JOURNAL OF MARITIME RESEARCH

Vol XXIII. No. I (2026) pp 260–273

ISSN: 1697-4840, **www.jmr.unican.es**

Gompertz Distribution Modeling of Vessel Characteristics and Maritime Accident Propensity in West African Territorial Waters

Ayodele Adekunle Faiyetole[1,*], Kolade Emmanuel Akeredolu[1]

ARTICLE INFO

Article history:
Received 01 May 2025;
in revised from 01 Aug 2025;
accepted 05 Sep 2025.

Keywords:
Gompertz distribution model, Flag state, Flag of convenience, Vessel tonnage, Ship type, Hazard ratio.

ABSTRACT

This study investigates vessel characteristics associated with maritime accident propensities in West African territorial waters, focusing on ship type, size, and purpose, and their interactions with flag state, accident location, accident types, and casualty characteristics. The aim is to provide empirical evidence for targeted safety measures and policy interventions in the region. Using a survival analysis framework, the study analyzed maritime accident data from 1997 to 2022, employing six survival distribution models: Cox proportional hazards, Gompertz, Weibull, lognormal, loglogistic, and exponential. Model selection was based on log-likelihood values' goodness-of-fit criteria. The analysis also incorporated reparametrized interaction effects to assess the joint influence of flag states, accident locations, accident types, causes, and casualty degrees on accident risk. Vessels were stratified by tonnage (100 to 100,000 tons), and discrete vessel types and ship purposes were systematically examined. The Gompertz distribution model emerged as the most suitable for the dataset. Results indicated that ship type was statistically significant ($\alpha = 5\%$), with fishing vessels showing a 6.5-fold increase in accident risk compared to other vessel types. Smaller tonnage vessels (100 to 1,000 tons) were more prone to accidents. Interaction effects revealed that flag states and casualty degrees were statistically significant ($\alpha = 5\%$ and 1%, respectively). Vessels registered in Nigeria and operating under 1,000 tons exhibited a lower hazard ratio, while Nigerian-flagged fishing vessels were significantly more accident-prone. Capsizing and parted mooring ropes were critical risk factors for smaller vessels, particularly under adverse environmental conditions. The findings highlight the significant role of vessel characteristics, particularly ship type and tonnage, in shaping maritime accident risk in West African waters. By employing survival models, the study provides a robust methodological approach to maritime risk assessment, offering insights for enhanced safety protocols and policy formulation. Targeted interventions could prioritize smaller and fishing vessels, with attention to interactions among flag state, accident location, and casualty severity. These results underscore the need for West African region-specific maritime safety protocols to mitigate risks and improve overall maritime safety.

1. Introduction.

Maritime accident refers to the occurrence of an event or chain of events during the normal operation of a vessel that leads to significant harm or damage. This includes loss of life, serious injuries, or a person going missing from the ship, as well as the loss, abandonment, stranding, or disabling of the vessel itself (Bbtrial, 2025; Schellhammer, 2014). It also encompasses collisions, substantial damage to marine infrastructure that could endanger other ships or individuals, and severe environmental harm, or the threat of such harm, resulting from damage to the vessel (Dominiquez-Pery et al., 2023; MAIB, 2008). These incidents pose serious risks to human safety, maritime operations, ecological stability, and environmental sustainabil-

---

[1] Sustainable, Spatial & Intelligent Transport Labs (StLab), Department of Logistics and Transport Technology, Federal University of Technology, Akure, Akure, Ondo State, Nigeria.

[*] Corresponding author: Ayodele Adekunle Faiyetole. E-mail Address: ayodele.faiyetole@theearthspace.com.

ity, making their prevention and investigation critical in marine safety management. Thus, maritime accident are an unexpected event or sequence of events resulting in serious injury, disappearance, presumed abandonment or death of a crew member or passenger, including damage to the ship, material and cargo, freezing, interoperability or entanglement of the ship, which may seriously endanger the safety of the ship or the seafarers (Maritime Injury Center, 2024; IMO, 2010). Maritime accidents cause serious negative effects on marine ecosystems in coastal countries (Chen et al., 2019; Chang et al., 2014). For example, a North Sea tanker collision spills pose risks to marine ecosystems, affecting species from plankton to top predators like birds, seals, and dolphins, especially with birds entering their breeding season (Wired Science, 2025), which all can be translated to economic losses (Nwokedi et al., 2023; IMO, 1997). Peters (2017) added that the range of effects can vary from minor injuries to severe environmental and property damage, underlining the broad and profound repercussions of maritime accidents. Generally, maritime accidents have extensive consequences, causing significant damage and disruptions both locally and globally (Bbtrial, 2025; Wired Science, 2025; Dominiquez-Pery et al., 2023). Smith and Jones (2015) highlight that these incidents lead to substantial direct and indirect costs, including compensation for damage, loss of livelihoods, and considerable expenses for environmental remediation.

Vessel characteristics such as tonnage or vessel size, ship type, and ship purpose play a crucial role in maritime accident rates, accident types and casualty type, among others. Faiyetole et al. (2026) established a strong association between vessel characteristics in West African waters, underscoring the disproportionate vulnerability of smaller, merchant, fishing, and tanker vessels. Lee et al. (2024) identified that vessel length, gross tonnage, and operational type are significant factors influencing accident likelihood, type, and severity. Wang et al. (2023) incorporated vessel characteristics such as ship types, ship ages and ship routes, demonstrating that these factors significantly impact accident rates and types (Chen, 2019). Knapp and Franses (2007) found that both vessel tonnage and age are significant factors in accident likelihood, with smaller and older vessels generally facing high accident rates. Fan et al. (2014) further noted that certain ship types, particularly cargo ships and tankers, are more susceptible to accidents due to their operational requirements and valuable cargo, especially in high-risk regions. In addition, the purpose of a ship also influences accident risk, as vessels engaged in complex or high-stakes operations face unique hazards. These insights highlight the importance of understanding vessel characteristics in improving maritime safety and emphasize the need for safety measures tailored to specific vessel types, tonnages, and operational purposes.

The flag state under which a vessel is registered plays a crucial role in maritime safety and accident frequency, as it signifies the level of regulatory standards and enforcement associated with the ship. The European Parliamentary Research Service's (2023) Report emphasized that while maritime safety levels in EU waters are high, over 2,000 marine accidents and incidents still occur annually. The Report underscores the crucial role of flag states in ensuring that ships under their jurisdiction are seaworthy, highlighting the need for effective inspections and the adoption of digital solutions to enhance information sharing between flag states. The United States Coast Guard's (2023) Flag State Control Domestic Annual Report documented that marine inspectors conducted 20,647 inspections on U.S.-flagged vessels, identifying 29,925 deficiencies. This data underscores the importance of stringent regulatory oversight by flag states to maintain vessel safety and reduce accident frequency. According to Li and Zheng (2015), vessels registered under open registries, often referred to as Flags of Convenience (FOCs), are more prone to accidents, largely due to weaker regulatory oversight and increased traffic in busy shipping routes (Li and Wonham, 1999). Consistent with Fan et al. (2014) who found that FOC-flagged ships are more frequently involved in accidents in environmentally sensitive areas, worsening ecological damage. Bloor et al. (2013) further pointed out that the less stringent regulations of some flag states correlate with accidents in isolated or inadequately monitored areas, where safety enforcement is often insufficient. These observations highlight the significant influence of flag state regulations on accident locations and stress the importance of enforcing stricter safety standards to improve maritime safety. Obafemi et al. (2016) further illustrated that in regions like the Gulf of Guinea, accidents such as collisions and groundings can severely disrupt shipping routes and trade, resulting in significant economic impacts.

