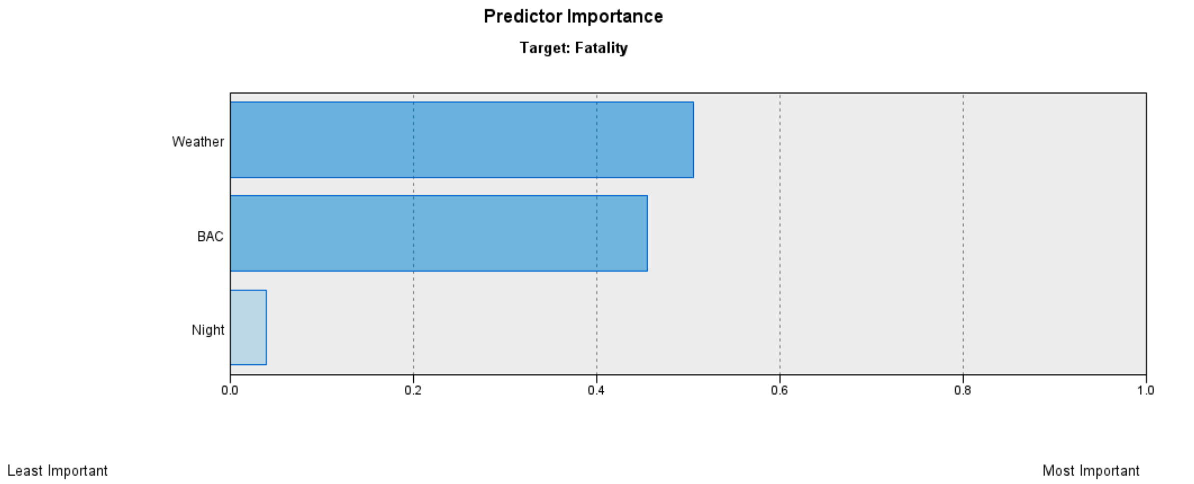

Figure 3. Predictor importance in the simple logistic regression model.

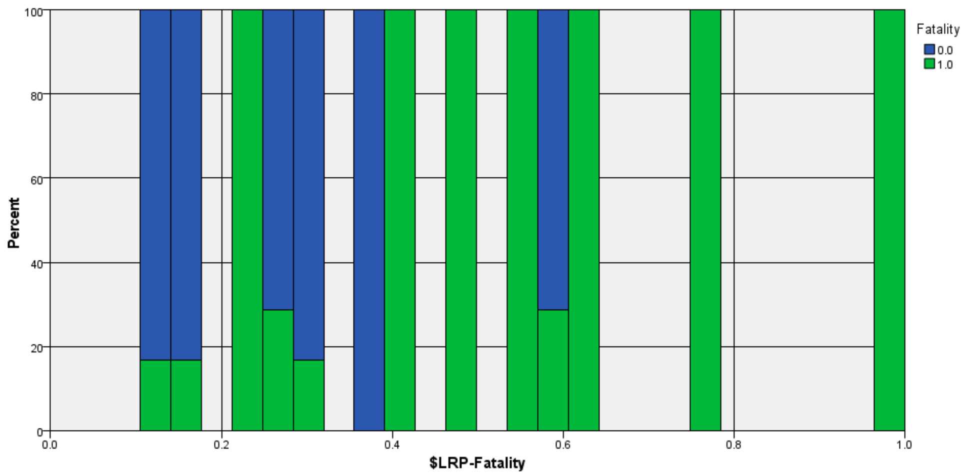

Figure 4. Normalised histogram of predicted probabilities of fatality using logistic regression.

Table 5. Classification table and evaluation metrics of the simple logistic regression model.

Actual Y	Predicted Y		Total
	0	**1**	
0	24	6	30
1	5	24	29
Total	29	30	59
	Accuracy (%)		81.4
	Sensitivity (%)		82.8
	Precision (%)		80.0
	AUC		0.83

The model correctly classified more than 81% of all accidents. It accurately predicted almost 83% of fatal accidents, and of the accidents predicted by the model as fatal, 80% were indeed fatal. The AUC (area under the curve) value under the ROC curve is 0.83, indicating a reasonably accurate model. Then, a decision tree model using the CART technique was created. The importance of the variables in this model is shown in Figure 5.