As complex as maritime accidents are (Chauvin et al., 2013), the causes are equally complex involving many different factors (Wang and Fu, 2022; Batalden and Sydnes, 2017). Luo and Shin (2016) classify the main causes of shipping accidents into equipment factors, environmental factors, navigation and operational factors, traffic factors and human factors. It is, however, widely understood that human factors play a crucial role in most of the accidents (Wang and Fu, 2022; Rothblum et al., 2002). Other empirical evidence has shown that human error is responsible for 84-88 percent of tanker accidents, 79 percent of tugboat groundings, 89-96 percent of collisions, 75 percent of all collisions, and 75 percent of fires and explosions. Considering the level of measures taken so far by local and international organizations to improve the quality of shipping and navigation, this is a terrifying statistic. Based on the above statistics, it would not be impossible to say that two thirds of shipping accidents are caused by human error, which according to O'Neil (2000) can include: carelessness or carelessness under commercial pressure, in the wrong place, a feeling of overconfidence or lack of knowledge or experience. Rothblum et al. (2002) pointed out that human factors include overload, excessive speed, lack of attention to weather conditions, fatigue, calculated risk, wrong load, lack of training, cultural differences, incompetence, inadequate navigational aids, wrong decision, incorrectly performed action, or inaction (Rothblum, 2000). Darbra and Casal (2004) showed that between 1941 and 2002 in Hong Kong, human factors caused approximately 57 percent of accidents while the ship was at sea and 43 percent happened at docks in ports. Similarly, the Canadian Transportation and Safety Board (1994) reported that between 1995 and

1996; 49 percent of shipping accidents were caused by human factors, 35 percent by technical factors and 16 percent by environmental factors. Transportation Safety Board of Canada (2023) reports that there were 235 marine transportation accidents, a slight decrease from 244 in 2022 and below the 10-year average of 274.

The National Transportation Safety Board (2015) reports that the sinking of the US cargo vessel *El Faro* was attributed, in part, to the loss of propulsion due to technical failures, and in another marine accident report, the National Transportation Safety Board (2016) investigation reveals that the fire aboard the *Caribbean Fantasy*, leading to a complete loss of propulsion and primary electrical power was caused by equipment failure. Technical factors could include loss of control system causing a crash, pipe burst and hose rupture causing an explosion, propulsion blackout and inadvertent blackout (DNV, 2020). Anyanwu (2014) stated that technical glitches often happen without warning. Vanem et al. (2008) opine that grounding is frequently caused by mechanical failures and inadequate charting (Charikias et al., 2015). Environmental factors of causes of accidents such as bad weather, and reduced visibility, have been found to lead to capsizing or sinking ships (Li et al., 2024; Akten, 2004). Although losses of modern ships due to bad weather may not be as common as older ships, as they can survive in rough seas. Current, tide, strong wind, stormy seas can affect the safe operation of a ship and lead to a marine accident. Sinkings, generally due to structural failures and severe weather (Rothblum, 2000); and fires or explosions, often resulting from electrical faults or mishandling of hazardous materials (Hetherington et al., 2006), underscore the need for targeted safety measures and improvements in training, maintenance, and environmental preparedness (OECD, 2024).

Despite significant efforts to ensure maritime safety and security through various approaches, the number of threats continues to escalate. Some maritime disasters have had a great impact on society and have also led to international protocols and agreements with unforeseen consequences (Okechukwu, 2014). There are specific accidents that fundamentally changed the maritime industry. Maritime accidents timeline compiled by Awal (2016) shows the major marine accidents that have occurred over the past century and the actions needed since then. Perhaps the most famous accident of all is the sinking of the Titanic, which gave the first shot at true international cooperation on safety regulations known as the International Convention for Safety of Life at Sea (SOLAS). According to the IMO Ship Safety and Accident Report (2021), there were 2,703 accidents and 49 losses worldwide in 2020. Among the total losses cargo accounted for 18 incidents, (36.73 percent), representing the most affected ship type. Fishing vessels followed with 10 incidents (20.41 percent), while five passenger vessels recorded 5 incidents (10.20 percent), making them the third most affected category. Various accidents not only resulted in human casualties and property damage but also polluted the environment to varying degrees. At the same time, their dangers have also scared away many people who want to work in this field (Lloyd, 2021).

Aside from Faiyetole et al. (2026), the literature on maritime accident in West African waters is largely fragmented along national lines, with studies focusing on individual countries such as Nigeria, Ghana, and Senegal. Hence, there is a paucity of information on a holistic West Africa maritime accidents studies. Therefore, the aim of this study is to conduct a holistic West African coastal areas accidents examination shedding light on vessel characteristics' propensity for accidents, investigating causes, types and degrees of casualty, flag states and locations of maritime accidents in the region.

2. Methodology.

2.1. Data Types and Source.

Maritime accident records of vessels from 1997 to 2022, a period of 25 years, were sourced from the Global Integrated Shipping Information System (GISIS) of the International Maritime Organization (IMO) database (IMO GISIS, 2024). Gleaned from the GISIS database included the dates of the accidents and vessels' year of build. Time to Maritime Accident (TtMA) was determined as the difference between the date of vessel's year of build and accident, which is essentially the age of the vessel before the accident's occurrence. Vessel characteristics in types, sizes and purposes were categorized, as merchant and fishing for vessel type. Ship sizes were serialized from 100-, 1,000-, 10,000-, and 100,000-tons cargo-carrying capacity, while ship purpose, which is the ship's primary operational purpose, includes tanker boat, tugboat, specialty ship, roll-off/roll-in (Ro-Ro) cargo ship, bulk carrier, fishing vessel, among others.

The vessel's registration number was utilized in search of missing dates. Other information gleaned includes accident types, the causes of accidents, and casualty types. It includes the consequential damage (C&D), and fatalities involved, comprising the severity of injuries, and number of deaths. The fatality rate was determined as the ratio of fatalities and the total number of vessel's occupants, measured from '0' to '1', where '0' implies no fatality (no death), while 1.0, implies all passengers onboard died, for fatality (death), for instance. For fatality (injuries), '0' implies no injury, while '1' connotes very serious injury or death. Therefore, the criterion (or indicator variable) is the vessel accident, while fatality (injuries) was used as the principal predictor. From the marine safety investigations reports on each accident event, information on the locations of accidents and flag administration were inclusively collected. All these parameters form the independent variables. The statistical analyses were performed using Stata/SE 14.2 for Windows.

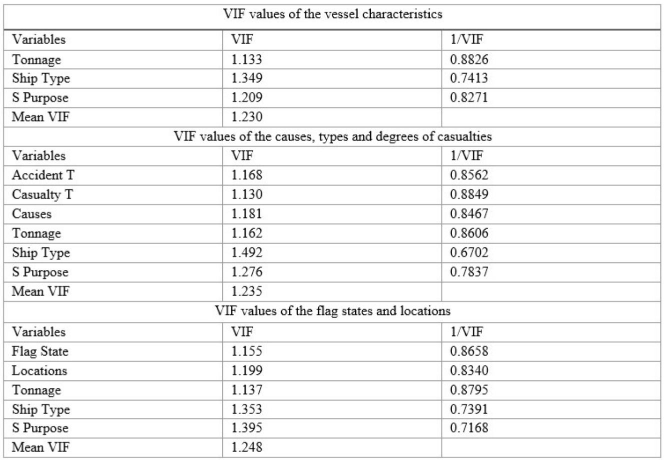
2.2. Multicollinearity Tests with the Predictor Variables.

Thevariance inflation factor (VIF) test was conducted to assess multicollinearity among the potential predictors (Faiyetole, 2023). For an estimated regression coefficient b_i, denoted by VIF_i, represents the factor by which the variance of b_i is inflated because of correlations among the predictor variables (ARA, 2018; Thompson et al., 2017; Miles, 2005). Eqn. 1 illustrates the VIF for the i^{th} predictor.

$$VIF_i = \frac{1}{1 - R_i^2} \tag{1}$$

R_i^2 is the R^2-value obtained by regressing the i^{th} predictor on the remaining predictors. As a rule of thumb, a VIF of 1 means no multicollinearity issue, if greater than 4, it needs further investigation, while a VIF exceeding 10 indicates multicollinearity (Dormann et al., 2013; O'brien, 2007), requiring correction or discarding such a predictor (ARA, 2018). The VIF and tolerance values for the variables are shown in Table 1.

Table 1: VIF values of vessel characteristics.



VIF values of the vessel characteristics		
Variables	VIF	1/VIF
Tonnage	1.133	0.8826
Ship Type	1.349	0.7413
S Purpose	1.209	0.8271
Mean VIF	1.230	
VIF values of the causes, types and degrees of casualties		
Variables	VIF	1/VIF
Accident T	1.168	0.8562
Casualty T	1.130	0.8849
Causes	1.181	0.8467
Tonnage	1.162	0.8606
Ship Type	1.492	0.6702
S Purpose	1.276	0.7837
Mean VIF	1.235	
VIF values of the flag states and locations		
Variables	VIF	1/VIF
Flag State	1.155	0.8658
Locations	1.199	0.8340
Tonnage	1.137	0.8795
Ship Type	1.353	0.7391
S Purpose	1.395	0.7168
Mean VIF	1.248	

Source: Authors.

Considering Table 1, no potential multicollinearity of the predictor variables using VIF was identified. Nonetheless, when a predictor exceeds the conventional VIF threshold, here set at 10, we could undertake additional diagnostic analyses to pinpoint the source of the issue. Depending on the outcome, we could consider several remediation approaches: 1. According to Dormann et al. (2013), if a predictor is highly redundant, with a VIF above 10, it implies it does not contribute unique theoretical insight, we may opt to remove it from the model. 2. For predictors of critical importance that exceed the threshold, variable transformations such as centering or scaling to reduce collinearity without losing the variable's conceptual value could be applied (Aiken and West, 1991). While in cases where multiple variables are highly correlated, we could combine them into a composite index by averaging, thereby capturing their joint effect while mitigating multicollinearity (Bollen and Lennox, 1991). By removing redundant predictors, transforming key variables, or combining highly correlated predictors into composite measures, the robustness and reliability of the models are ensured. However, this study has its highest predictor's VIF under 1.5, far less than 10, which suggests that there is no multicollinearity and thus the remediation approaches are not necessitated.

2.3. *Survival Distribution Regression Models.*

A fundamental aspect of survival analysis is the definition of a specific event, often referred to as the failure time (Cox and Oakes, 1984). In this study, the failure event is the occurrence of a maritime accident, with TtMA serving as the failure time. The time origin, or the starting point for observation, is defined as the year the ship was built. The passage of time T_i is measured from this origin until the failure event.

However, a significant challenge in survival analysis arises from the possibility of censoring, where some observations do not experience the failure event within the study period. Cox and Oakes (1984) describe censoring as the incomplete observation of failure times, which must be recorded as a distinct event within the observation period.

The survival function, denoted as *S(t)*, is fundamental in survival analysis. It represents the probability that TtMA exceeds a specific time *t*, mathematically expressed as Eqn. 2:

$$P(T > t) \tag{2}$$

This function provides insight into the likelihood of survival beyond a given time point and is essential for understanding the distribution of failure times within the study population. To identify the optimal survival model for our dataset, we applied both non-parametric and parametric approaches. Specifically, we utilized the Cox proportional hazards model (non-parametric) alongside parametric models, including the Weibull, Gompertz, log-normal, log-logistic, and exponential distributions.

2.3.1. *Dickman and Weibull reparameterization procedure.*

To evaluate the impact of exposure variables (e.g., vessel type, ship size, ship purpose, accident causes, flag administration, location, fatality, and consequential damages) across different levels of modifiers, a reparameterization procedure was employed, following Dickman and Weibull's (2019) Stata methodology. The process began by coding the exposure variables and modifiers, followed by configuring the dataset using the stset command with maritime accidents as the outcome. A main effects model was then fitted using the stcox command (Cox regression with Breslow method for ties), generating hazard ratios for each variable. To streamline the estimation of effects (including confidence intervals) without the double hash [##] command, the model was reparameterized. This involved specifying the interaction term with a single hash [#] and including the main effect of the modifier, directly estimating interaction effects between the exposure and all modifier levels (Dickman, 2023). For reparameterization, maximum log-likelihood (Log *L*) estimation is recommended (Li et al., 2021; Zhao et al., 2017; Barndorff-Nielsen and Cox, 1984; Barndorff-Nielsen, 1983, 1980; Cox, 1980). Computer simulations were conducted to assess the Cox proportional hazards model and parametric distributions (Weibull, Gompertz, exponential, lognormal, and loglogistic) using maximum likelihood estimates. The best-fitting distribution was selected to analyze predictor interactions. For fitting parametric survival models, the streg command replaced stcox, as follows:

Weibull distribution, *streg $xlist, dist (weibull);* Gompertz distribution, *streg $xlist, dist (gompertz);* exponential distribution, *streg $xlist, dist (exponential);* lognormal distribution, *streg $xlist, dist (lognormal); and* loglogistic distribution, *streg $xlist, dist (loglogistic).*

Through Log L goodness-of-fit assessments, we determined that the Gompertz regression model provided the best fit for our data. This finding aligns with existing literature, where parametric models often outperform the Cox model in certain contexts. For instance, a study comparing various survival models found that the log-normal model provided the best fit and was a good substitute for the Cox regression model (Habibi et a., 2018; Teshnizi and Ayatollahi, 2017). Particularly, studying aircraft accidents, Faiyetole (2023) demonstrated the best fitting of Gompertz survival analysis for the data. These studies highlight the potential advantages of parametric models, such as the Gompertz distribution, in survival analysis.

2.3.2. Gompertz distribution modelling.

To model the effects of vessel types (v), tonnage or ship size (s), ship purpose (p) on the hazard ratio (HR) associated with maritime accidents, to analyze how these vessel characteristics impact the time until TtMA, maritime accident, for example, Gompertz distribution regression model showed the best goodness-of-fit for the datasets among all the survival models tested.

The standard Gompertz hazard function is given by Eqn. 3:

$$h_0(t) = \lambda e^{\alpha t} \tag{3}$$

Where,

λ > 0 is the baseline hazard level,

α governs the rate at which the hazard changes over time,

t the time variable (e.g., time until a disruption in maritime operations such as maritime accidents).

To incorporate the covariates, we let the baseline hazard parameters λ depend on the covariates. A common approach is to use an exponential link function, shown in Eqn. 4:

$$\lambda(v, s, p) = \lambda \exp\left(\beta_0 + \beta_1 v + \beta_2 s + \beta_3 p\right) \tag{4}$$

Where,

β_0, the intercept,

β_1, coefficient of vessel type: A positive β_1 implies vessel types increases hazard or adverse effect,

β_2, coefficient of ship size: A positive β_2 indicates ship size raises risk,

β_3, coefficient of ship purpose: A negative β_3 means ship purpose magnifies hazard.

The hazard function conditional on the covariates becomes Eqn. 5:

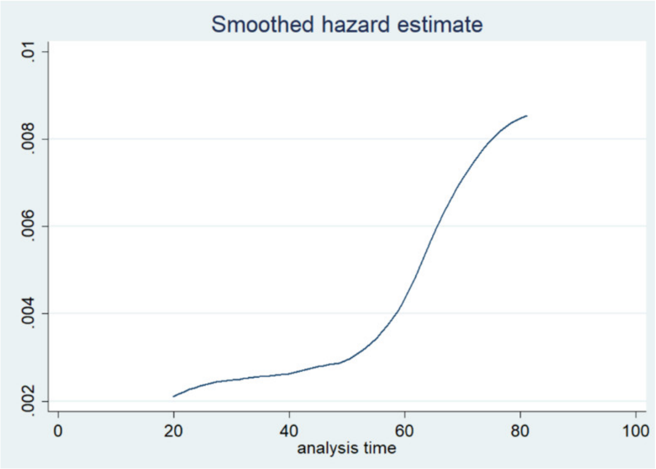
$$h(t \mid v, s, p) = \lambda \exp\left(\beta_0 + \beta_1 v + \beta_2 s + \beta_3 p\right) e^{\alpha t} \tag{5}$$

Figure 1, the smoothed hazard estimate, provides a continuous estimate of the instantaneous hazard function *h(t)* as in Eqn. 5, which represents the failure rate at an exact time t. It smooths fluctuations to show underlying trends.

Integrating the hazard function over time gives the cumulative hazard function as Eqn. 6:

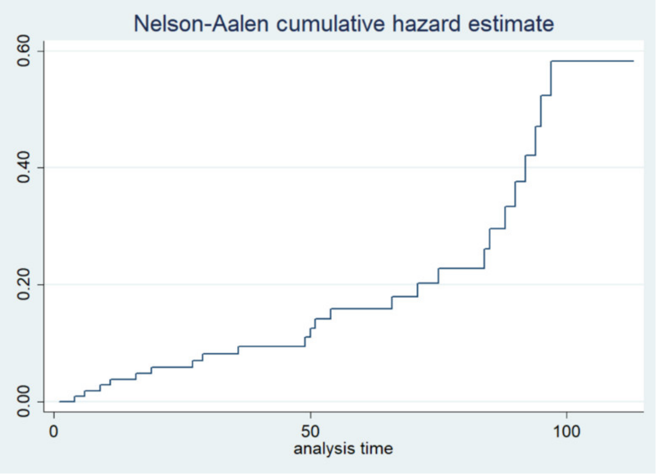
$$H(t \mid v, s, p) = \frac{\lambda \exp(\beta_0 + \beta_1 v + \beta_2 s + \beta_3 p)}{\alpha}\left(e^{\alpha t} - 1\right) \tag{6}$$

Figure 1: Smoothed hazard estimate.