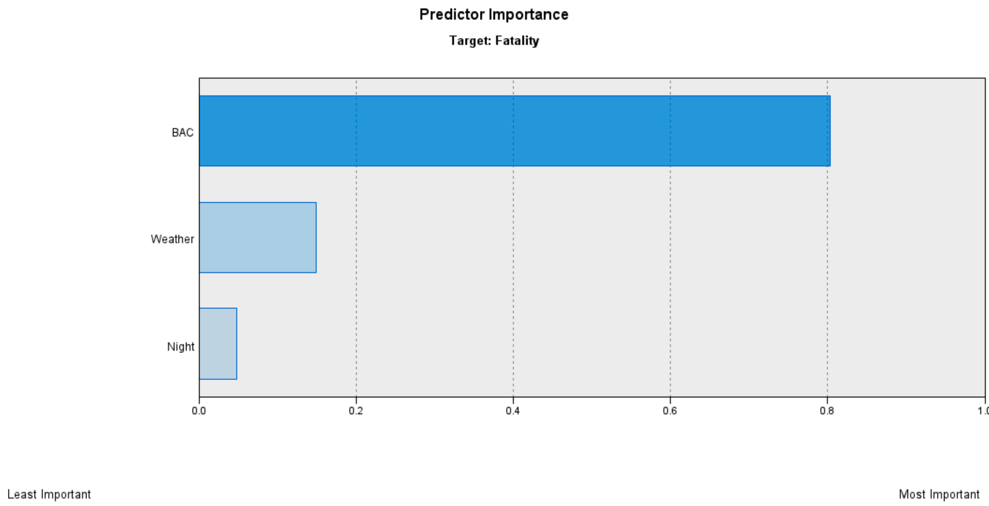

Figure 5. Predictor importance in the simple CART model.

The most important variable in the classification tree is BAC (importance = 0.80), followed by weather (importance = 0.15), and the least important variable in this model is night (importance = 0.05). The classification tree is shown in Figure 6.

Figure 6 presents the classification tree generated by the CART methods to predict the likelihood of fatalities in maritime accidents. This decision tree illustrates the most influential factors contributing to accident outcomes, with BAC as the primary variable. The figure shows that accidents where the BAC exceeds 0.274 are always classified as fatal (node 4), whereas accidents with BAC under 0.086 are always classified as non-fatal (node 1), indicating that high alcohol levels significantly increase the risk of fatalities.

This figure also shows that additional factors like weather contribute to fatal outcomes in cases with moderate BAC levels (nodes 7 and 8).

The first condition for branching is set by the BAC variable with a threshold value of 0.086. Accident cases where the responsible person had a blood alcohol level up to this value are all classified as non-fatal (the predicted category is always marked by grey colour in the tree). If BAC ≥ 0.274, every such accident is classified as a fatal accident. Additionally, accidents are classified as fatal if BAC is $\in \langle 0.256; 0.261 \rangle$, as are those with BAC $\in \langle 0.086; 0.256 \rangle$ combined with weather levels 1 to 4. In cases where the individual had a high blood alcohol concentration, it can be asserted that a fatality always occurred. The most common cause of death in such cases was a fatal fall, either on deck or in the cabin. In cases of moderately high blood alcohol levels, fatalities also almost invariably occurred. However, when the blood alcohol level was lower, fatalities were still present, but these occurred because of the combination with additional factors such as adverse weather conditions or poor visibility. Certainly, there are exceptions where, despite a high blood alcohol concentration, no fatality occurred. These exceptions can be attributed to extraordinary circumstances or favourable conditions that mitigated the risk, rather than mere good fortune. Other cases were classified as non-fatal accidents, although in some nodes, there are only a few cases. Table 6 is the classification table for the CART model.

The accuracy of this model in classifying all accidents is almost 97%. Sensitivity at a level of over 93% means the proportion of fatal accidents correctly predicted by the model. All accidents classified by the model as fatal were indeed fatal. The AUC value is very close to one, indicating a high-performing model.

In addition to these simple models, we also created models with interactions between variables to highlight the combined effect of factors on the occurrence of fatalities in accidents. The first of these models was again a logistic regression model. The complete model is presented in Table 7.