Source: Authors.

Figure 2: Nelson-Aalen cumulative hazard estimate.



Source: Authors.

Figure 2, the Nelson-Aalen cumulative hazard estimate, estimates the cumulative hazard function *H(t)* as in Eqn. 6, which represents the total risk of failure up to time t. It measures the accumulated risk over time.

The survival function, representing the probability that the event (e.g., disruption in maritime operation such as maritime accidents) has not occurred by time t, is shown as Eqn. 7:

$$\begin{aligned} S(t \mid v, s, p) &= \exp\{-H(t \mid v, s, p)\} \\ &= \exp\left\{-\frac{\lambda \exp(\beta_0 + \beta_1 v + \beta_2 s + \beta_3 p)}{\alpha}\left(e^{\alpha t} - 1\right)\right\} \end{aligned} \tag{7}$$

The Probability Distribution Function (PDF), for likelihood-based estimation, is given by Eqn. 8:

$$f(t \mid v, s, p) = h(t \mid v, s, p)\, S(t \mid v, s, p) \tag{8}$$

Thus Eqn. 9,

$$f(t \mid v, s, p) = \exp(\beta_0 + \beta_1 v + \beta_2 s + \beta_3 p)\, e^{\alpha t} \times \exp\left\{ -\frac{\lambda \exp(\beta_0 + \beta_1 v + \beta_2 s + \beta_3 p)}{\alpha} \left(e^{\alpha t} - 1\right) \right\} \tag{9}$$

For observed event times t_i and censoring indicators δi (δi = 1 if maritime accident occurred, 0 otherwise).

The log-likelihood is Eqn. 10:

$$\log L = \sum_{i=1}^{n} \left\{ \delta_i \left(\beta_0 + \beta_1 v_i + \beta_2 s_i + \beta_3 p_i + \alpha t_i\right) - \frac{\exp(\beta_0 + \beta_1 v_i + \beta_2 s_i + \beta_3 p_i)}{\alpha} \left(e^{\alpha t_i} - 1\right) \right\} \tag{10}$$

Model assumptions:

Time invariant covariates: vessel types, tonnage or ship size and ship purpose are fixed at the start of observation.

For increasing hazard: $\alpha > 0$, reflecting accumulating risk over time.

This model quantifies how vessel characteristics like vessel types, tonnage or ship size and ship purpose non-linearly affect maritime operation risk over time, and uses maximum likelihood estimation to fix parameters $\beta_0, \beta_1, \beta_2, \beta_3$, α.

3. Results and Discussion.

3.1. *The Vessel Characteristics with Propensities for Maritime Accidents in the West African Territorial Waters.*

The survival distribution regression models, including Cox regression (semi-parametric), Gompertz distribution regression (parametric), Weibull distribution regression (parametric), lognormal regression (parametric), loglogistic regression (parametric), and exponential regression (parametric), were fitted to the data on ship type, ship purpose, and ship size or tonnage. These factors are consistent with Mansyur et al. (2021) and Wang et al. (2021) subdivision of ship factors, which include ship type and ship scale (Faiyetole et al., 2026). The goal was to determine the optimum distribution for the survival data by considering the Log *L* values and checking for goodness-of-fit, as shown in Table 2.

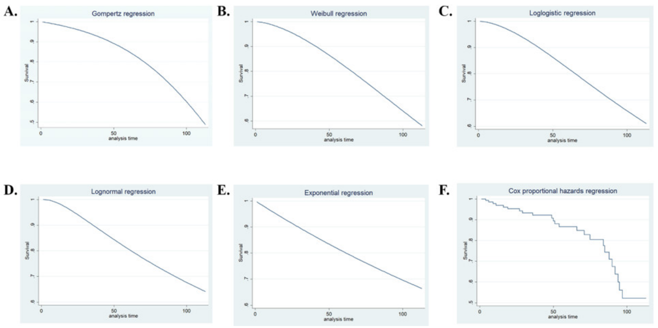
The Gompertz distribution regression model, significant (α = 10%), which has the highest Log *L* value (-62.12) is the most fitting according to Faiyetole (2023), for the captured vessel characteristics dataset. Consequently, the Gompertz distribution regression model was employed to analyze the dataset. See the distribution graphs in Figure 3.

Table 2: Survival models goodness-of-fit for vessel characteristics.

Survival Model	Log *L*	*p*
Gompertz distribution regression	-62.119169	0.0585
Weibull distribution regression	-64.320549	0.0958
Loglogistic distribution regression	-65.576388	0.1459
Lognormal distribution regression	-67.445821	0.1952
Exponential distribution regression	-67.49572	0.1799
Cox proportional hazard regression	-90.220119	0.0555

Source: Authors.

Figure 3: Survival models for (A) Gompertz distribution regression (B) Weibull distribution regression (C) Loglogistic distribution regression (D) Lognormal distribution regression (E) Exponential distribution regression (F) Cox proportional hazards regression.



Source: Authors.

The vessel's survivability was determined by considering their TtMA, as the difference between the vessel's build year and the time of accident, which is essentially the defined point event of failure or specifically the maritime accident. This point event is configured as the dependent variable, while the vessel characteristics are the predictor variables. As presented in Table 3, the likelihood ratio (*lr*) for the model displays $\chi^2 = 7.47$, with significant *p-value* (0.0585) at α = 10 %. It is noteworthy to state that it was the accident effects with fatality (injuries) rather than deaths that offered a more fitting dataset for the survival analysis, hence modelled.

The result shows that ship type, which is categorized into two, fishing and merchants, has about 6.5 times the likelihood of association with maritime accidents, and significant at 5% (*p* = 0.02), consistent with Dominiguez-Pery et al. (2023), who reported that vessel types, including fishing vessels, influence the severity and frequency of accidents. This heightened risk is often attributed to factors such as the operational environments of fishing vessels and varying safety standards. Ship size or tonnage, categorized as 100-, 1,000-, 10,000-, and 100,000 tons of vessels, with a HR of 0.92, demonstrates the vessel characteristics with about 8% rates effect reduced risk of accidents, supported by Talley (1999a) who found no direct correlation between ship size and accident. Agreeably, larger ships, due to better stability and more advanced safety features, may experience fewer accidents. While ship purpose, broadly categorized into seven, including roll-on/roll-off (Ro-Ro), specialty, tanker ships, fishing vessels, among others, has the reduced risk effect of (HR: 0.83), about 17% reduction in the rate of risk to maritime accidents in the region, consistent with Dominiguez-Pery et al. (2023).

3.1.1. The Interaction Effects Among the Vessel Characteristics.

Interactions between vessel tonnage and ship types on accidents in the region.

From Table 4, which presents the connection between ship size and ship types in the reparametrized interaction for maritime accidents; the likelihood ratio shows Chi-square value of 8.28 with no significant evidence ($p = 0.2185$). The interaction turns out results for fishing vessels in the 100 tons of sizes to have a very high probability of causing an accident at HRs = 2,704,039, with no significant effect on the accident, implying that probability of occurrence is by chance. The result is supported by Weng and Li (2019) positing that in the Fujian Province, China, small fishing vessels, such as 100 tons fishing, involved more in maritime accidents.

Interactions between vessel tonnage and ship purpose on accidents on the west African territorial waters.

The relationship between ship purpose and tonnage in the reparametrized interaction is displayed in Table 5; the likelihood ratio displays Chi-square value of 33.14 with no significant evidence ($p = 0.326$). However, the interaction result implies that 1,000 tons of specialty ships do not appear to have significant effect on maritime accidents, while its HR of 1.90 suggests that the risk likelihood if an accident occurred is of about 100% of impact. Consistent with Weng and Li (2019) who posited that vessels transporting cargo of a particular nature or purpose were more likely to be involved in serious marine accidents. The result further supports Chen et al. (2019), showing that the Liquified Petroleum Gas (LPG), Ro/Ro and chemical tankers are more likely to have a total loss accident.

Table 3: Gompertz regression model sufficiency for vessel characteristics of maritime accidentGompertz regression model sufficiency for vessel characteristics of maritime accident.

Variables	HR	SE	z	p	95 % CI Lower	For HR Upper	l	LR $\chi^2(3)$	$p > \chi^2$
Ship Size	0.92439	0.24340	-0.30000	0.76500	0.55173	1.54876	-62.12	7.47	0.0585
Ship Type	6.45195	5.14145	2.34000	0.01900	1.353265	30.76087			
Ship Purpose	0.82546	0.09918	-1.60000	0.11000	0.65226	1.04463			
Constant	0.00037	0.00056	-5.23000	0.00000	0.00002	0.00716			
Gamma	0.02467	0.00760	3.28000	0.00100	0.00991	0.03943			

Source: Authors.

Table 4: Tonnage-ship types reparameterized interaction using Gompertz distribution regression mode.

Tonnage (tons) Ship Type	HR	SE	z	p	95 % CI Lower	For HR Upper	l	LR $\chi^2(6)$	$p > \chi^2$
100-fishing vessels	2,704,039.00	3.72e+9	0.01	0.99			-61.71	8.28	0.2185
Constant	3,243.8340	4463144.00	0.01	0.99					
Gamma	0.02195	0.01	3.02	0.003	0.0077	0.0362			

Source: Authors.

Table 5: Tonnage-ship purpose reparameterized interaction using Gompertz distribution regression model.3.2. Vessel Flag States and Locations of Maritime Accidents in the West African Territorial Waters.

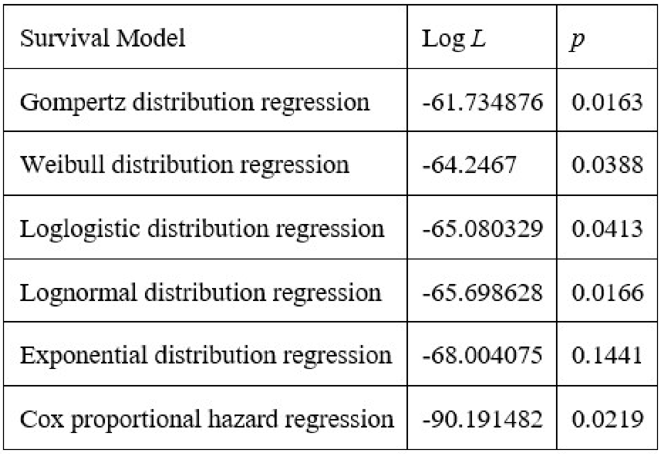
Tonnage (tons) Ship Purpose	HR	SE	z	p	95 % CI Lower	For HR Upper	l	LR $\chi^2(20)$	$p > \chi^2$
1,000-speciality ships	1.90	21199.10	0.00	1.00			-49.28	33.14	0.3260
Constant	35746.99	1.82e+8	0.00	0.99					
Gamma	0.03120	0.00821	3.80	0.00	0.0151	0.0473			

Source: Authors.

3.2. Vessel Flag States and Locations of Maritime Accidents in the West African Territorial Waters.

The survival distribution regression models were fitted to the data on flag states, country of vessel registration, and location within the west African territorial waters where the maritime accident occurred. The Gompertz distribution regression model, significant ($\alpha = 5\%$), which has the Log L value (-61.74), as shown in Table 6, is the most fitting for the captured flag states and accident locations dataset. Thus, the Gompertz distribution regression model was adopted to analyze the dataset.

Table 6: Survival models goodness-of-fit for vessel flag states and locations of accidents.

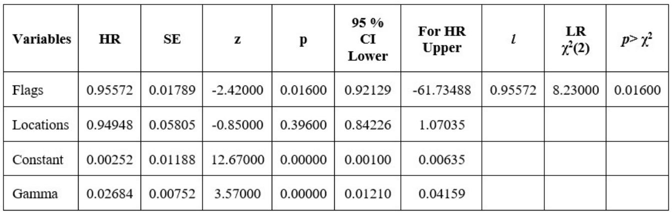


Survival Model	Log L	p
Gompertz distribution regression	-61.734876	0.0163
Weibull distribution regression	-64.2467	0.0388
Loglogistic distribution regression	-65.080329	0.0413
Lognormal distribution regression	-65.698628	0.0166
Exponential distribution regression	-68.004075	0.1441
Cox proportional hazard regression	-90.191482	0.0219

Source: Authors.

Vessel flag states and locations of accidents within the west African territorial waters were configured as the predictor variables. As presented in Table 7, the *lr* for the model $\chi = 8.23$ is with significant *p-value* (0.02) at $\alpha = 5\ \%$. The results indicate that flag states had a (HR: 0.96), with about 4 % rates effect decreased risk of accidents, significant at $p = 0.02$, consistent with Li et al. (1999) who opined a relationship exists between accidents and flag states using the Lloyd's Register of Ships database. Specifically, Li et al. (2014) opined that vessels flying a national flag are safer. While locations had 5% rates effect reduced risk of accidents occurring by chance, in line with Jiang et al. (2020), considering ports, coastal waterway and sea, postulated that at such locations, the probability of the accident risk is high, which is consistent with Weng and Li (2019) with an analysis of environmental factors during navigation. Chen et al. (2019) found that the West Mediterranean and West African locations were more prone to ship total loss accidents.

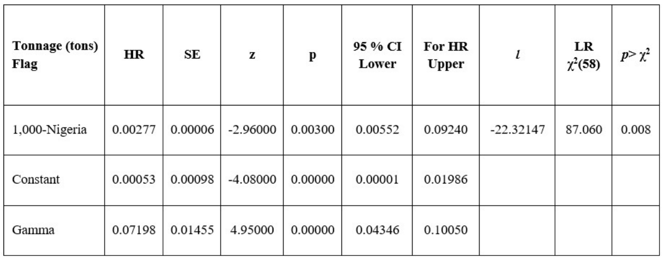
Table 7: Gompertz regression model for flag states and location Maritime Accident.



Variables	HR	SE	z	p	95 % CI Lower	For HR Upper	*l*	LR $\chi^2(2)$	$p > \chi^2$
Flags	0.95572	0.01789	-2.42000	0.01600	0.92129	-61.73488	0.95572	8.23000	0.01600
Locations	0.94948	0.05805	-0.85000	0.39600	0.84226	1.07035			
Constant	0.00252	0.01188	12.67000	0.00000	0.00100	0.00635			
Gamma	0.02684	0.00752	3.57000	0.00000	0.01210	0.04159			

Source: Authors.

Table 8: Tonnage-flags reparameterized interaction using Gompertz distribution regression model.



Tonnage (tons) Flag	HR	SE	z	p	95 % CI Lower	For HR Upper	*l*	LR $\chi^2(58)$	$p > \chi^2$
1,000-Nigeria	0.00277	0.00006	-2.96000	0.00300	0.00552	0.09240	-22.32147	87.060	0.008
Constant	0.00053	0.00098	-4.08000	0.00000	0.00001	0.01986			
Gamma	0.07198	0.01455	4.95000	0.00000	0.04346	0.10050			

Source: Authors.

3.2.1. Flag States and Locations of Accidents Interactions with Ship Size, Type and Purpose.

Interactions between vessel tonnage and flag states of maritime accidents.

As shown in Table 8, the statistical significance of the interaction effect of the estimated hazard ratios for 113 accident records with 58 degree of freedom suggests that the likelihood ratio test statistic ($\chi^2 = 87.06$) has strong evidence ($p = 0.0081$) of interaction at $\alpha = 1\ \%$. However, of the 58 interactions analyzed, only 1 returned. The hazard ratio and the *p* value for the interaction between 1,000 tons vessels and vessels registered in Nigeria are (HR: 0.0028; $p = 0.003$). This finding indicates that small vessels of about 1,000 tons registered in the Nigerian territory have a low hazard ratio to accident which is very significant, consistent with Lee et al. (2024), who found larger vessels with higher gross tonnage were found to have different risk profiles compared to smaller vessels. This is in accordance with Ukoji and Ukoji (2015), who showed that the predominant type of accident that causes the most loss of lives in Nigeria waters is the boat and ferry accidents (smaller vessels). It implies that in Nigeria although the propensity of small vessels under 1,000 tons carrying capacity is statistically significant, when it happens, hazard risk could be about 1 percent.

Interactions between vessel tonnage and locations of accidents.