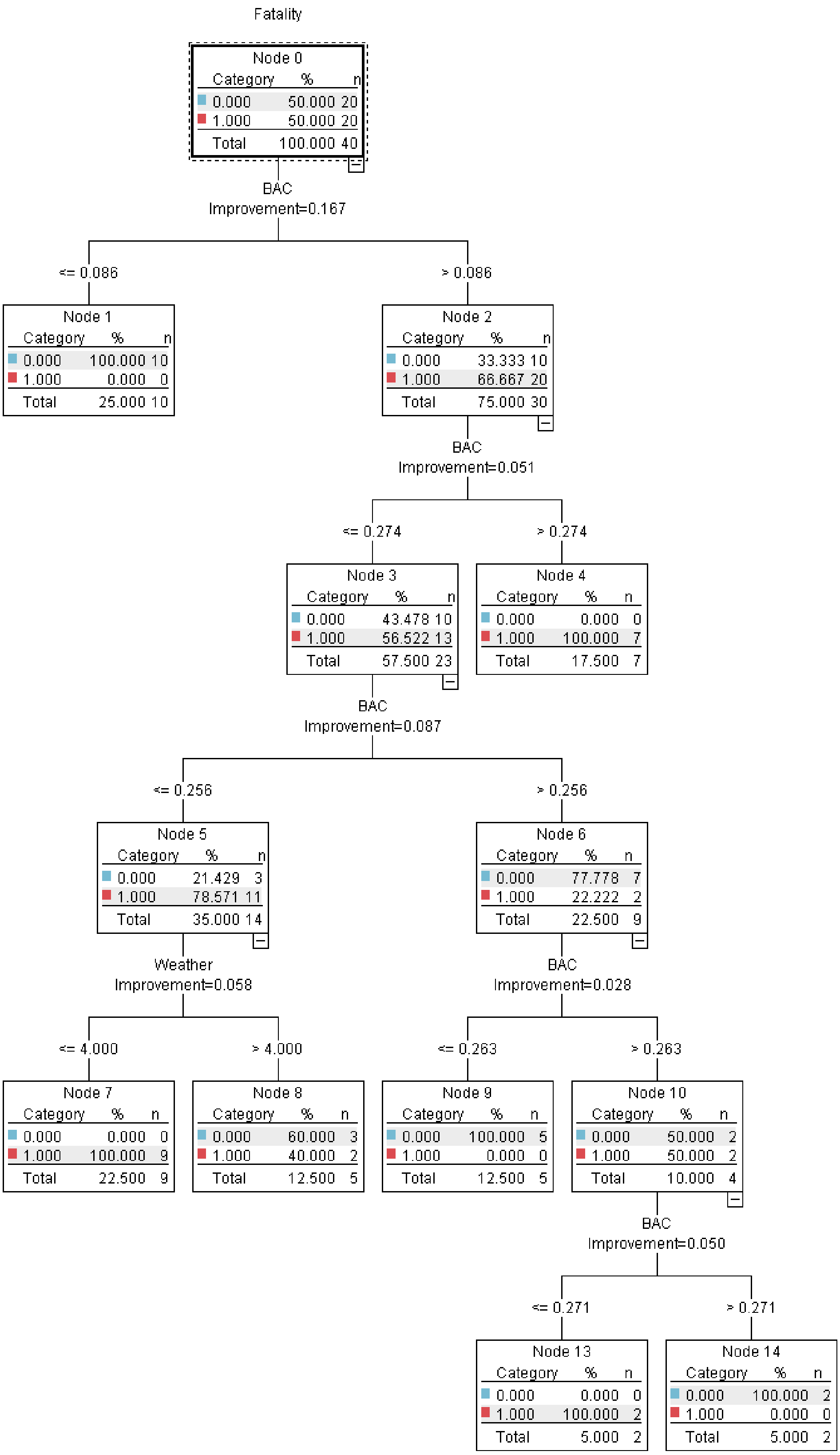

Figure 6. CART classification tree for predicting fatality in accidents.

Table 6. Classification table and evaluation metrics for simple CART model.

Actual	Predicted		Total
	0	1	
0	30	0	30
1	2	27	29
Total	32	27	59
	Accuracy (%)		96.6
	Sensitivity (%)		93.1
	Precision (%)		100.0
	AUC		0.994

Table 7. Logistic regression model with interactions.

Variable	B	Std. Error	Wald	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
						Lower Bound	Upper Bound
Intercept	−47.21	1191.83	0.001	0.98			
BAC	420.82	6.24	4546.49	<0.01	5.77×10^{182}	2.81×10^{177}	1.185×10^{188}
time_1 × weather_4	−46.27	1917.83	4335.87	<0.01	1.24×10^{-20}	.	.
BAC × weather_6	422.16	4.96	7249.96	<0.01	4.56×10^{188}	7.60×10^{180}	2.75×10^{188}
BAC × time_0 × weather_3	421.13	0.00	.		1.27×10^{183}	1.27×10^{183}	1.27×10^{183}

By the stepwise selection of variables, we identified the set of significant variables at a significance level of 0.05. The importance of these variables in the regression model with interactions is illustrated in Figure 7.

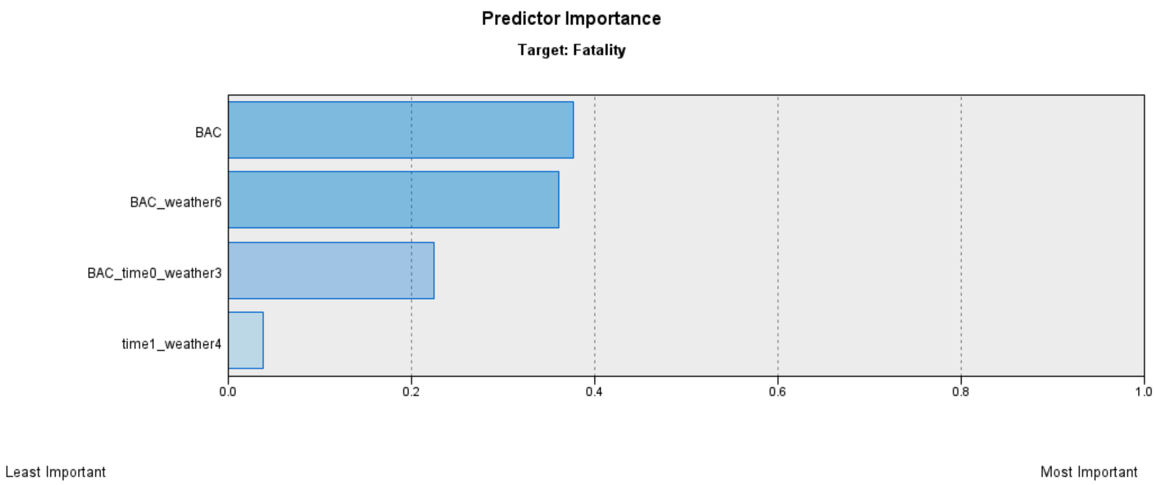

Figure 7. Predictor importance in the logistic regression model with interactions.

The most important variable in this logistic regression model was BAC (importance = 0.41), followed by BAC in combination with weather of type 6 (importance = 0.32). The third most important factor was the three-way interaction of the variables BAC, time_0 (i.e., day) ((importance = 0.22), and the fourth variable in this model, which is the interaction of time_1 (i.e., night) and weather of type 4 (importance = 0.05). According to their coefficients in Table 7, we can conclude that BAC significantly increases the probability of fatality in the accident by $exp\{420.82\}$ multiple for each additional unit of blood alcohol, with other conditions (i.e., weather and time of day) unchanged. Moreover, the combination of BAC, daytime, and weather of type 3 increases the probability of fatality by $exp\{421.13\}$ multiple for each additional unit of blood alcohol, compared to other combinations of daytime or nighttime and weather types. Last but not least, the combination of BAC and weather of type 6 increases the probability of fatality by $exp\{422.16\}$ multiple for each additional unit of blood alcohol compared to other weather types. Finally, the combination of nighttime and weather of type 4 is notable because it decreases the probability of fatality by $exp\{-46.27\}$ multiple.

Table 8 presents the classification performance of the logistic regression model with interactions of variables. This model correctly classifies 88.1% of all accidents; among them, 79.3% of the fatal accidents were identified correctly by the model. If an accident was fatal, the model correctly classified it in almost 96% of cases.

Table 8. Classification table and evaluation metrics for logistic regression model with interactions.

Actual	Predicted		Total
	0	**1**	
0	29	1	30
1	6	23	29
Total	35	24	59
	Accuracy [%]		88.1
	Sensitivity [%]		79.3
	Precision [%]		95.8
	AUC		0.93

The final model was the CHAID tree with interactions of variables (Figure 8). This model uses only two of the variables: BAC in combination with night and BAC in combination with weather of type 3. According to Figure 8, BAC in combination with night is a more important variable, with an importance of 0.73, while the remaining importance of 0.27 belongs to the second variable.

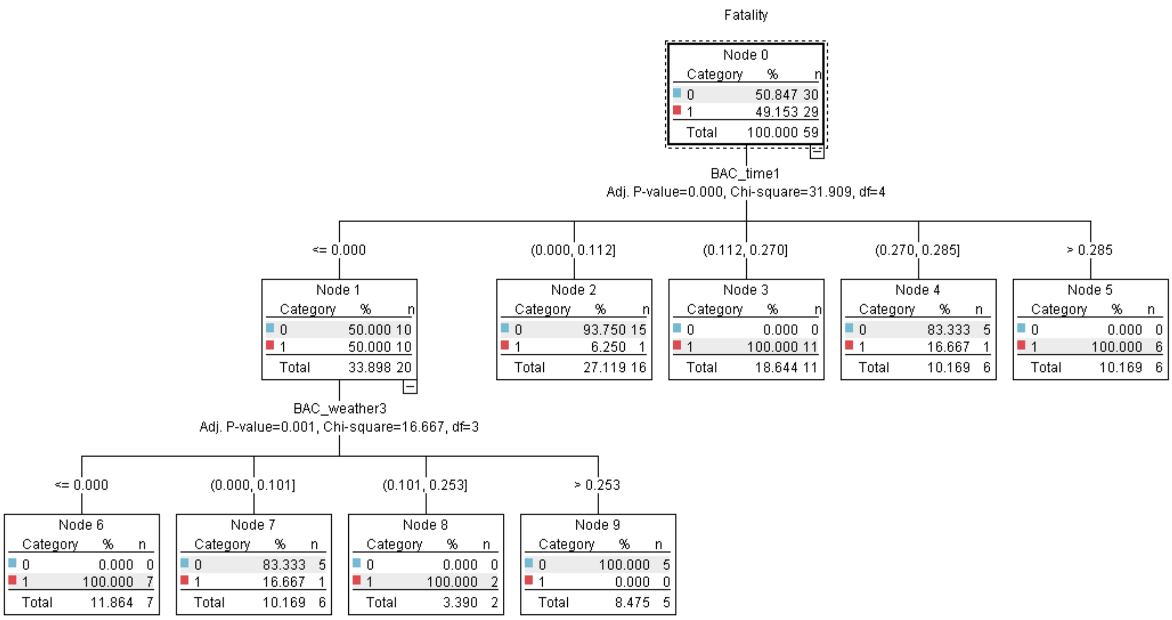

Figure 8. CHAID classification tree with interactions.