From Table 9, with 28 degrees of freedom, three results were returned. At $p = 0.043$, Liberian territorial waters significantly interact with vessels approximating 1,000 tons, though at low risks (0.047) of accidents. The interaction between ship sizes weighing about 100 tons and 1,000 tons and possible of accidents in the Senegal territorial waters respectively displays HRs of (4.4; 2.5), occurring by chance. It suggests that smaller ships of 100 tons had 4.4x risk likelihood if accident occurred, while for 1,000 tons in the same location of Senegal, the risk likelihood is about 2.5x, suggesting that smaller vessels had a higher risk of accidents in the Senegalese territorial waters.

Interactions between ship types and flag states to accidents.

As shown in Table 10, the Gompertz distribution regression model is fitting for the ship types and flag states dataset, statistically significant ($p = 0.017$). The interaction between Nigeria as vessel registration state and fishing vessels was returned, with very high risk of about 34x risk likelihood and significant at $\alpha = 10\ \%$. Specifically, it reveals that fishing vessels flying the Nigerian flag states, i.e., fishing vessels registered in Nigeria, are significantly more likely to be involved in accidents with very high risks. This is corroborated by Dominiguez-Pery et al. (2023) who reported that the severity and frequency of accidents of fishing vessels is high. Nonetheless, unlike the stringent regulatory enforcement observed in EU waters, as reported by the European Parliamentary Research Service (2023), and the rigorous inspection regime imposed on U.S.-flagged vessels by the United States Coast Guard (2023), Nigeria presents a stark contrast. According to Oyewole (2023), the country struggles with weak institutional capacity to effectively regulate and enforce maritime laws. Specificaly, Abubakar (2023) opines that poor funding, inadequate training and limited equipment are some limitations and challenges acting as showstoppers to enforcing stringent maritime regulations by Nigerian Maritime Administration and Safety Agency (NIMASA), the agency with the mandate to regulate and promote maritime safety. This regulatory gap has fostered an environment where piracy thrives, and uninspected vessels operate unchecked, exacerbating safety risks and contributing to the high incidence of maritime accidents within Nigeria's territorial waters.

Table 9: Tonnage-location reparameterized interaction using Gompertz distribution regression model.

Tonnage (tons) Location	**HR**	**SE**	**z**	***p***	**95 % CI Lower**	**For HR Upper**	*l*	**LR χ^2(28)**	$p > \chi^2$
100-Senegal	4.42730	6.77935	0.97000	0.331	0.22015	89.03296	-48.48430	34.73000	0.17770
1,000-Liberian	0.04678	0.07066	-2.03000	0.043	0.00242	0.90340			
1,000-Senegal	2.44548	3.89360	0.56000	0.574	0.10792	55.41335			
Gamma	0.03141	0.00844	3.72000	0.000	0.01487	0.04795			

Source: Authors.

Table 10: Ship types-flags reparameterized interaction using Gompertz distribution regression model.

Ship Type Flags	**HR**	**SE**	**z**	***p***	**95 % CI Lower**	**For HR Upper**	*l*	**LR χ^2(42)**	$p > \chi^2$
Fishing-Nigeria	34.43378	70.33062	1.73000	0.08300	0.62866	1886.05500	-34.43378	63.68000	0.01700
Constant	0.00054	0.00044	-9.20000	0.00000	0.00011	0.00269			
Gamma	0.04636	0.01049	4.42000	0.00000	0.02580	0.66923			

Source: Authors.

Table 11: Ship types-location reparameterized interaction using Gompertz distribution regression model.

Ship Type Location	**HR**	**SE**	**z**	***p***	**95 % CI Lower**	**For HR Upper**	*l*	**LR χ^2(17)**	$p > \chi^2$
Fishing-Ghana	2.97867	36522.55000	0.00000	0.998			-50.87409	15.960	0.527
Fishing-Cote d'Ivoire	2.04439	24219.50000	0.00000	1.000					
Constant	0.00123	0.00063	-13.01000	0.000	0.00045	0.00338			
Gamma	0.02679	0.00792	3.38000	0.001	0.01127	0.04232			

Source: Authors.

Interactions between vessel tonnage and locations of accidents.

The relationship between ship types and locations of accidents in the West African territorial waters is shown in Table 11, showing the hazard ratios and the *p*-values for two interactions of fishing vessels with Ghana and Cote d'Ivoire, which both show no statistical significance. The HRs reveal that Ghanaian territorial waters have about 3x the risk likelihoods of accident while it was 2x in the Ivorian waters, suggesting that there is a higher risk of having maritime accidents in the Ghanian territorial waters than in Cote d'Ivoire. In summary, fishing vessels near the territorial waters of Ghana and Cote d'Ivoire have high hazard rates if accident occurred, oftentimes by chance. The higher risk in Ghana over Cote d'Ivoire may be due to the high fishing intensity in Ghana territorial waters, which according to Beick-Baffour (2000), fishing is the most important activity in the entire Ghanian coastal zone regarding the number of people dependent on it (Aning et al., 2021).

3.3. Causes, Types, and Degrees of Casualties of Maritime Accidents in the West African Territorial Waters.

The results in Table 12 show that the degree of casualty, which is categorized into three, less serious, serious, and very serious, has a low likelihood of risk association, 11 percent, with maritime accidents but significant at 1% ($p = 0.001$). The accident types, while categorized into eight, including explosion and fire, capsizing, grounding, sinking, among others, have 1.06 HR but occurring by chance. Thus, accident types such as collision, explosion, fire, capsizing, grounding, man overboard, and sinking, among others, may occur, but may not necessarily lead to injuries for any of the passengers or crew members.

Chen et al. (2020) however found that severity of marine accidents and sinking or collision had a greater impact on the severity of damage, while hull structural failures and grounding had a relatively less impact on the severity of an accident. The extent of the injuries sustained onboard during the accident will depend on the severity of the accident. And this is because maritime system is heavily human-controlled, and injuries sustained by humans will significantly impact the vessels' operations. This is in line with the conclusion reached by the human error analysis of maritime accidents conducted by Maternova et al. (2023), who highlighted that the severity of injuries significantly impacts overall outcomes. Wang et al. (2023) considered two states of injury, free and prone states, of which the latter represents the hypothesis of casualty severity levels, with significance, as calibrated for this study are very serious, serious, and less serious, are hereby corroborated.

While causes of maritime accidents, categorized into three as mechanical, human, and environmental factors, with a hazard ratio of 1.24 but occurring by chance. Of these three predictors, the cause has the highest risk likelihood of maritime accident. Consistent with Deng et al. (2022), who harped on the complexities of maritime accidents because they involved coupling of causal factors and concluded that as the number of risk factors participating in the coupling increases, the coupling value increases, and the multi-factor coupling is more likely to cause accidents.

Table 12: Gompertz regression model for causes and types of Maritime Accident.

Variables	**HR**	**SE**	**z**	***p***	**95 % CI Lower**	**For HR Upper**	*l*	**LR χ^2(3)**	p> χ^2
Accident Types	1.05651	0.08856	0.66000	0.51200	0.89644	1.24516	-49.80958	32.08000	0.00000
Casualty Types	0.10712	0.07185	-3.33000	0.00100	0.02877	0.39885			
Causes	1.24169	0.29347	0.92000	0.36000	0.78133	1.97330			
Constant	0.01180	0.01236	-4.24000	0.00000	0.00115	0.09191			
gamma	0.26083	0.00774	3.37000	0.00100	0.01090	0.04126			

Source: Authors.

3.3.1. Causes, Types, and Degrees of Casualty Interactions with Tonnage, Ship Type and Ship Purpose.

Interactions of the causes and types of maritime accidents together with the degrees of casualty of seafarers were interacted with the vessel characteristics.

Interactions between vessel tonnage and accident types. Vessel tonnage, a ship's cargo-carrying capacity, measured in tons. Once more, for this study, the ship's cargo-carrying capacity is categorized as 100-, 1,000-, 10,000-, and 100,000 tons.

The findings of its interactions with accident types are shown in Table 13. The model, with 28 degrees of freedom, is statistically significant, whereas three of the interactions are turned out. The results show that capsizing has interactions with both 100 tons ship and 1,000 tons, both with low risks of likelihood. However, for the smaller ship of 100 tons, it is significant at α = 1%. Parted mooring ropes, perhaps out of negligence, a form of human error, also shows interaction with 1,000 tons of vessels. Generally, the findings indicate that smaller vessels are more prone to capsizing accident types. Consistent with Shin (2017) who found that of all the vessels that have majorly capsized were in the smaller vessel category (Gwaday, 2019; Talley, 1999b). The later author further revealed that capsizing is caused mainly by overloading, which is human factor, and severe weather, which is environmental. In contrast, however, with Bijwaard and Knapp (2009) who discovered that larger cargo ships have a greater accident rate, supporting Li et al. (2014), who opined that large ships have more accidents due to poor maneuverability. Aligning with Mikelis (2008), who found that smaller ships had a longer lifespan, while larger ships have a shorter lifespan.