Figure 8 represents the CHAID classification tree, predicting the likelihood of fatalities in maritime accidents. The decision tree shows the most contributing factors with BAC as the primary variable in an interaction with the time of day. Figure 8 highlights specific combinations of BAC, time of day, and weather conditions, demonstrating how these interactions heighten the fatality risk.

Both tree models, CHAID and CHART (Figure 6), help simplify complex relationships between variables and make the model's predictions more interpretable, offering a practical tool for assessing risk in maritime safety protocols.

According to the CHAID tree, the model classifies accidents with the level of BAC below 0.112 as fatal (node 2), as well as cases with BAC over 0.285 (node 5). Interestingly, the accidents with BAC between 0.27 and 0.285 are classified as non-fatal, but this represents only a small group of cases (node 4).

The accidents where the combination of BAC and night has a value of zero (i.e., the cases where either BAC was 0 or the accidents happened during the day, node 1) are further classified according to the combination of BAC and the weather of type 3. Among these, the accidents that occurred during the day with a level of BAC between 0.101 and 0.253 are classified as fatal (node 8). The remaining cases, with a level of BAC between 0 and 0.101 or over 0.253 (nodes 7 and 9), but all occurring during the day and with weather conditions of type 3, are classified by the model as non-fatal. The last category to mention is the one where the combination of BAC and the weather of type 3 equals zero (node 6), i.e., either BAC was zero (but there was no case in the data with such a level of BAC) or the weather was not of type 3 (i.e., the weather during the accident was of another type) and the accident happened during the day. All these accidents were categorised by the model as fatal. To conclude, according to the CHAID model shown in Figure 9, the combination of day and weather different from that of type 3 means a fatal accident for all levels of BAC.

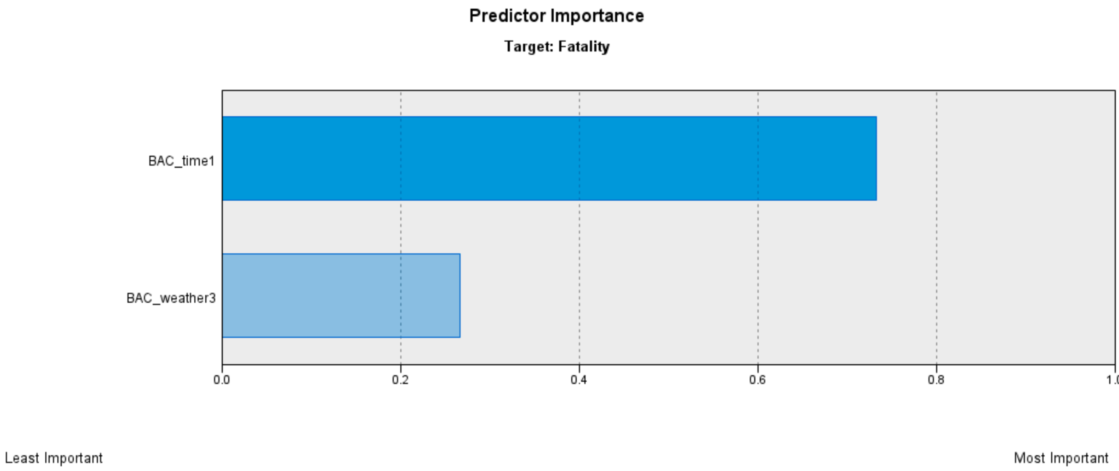

Figure 9. Predictor importance in CHAID model with interactions.

The classification performance of the CAHID model is illustrated in Table 9. This model correctly classified 91.5% of all accidents of both types. Among the fatal accidents, the model correctly found almost 90% of them. Finally, when the model predicted the accident as fatal, the prediction was correct in almost 93% of cases.

Table 9. Classification table and evaluation metrics of CHAID model with interactions.

Actual	Predicted		Total
	0	1	
0	28	2	30
1	3	26	29
Total	31	28	59
	Accuracy [%]		91.5
	Sensitivity [%]		89.7
	Precision [%]		92.9
	AUC		0.96

6. Discussion

In our paper, we provide new insights into the contributing factors of fatality risks in maritime accidents, with a special focus on alcohol impairment. The findings emphasise the importance of understanding how multiple variables interact to create risky situations. While underscoring the effects of alcohol on cognitive functions and physical abilities, our paper enhances this knowledge using a predictive model that quantifies the impact of alcohol in combination with meteorological conditions and time of day. This model not only confirms the significant effect of alcohol on fatality risks but also reveals how these risks are amplified when alcohol consumption coincides with adverse weather or nighttime operations. This interactive effect, which has not been explored in previous studies, fills a critical gap by providing a more nuanced understanding of the factors contributing to maritime fatalities.

The findings highlighted the significance of the role of alcohol in fatal maritime accidents by using logistic regression. The analysis showed that alcohol consumption is a major predictor of fatality. Each additional unit of BAC increased the probability of a fatality by approximately 8.78 times. However, the results also demonstrated that alcohol does not act in isolation. Adverse weather conditions, often affecting visibility, significantly increase the likelihood of fatal accidents, especially when combined with alcohol consumption. Poor visibility can severely affect safe navigation and the crew's ability to respond to hazards. Nighttime conditions make this even worse by reducing vision further, as there is no natural light and crews must rely on artificial lighting.

Although nighttime conditions alone did not significantly increase fatality risk, when coupled with high BAC levels and poor weather, the risk increased. The use of the CHAID tree model illustrated how this combination of high BAC, nighttime, and specific weather conditions create a key predictor of fatal accidents.

Existing maritime regulations need to adapt to the broader conditions in which accidents happen. Current rules should be improved with evidence-based changes, like stricter alcohol testing during high-risk situations, mandatory sobriety checks before night voyages, and more monitoring during bad weather. Additionally, our findings suggest that safety protocols and training for maritime staff should be adjusted to address the higher risks linked to these conditions.

Our paper also identifies several gaps in the earlier research, particularly the failure to investigate the combined effects of alcohol, weather, and time of day. The majority of the previous works focused on these variables in isolation, leaving the complex interplay between them unexplored. By integrating these factors into our predictive model, we provide a more comprehensive understanding of when fatalities are most likely to occur. For example, even moderate levels of alcohol, when compounded by poor weather or nighttime conditions, can lead to fatal outcomes. This supports the need for integrated risk management strategies that address multiple interacting factors rather than isolated risks.

Previous research on the effects of alcohol on maritime safety underscores the significant role it plays in causing maritime accidents. Various studies have examined how alcohol affects critical skills, like navigation and decision making, as well as broader human factors that contribute to accidents. Across different geographical contexts, such as the Baltic Sea, Korea, and Norway, alcohol consumption has been identified as a major contributing factor to maritime accidents, highlighting the need for stricter regulations and better safety management systems [2,7,8].

Various studies have focused on alcohol's direct impact on the cognitive and motor skills essential for ship navigation. From these studies it was evident that even small amounts of alcohol impair decision making, coordination, and reaction times, significantly increasing the likelihood of accidents [3,16]. These findings point to the urgent need for stringent alcohol regulations, especially during high-risk situations. However, most studies focus on the immediate effects of alcohol, and the authors do not examine the long-term operational risks, an area where our research aims to contribute new insights.

On a broader level, human factors play a critical role in maritime accidents. Errors in judgment, lapses in situational awareness, and leadership failures are all common contributors [4,10]. While existing research covers these general factors, fewer studies directly link alcohol to specific accident types like groundings and falls overboard. Our research fills this gap by investigating how alcohol directly contributes to these types of incidents, offering a deeper understanding of its role in maritime safety.

From a regulatory point of view, proactive safety measures, such as strict alcohol testing and robust safety management systems, have been shown to effectively reduce accident rates [12,15]. However, there is often inconsistency in how these rules are enforced across different regions. This requires more consistent, global policies. Our research highlights the need for unified international guidelines, with a particular emphasis on alcohol testing during high-risk conditions, such as nighttime operations or adverse weather.

Methodologically, much of the previous research has relied on retrospective qualitative studies, which offer valuable insights but often lack the ability to predict future accidents. Our paper addresses this gap by adopting a quantitative approach, using predictive models in order to analyse the factors that lead to fatalities. By taking this approach, we provide a clearer, data-driven understanding of how alcohol contributes to maritime accidents.

Logistic regression, as used in our study, allows the use of all types of variables, quantitative and qualitative, in one common model and the assessment of the influence of each predictor while controlling for the others. As a main advantage of the logistic model, we consider the interpretability of its results. Another advantage of this technique is that it does not require predictors to be normally distributed, which is particularly useful in our study, where some variables, such as weather conditions, may not follow a normal distribution.

However, while we chose logistic regression and classification trees as the most appropriate methods for this study, we acknowledge that other techniques, such as discriminant analysis, neural networks, nearest neighbour, support vector machines, and others, could also be considered. Nowadays, neural networks are a popular powerful machine learning technique that can model highly complex, non-linear relationships between variables. However, they are well suited for large datasets and can excel at prediction tasks. In our case, we focused on the explanation task and the description of the relationship between the input variables and the outcome. In comparison with the techniques used in our study, which provide transparent and interpretable results, neural networks are often considered "black boxes". Moreover, neural networks typically require large datasets to perform optimally. Discriminant analysis is a very useful technique often used for classifying binary outcomes. Compared to logistic regression, its key assumption is that the independent variables follow a normal distribution. In our study, variables like alcohol consumption and weather conditions are unlikely to follow a normal distribution, making logistic regression more appropriate. Discriminant analysis usually allows only the quantitative type of explanatory variables, which prevents the use of some variables (weather and time of day) in the model.