Table 13: Tonnage-accident types reparameterized interaction using Gompertz distribution regression model.

Tonnage (tons) Accident Type	HR	SE	z	p	95 % CI Lower	For HR Upper	l	LR $\chi^2(28)$	p> χ^2
100 – capsizing	0.00799	0.01521	-2.54000	0.01100	0.00019	0.09239	-31.40661	68.89000	0.00000
1,000-parted mooring ropes	0.83674	1.38851	-0.11000	0.91400	0.03237	21.63196			
1,000-capsizing	0.08370	0.13114	-1.58000	0.11300	0.00388	1.80429			
Constant	0.00001	0.00001	-5.80000	0.00000	0.00000	0.00036			
gamma	0.04986	0.01044	4.77000	0.00000	0.02939	0.07033			

Source: Authors.

Table 14: Tonnage-causes reparameterized interaction using Gompertz distribution regression model.

Tonnage (tons) Causes	HR	SE	z	p	95 % CI Lower	For HR Upper	l	LR $\chi^2(14)$	p> χ^2
100-environmetal	2.30817	3.84406	0.50000	0.61500	0.08824	60.37712	-59.98190	11.74000	0.62720
100-human	0.99822	1.49804	0.00000	0.99900	0.05270	18.90713			
1,000-environmetal	2.61002	4.39826	0.57000	0.56900	0.09599	70.96446			
1,000-human	1.66966	2.33271	0.37000	0.71400	0.10799	25.81420			
Constant	0.00303	0.00020	0.00000	-4.20000	0.04550	0.04550			

Source: Authors.

Interactions between vessel tonnage and causes of accidents.

The results in Table 14 returned four of the 14 degrees of freedom with none of them showing significance. But the interactions between the vessel's cargo-carrying capacity and environmental factor of causes of accidents revealed the risk likelihood is 2.6x for 1,000 tons, while 2.3x for 100 tons. It implies that environmental factors had a higher risk of causing maritime accidents than human factors, which of course had lower HRs, the 1,000 tons vessel interacting with human factors do have a hazard level likelihood of 1.7x causing maritime accidents. The results broadly show the extent to which tonnage and causes of accidents influence maritime accidents. In summary, these findings indicate that environmental factors of causes of accident pose higher risk with vessel sizes of 100 and 1,000 tons than human factor interactions, but the chance of happening is not statistically significant. This finding is inconsistent with Wang and Fu (2022) for asserting that human factors are more maritime accident causing. The result is however in line with Wang et al. (2005), stating that smaller vessels are particularly vulnerable to severe weather, which is an environmental factor. Heavy weather can weaken the hull structure of the vessel and at the same time, cause deck fittings to loosen and lead to an accident.

Interactions between ship types and accident types.

The results of the effects of the reparametrized interactions between ship types and accident types are presented in Table 15; the likelihood ratio reveals Chi-square value of 50.61 with significant evidence (p = 0.0000). The Gompertz distribution regression model fits the ship types and accident types of maritime accident dataset quite well. The interaction between fishing and parted mooring ropes of accident types, however, has a relatively low HR (0.01088) but shows a significant effect on the accident at p = 0.01. Fishing and capsizing interaction with equally low HR but higher than parted mooring ropes, which is not statistically significant. This is contrary to Fawzy et al. (2024), revealing that the riskiest type of accident is capsizing for fishing vessels, based on records of casualties. The lack of statistical significance in the interaction between fishing vessels and capsizing incidents, nevertheless, may be attributed to various factors, including the implementation of safety measures, vessel design improvements, and effective crew training. These factors can mitigate the risk of capsizing, thereby reducing the strength of the association between fishing vessels and such accidents. The results reveal that fishing vessels significantly interacted with mooring rope accident types. In comparison to other ship types, i.e., merchant vessels, fishing vessels have a substantial significant impact when considered with parted mooring ropes. Fishing vessels often operate under challenging conditions, including frequent docking and undocking, which necessitates the use of mooring ropes to secure the vessels. The significant interaction between fishing vessels and parted mooring ropes accidents suggests that these vessels are particularly susceptible to incidents where mooring lines fail. Such failures can lead to uncontrolled vessel movements, posing risks to crew safety and resulting in potential vessel damage. Jin (2014) shows that fishing vessel accident severity in the Northeastern United States found that certain types of accidents, including those related to equipment failures like parted mooring ropes, significantly affect vessel damage severity, with factors such as loss of stability and sinking. This underscores the critical importance of maintaining equipment integrity to ensure vessel safety. Table 15 Ship types-accident types reparameterized interaction using Gompertz distribution regression model.

Interactions between ship types and accident types.

Table 16 shows the results for the ship types and causes of accidents interaction; the likelihood ratio shows Chi-square

Table 15: Ship types-accident types reparameterized interaction using Gompertz distribution regression model.

Ship Type Accident Type	HR	SE	z	p	95 % CI Lower	For HR Upper	l	LR $\chi^2(14)$	p> χ^2
Fishing-parted mooring ropes	0.01088	0.01943	-2.53000	0.01100	0.00033	0.36030	-40.54433	50.61000	0.00000
Fishing-capsizing	0.16510	0.23176	-1.28000	0.19900	0.01054	2.58591			
Constant	0.00050	0.00038	-10.12000	0.00000	0.00012	0.00218			
Gamma	0.03658	0.00890	4.11000	0.00000	0.01914	0.05403			

Source: Authors.

Table 16: Ship types-causes reparameterized interaction using Gompertz distribution regression model.

Ship Type Causes	HR	SE	z	P	95 % CI Lower	For HR Upper	l	LR $\chi^2(7)$	p> χ^2
Fishing- environment	0.23268	0.37229	-0.91000	0.36200	0.01011	5.35430	-58.83041	14.04000	0.05040
Fishing-human	0.51640	0.72228	-0.47000	0.63700	0.03330	8.00859			
Constant	0.00050	0.00038	-10.03000	0.00000	0.00011	0.00221			
Gamma	0.02385	0.00746	3.20000	0.00100	0.00923	0.03846			

Source: Authors.

value of 14.04, significant $p = 0.0504$. With degrees of freedom of seven, two interactions were returned. These are fishing vessel types and environmental and human factor accident types. In general, neither of the two interactions show a significant p-value and the hazard ratios are low. Implying that environmental and human factors account to a certain degree the risk of leading to fishing vessel accidents. This is particularly consistent with studies such as Wang et al. (2020), Rothblum, (2000), Uberti (2001), Ozguc (2019), who concluded that fishing vessel accidents are mainly caused by human-related factors.

Further in line with Uğurlu et al. (2018) who posited that environmental factors are also playing a significant role in accidents' occurrence. These factors include poor weather conditions, vessel's operational status, and the neglected or inadequate fishing vessel structures (Jaremin and Kotulak, 2004; Roberts, 2004; Wang et al., 2005; Laursen et al., 2008). For example, according to Jin and Thunberg (2005), there is a strong direct correlation between high wind speed and fishing vessel accidents. It is also noted that accidents are more likely to occur in coastal waters during the winter season. Fawzy et al. (2024) also reveal that the major causes of accidents are human action, bad weather, and the loss of total or partial control of machinery or handling equipment.

Conclusions.

This study provides a comprehensive analysis of the relationship between vessel characteristics and the propensity for maritime accidents in West African territorial waters, utilizing survival distribution models. The findings reveal that certain vessel attributes, including size and type, significantly influence the likelihood and timing of accidents in this region. Fishing vessels, particularly those of smaller tonnage exhibit a higher likelihood of maritime accidents. Also, vessels used for certain purposes such as tankers and cargo ships exhibit a higher propensity for accidents, underscoring the importance of targeted safety measures for these categories. The use of survival distribution models has proven effective in capturing the temporal aspects of accident risk, allowing for a more nuanced understanding of how vessel characteristics impact accident probability over time. This approach not only enhances the predictive accuracy of maritime risk assessments but also provides valuable insights for policymakers and maritime authorities aiming to improve safety in West African waters. Given the growing maritime traffic and the strategic importance of West African waters, the study's findings highlight the need for stricter compliance and enforcement of safety regulations in flag states and the national waters, particularly for smaller fishing vessels. Additionally, the results suggest that improving vessel maintenance and upgrading aging fleets could be critical steps in reducing maritime accidents in the region. In conclusion, this study underscores the necessity for continued monitoring and analysis of vessel characteristics to mitigate accident risks effectively. The integration of survival distribution models in maritime safety assessments offers a robust framework for identifying high-risk vessels and implementing preventive measures, ultimately contributing to safer maritime operations in West Africa.