Among the studies published so far, the authors employed various methodologies, each with its strengths and limitations. For example, in [7], the authors utilised a standard regression approach to find significant human factors involved in maritime accidents. In comparison to our study, the authors did not include the kind of machine learning technique. While their analysis provided valuable insights into the role of human error, individual accidents were for the purpose of this study cumulated into the number of accidents. From this perspective, our use modelling techniques adds greater interpretability of the results, particularly in analysing interactions between variables.

However, our research also has limitations that must be considered. One significant limitation is the relatively small effect size and lack of statistical significance for the time-of-day variable. This suggests that time of day may not be as crucial as blood alcohol concentration (BAC) and weather conditions in predicting fatal outcomes in maritime accidents. In particular, BAC and adverse weather were found to have a much stronger influence on the risk of fatality, indicating that they should be prioritised when developing safety protocols or predictive models.

Another limitation of our paper is the small sample comprising 38 accident investigation reports. A review of comparable studies mentioned in our paper reveals that similar research based on accident reports often involves smaller datasets due to the specificity and detail of the cases analysed. On the other hand, studies that typically have larger sample sizes either use questionnaires or are focused on accidents in general without a specific focus on alcohol consumption. In the first category, we can mention [10], for example, where the author examined 39 collisions. Despite the smaller sample, the research effectively identified key human factors contributing to these accidents, demonstrating that even small datasets of accident reports can provide valuable insights into accident causality. Ritz-Timme et al. (2006) [17] also focused on a similar experimental approach with 21 ship captains using a simulator to assess nautical performance under the influence of alcohol. Gug et al. (2022) [6] used 10 participants (5 cadets and 5 experienced navigation officers) who carried out simulations where different blood alcohol concentration (BAC) levels were involved. The smaller sample size reflects the controlled environment of a simulation study, where the primary focus was on understanding the direct effects of various BAC levels on navigation performance. Similarly, Howland et al. (2001) [19] examined the effects of alcohol (between 0.04 and 0.05 g% BAC) on simulated ship handling with 38 cadet volunteers. This study was focused on a specific subgroup of seafarers and mirrors our approach in targeting a precise aspect of alcohol-related accidents, and their sample size aligns closely with our own.

Other studies in the field utilise larger sample sizes, though they predominantly rely on questionnaires or simulations. For example, Hasanspahic et al. (2021) [7] examined 135 accident reports, though not exclusively focused on alcohol-related cases. A study by Wang et al. (2021) [8] analysed 1207 accidents, with a focus on 87 collision cases. The larger datasets were not limited by the need for detailed alcohol consumption information. Komulainen (2024) [5] employed a comprehensive survey targeting 144 students, focusing on perceptions of on-board safety, alcohol consumption, and security. This large sample size was feasible due to the broad scope and demographic accessibility of the study participants. A study by Nævestad et al. (2018) [11] involved 192 Norwegian and Greek respondents to examine the influence of national culture, which we measure partly as what kind of behaviours respondents expect from seafarers from their own country. Oluseye and Ogunseye (2016) [12] used a survey design to collect data from 284 marine service operators in Nigeria. Data for the study were collected through questionnaires, and the analysis focused on several human-related factors as major causes of marine accidents, with drugs and alcoholism among them. A questionnaire involving 118 officers was also used by Kim et al. (2007) [16], where the authors examined the drinking status of officers on board. Also, with a ship handling simulator, the effect of alcohol on maritime navigational performance was studied for the three blood alcohol concentration (BAC) levels.

Expanding the dataset in future research could provide a wider base for analysis and improve the robustness of predictive models. This expansion would also allow the inclusion of additional variables, such as fatigue, vessel maintenance, and the competency of responsible personnel, which are known to play critical roles in maritime safety but were outside the scope of our current analysis. Even though the dataset might seem small for robust statistical analysis, it still provided valuable insights into the role of alcohol in maritime accidents. Of course, using more reports would improve the accuracy and generalisability of the results. But despite the smaller sample size, our study clearly illustrates the significant impact alcohol has on maritime safety, especially when combined with adverse weather or nighttime operations.

In conclusion, our research shows just how important it is to take a detailed, data-driven approach to improving maritime safety. While future studies with larger datasets can build on our findings and enhance the models we have developed, this paper already provides important insights into how multiple risk factors interact to increase the likelihood of fatal accidents at sea.

7. Conclusions

Maritime safety is critically important as about 90% of global goods are transported by sea, making the safety of maritime transport essential for the global economy and supply chains [47]. In the fast-paced and unpredictable world of shipping, where operations run 24/7, even small mistakes can have serious consequences, including loss of life, environmental harm, and interruptions to global trade. To ensure the on-board safety of as well as the protection of the environment, it is essential to understand and address the various factors that lead to accidents, especially those that result in fatalities.

Our paper focuses critical attention towards alcohol as the findings reveal that alcohol consumption is a significant predictor of fatal outcomes in maritime accidents. Specifically, each additional unit of BAC drastically increases the probability of a fatality. The data suggest that even moderate levels of alcohol consumption can impair judgment and motor skills to a degree that significantly elevates the risk of fatal accidents.

Firstly, the research included a data collection process—the data were compiled and curated from a range of maritime accident investigation reports. This involved the careful selection of cases where alcohol consumption was confirmed as a contributing factor. The database was constructed using reports from 13 different national and international maritime safety agencies, ensuring that the data represented various types of maritime accidents. Then, the data analysis and model development were conducted using several methods to create predictive models. This involved selecting the variables, selecting the potential methods for modelling, creating several predictive models, selecting the suitable model, performing statistical tests, and validating the model's accuracy. After these steps, the interpretation of findings was provided. The results were critically analysed, especially the interactions between alcohol consumption, weather conditions, and time of day.

Moreover, a literature overview was conducted. This review was not limited to just academic sources; it also included industry reports and data from the World Health Organization and the National Institute on Alcohol Abuse and Alcoholism, providing a well-rounded understanding of the topic. The analysis shows that adverse weather conditions notably increase the dangers posed by alcohol consumption. When combined with poor visibility or nighttime operations, the risk of fatal accidents increases markedly. This points to the fact that not only individual risk factors like alcohol consumption influence the probability of fatality, but also the interactions between multiple risk factors. The CHAID tree model identified the combination of high BAC, nighttime operations, and specific weather conditions as critical predictors of fatal outcomes.

The results have important implications for maritime safety management. Traditional approaches to safety may not be sufficient if they focus only on individual risk factors. Instead of that, a more developed approach is needed—one that recognises and addresses the complex interplay between different variables that contribute to accidents. This could include more comprehensive training programs that educate crew members on the dangers of alcohol consumption, especially when combined with adverse weather and low visibility conditions. Additionally, implementing stricter enforcement of alcohol regulations or policies, especially during high-risk periods such as nighttime or bad weather, could significantly reduce the likelihood of fatal accidents.

In conclusion, enhancing maritime safety requires a comprehensive approach that goes beyond addressing individual risk factors. As the maritime industry continues to evolve, it is essential that safety measures evolve as well, ensuring that all possible risks are minimised.

Author Contributions: Conceptualisation, A.M.; methodology, A.M. and L.S.; software, L.S.; validation, L.S.; formal analysis, A.M. and L.S.; investigation, A.M.; resources, A.M.; data curation, A.M. and L.S.; writing—original draft preparation, A.M. and L.S.; writing—review and editing, A.M.; visualisation, A.M.; supervision, A.M. 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: Not applicable.

Data Availability Statement: The original contributions presented in the study are included in the article; further inquiries can be directed to the corresponding author.

Acknowledgments: The paper is supported by the VEGA Agency by the Project 1/0485/24 "Increasing the efficiency and sustainability of rail and water transport in the context of environmental impacts" that is solved at the Faculty of Operation and Economics of Transport and Communications, University of Žilina.

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

Appendix A

Table A1. Data on contributing factors for selected accidents.

Accident ID	Type of Accident	BAC [1] (%)	Fatalities	Weather and Sea State [2]	Time of Day [3]
1	man overboard	0.270	1	4	1
2	collision	0.265	1	3	1
3	fatal fall	0.110	1	8	1
4	collision	0.258	0	3	0
5	crush incident	0.570	1	2	1
6	grounding	0.660	0	2	0
7	man overboard	0.182	1	2	1
8	grounding	0.690	0	2	0
9	collision	0.324	1	0	0
10	sinking	0.101	1	3	0
11	man overboard	0.154	1	8	1
12	man overboard	0.318	1	2	1
13	grounding	0.271	0	6	1
14	collision	0.600	0	6	1
15	man overboard	0.122	1	4	0
16	fatal fall	0.227	1	2	1
17	man overboard	0.291	1	6	1
18	man overboard	0.346	1	2	1
19	crush incident	0.193	1	1	1
20	fatal fall	0.190	1	3	1
21	grounding	0.112	0	6	1
22	man overboard	0.268	2	4	0
23	fatal fall	0.430	1	1	1
24	fatal fall	0.253	1	3	0
25	man overboard	0.276	1	1	0
26	sinking	0.148	3	4	0
27	fatal fall	0.215	1	1	0
28	crush incident	0.117	1	1	0
29	fatal fall	0.160	1	3	1
30	collision	0.420	2	1	1
31	grounding	0.061	0	3	0
32	collision	0.071	0	4	1
33	grounding	0.058	0	4	1
34	man overboard	0.190	1	3	1
35	grounding	0.193	1	3	1
36	grounding	0.285	1	4	1
37	collision	0.150	2	4	1
38	other [4]	0.112	1	3	0

Source: Authors, based on investigation reports data. [1] of person under influence, who caused the accident/responsible for the process. [2] weather and sea state based on the Beaufort scale: 1–10; 10 = the worst. [3] 0 = daytime, 1 = nighttime. [4] oxygen insufficiency due to disabled breathing as a result of chloroform inhalation.

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