Conflict of Interest.

The authors declare that there is no conflict of interests, financial or non-financial, of any sort regarding this research.

References.

Abubakar, S. (2023). Law and policy in combatting piracy by maritime enforcement agencies: a Nigerian perspective: a Nigerian perspective. World Maritime University Dissertations. Accessed on 14 March 2025 from https://commons.wmu.se/cgi-/viewcontent.cgi?article=3263&context=all_dissertations&.

Aiken, L. S., & West, S. G. (1991). *Multiple regression: Testing and interpreting interactions.* Sage Publications, Inc.

Akten, N., 2004. Analysis of maritime accidents: Causes and preventive strategies. *Journal of Maritime Safety and Management*, *23* (2), 150-167.

Aning, A., Birikorang, E., Pokoo, J., Mensah, A.N.A., Tachie-Menson, E.A. (2021). Maritime Insecurity in the Gulf of Guinea: Ghana's Actual Maritime Crime Picture. Accessed on 16 March 2025 from https://www.safeseas.net/wp-content/uploads/2021/-11/Policy-Paper-KAIPTC-on-Maritime-Insecurity-and-Maritime-Crime.pdf.

Anyanwu, J. O., 2014. The Causes and Minimization of Maritime Disasters on Passenger Vessels. *Global Journal of Research in Engineering*, 14 (2), 1–13.

ARA, 2018. Applied Regression Analysis. Lesson 10.7 – Detecting Multi-collinearity using Variance Inflation Factors. Accessed on 2 November 2021 from PSU.edu at https://online.-stat.psu.edu/stat462/node/180/.

Awal, Z. I., 2016. Major accident occurrences in maritime transportation: Analysis and lessons learned. *Procedia Engineering*, 194, 267-275.

Barndorff-Nielsen, O, Cox, DR., 1984. Bartlett adjustments to the likelihood ratio statistic and the distribution of the maximum likelihood estimator. *Journal of the Royal Statistical Society, Series* B;46,3:483-495.

Barndorff-Nielsen, O., 1983. On a formula for the distribution of the maximum likelihood estimator. Biometrika*;* 70:343-65.

Barndorff-Nielsen, O., 1980. Conditionality resolutions. Biometrika; 67:293-310 (1980).

Batalden, B.M. and Sydnes, A.K. (2017). What causes 'very serious maritime accidents? Safety and Reliability – Theory and Applications – epin & Briš (Eds). Taylor & Francis Group, London, ISBN 978-1-138-62937-0. https://maritimesafetyinnovationlab.org/wp-content/uploads/2020/11/What-causes-very-serious-maritime-accidents.pdf.

Bbtrial (2025). Maritime Property Damage. Accessed on 16 March 2025 from https://www.bbtrial.com/practice-areas/maritime-accidents/maritime-property-damage/.

Beick-Baffour, M.K. (2000). Maritime safety and pollution prevention in Ghana : a review of implementation and enforcement of international conventions implementation and enforcement of international conventions. World Maritime University Dissertations.

Bijwaard, G. E., & Knapp, S., 2009. Analysis of ship life cycles – the impact of economic cycles and ship inspections. *Marine Policy*, 33 (2), 350-369.

Bloor, M., Sampson, H., Baker, S., & Dahlgren, K., 2013. The role of the flag state in maritime safety and environmental protection. *Marine Policy*, 40, 226-233.

Bollen, K., and Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. *Psychological Bulletin, 110* (2), 305–314. https://doi.org/10.1037/0033-2909.110.2.305.

Chang, C.-H., Xu, J., & Song, D.-P., 2014. an analysis of safety and security risks in container shipping operations: A case study of Taiwan. *Safety Science*, 63, 168–178.

Charikias, V., Liratzis, I., Tsiakas, P., & Karanikolas, N., 2015. The economic impact of maritime piracy. *Procedia Economics and Finance*, 19, 597-604. https://doi.org/10.1016/S22-12-5671 (15)00111-4.

Chauvin, C., Lardjane, S., Morel, G., Clostermann, J. P., & Langard, B., 2013. Human and organizational factors in maritime accidents: Analysis of collisions at sea using the HFACS. *Accident Analysis & Prevention*, 59, 26-37.

Chen, J., Bian, Z., Wan, Z., Yang, H., Zheng, P., & Wang, J., 2019. Identifying factors influencing total-loss marine accidents in the world: Analysis and evaluation based on ship types and sea regions. *Ocean Engineering*, 191, Article 106495.

Chen, X., Zhang, Y., & Li, H., 2020. *Analysis of maritime accidents: Causes, consequences, and prevention strategies.* Marine Safety Publications.

Cox, DR., *1980*. Local ancillarity. *Biometrika;* 67:279-286.

Cox, D.R., Oakes, D. (1984). Analysis of Survival Data, In Monographs on Statistics and Applied Probability, Eds: Cox, D.R., Hinkley, D.V., Reid, N., Rubin, D.B., and Silverman, B.W. Chapman and Hall/CRC, New York, USA.

Darbra, R. M., & Casal, J., 2004. Historical analysis of accidents in seaports. *Safety Science*, 42 (2), 85–98.

Deng, J., Liu, S., Xie, C., & Liu, K.**,** 2022. Risk coupling characteristics of maritime accidents in Chinese inland and coastal waters based on N-K model. *Journal of Marine Science and Engineering, 10 (1)*, 4.

Dickman, P.W. (2023). Index: Stata tutorials. https://www.-pauldickman.com/software/stata/.

Dickman, P, Weibull, C., 2019. Interpretation of Interaction Effects. Accessed on 7 November 2021 at Pauldickman.com, from https://www.pauldickman.com/software/stata/parameterising-interactions/.

DNV (2020). Managing the risk of blackouts. Accessed on 14 May 2025 from https://www.dnv.com/maritime/insights/topics/managing-the-risk-of-blackouts/Reasons-for-concern/.

Dominiguez-Pery, C., Tassabehji, R., Corset, F., Chreim, Z. (2023). A holistic view of maritime navigation accidents and risk indicators: examining IMO reports from 2011 to 2021. Journal of Shipping and Trade 8, 11. https://doi.org/10.1186/s-41072-023-00135-y.

Dormann, C.F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J.R.G., Gruber, B., Lafourcade, B., Leit ao, P.J., Münkemüller, T., McClean, C., Osborne, P.E., Reineking, Schröder, B., Skidmore, A.K., Zurell, D. and Lautenbach, S. (2013). Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. Ecography 36: 027–046. https://doi.org/10.1111/j.1600-0587.2012.07348.x.

European Parliamentary Research Service (2023). Revision of the Flag State Requirements Directive. EU Legislation in Progress. Accessed on 13 March 2025 from https://www.europarl.europa.eu/RegData/etudes/BRIE/2023/751432/EPRS_BRI-%282023%29751432_EN.pdf?.

Faiyetole, A.A., 2023. Accident Propensity Assessment of Boeing 737 Aircraft Variants using the Gompertz Distribution Model. *Aerospace Systems.* https://doi.org/10.1007/s42401-023-00202-z.

Faiyetole, A.A., Akeredolu, K.E., Abiodun, W.O., Buhari, S.O., Adepitan, A.A., and Oluwasakin, O.A., 2026. Linking vessel characteristics to accident severity in West African waters: a survival analysis. WMU J Marit Affairs 25, 353?383. https://doi.org/10.1007/s13437-026-00411-1.

Fan, L., Zhang, P., & Choi, K. K., 2014. The effect of flag state on ship accident risk: A panel data analysis. *Transportation Research Part A: Policy and Practice*, 67 (6), 194-205.

Fawzy, S., Kaddour, A., Hussein, A. W., & Ali, E. M., 2024. *Egyptian Journal of Aquatic Biology & Fisheries*, 28 (2), 1009–1024. DOI: 10.21608/EJABF.2024.35237.

Gwaday, M.K., 2019. A study of the provision of maritime search and rescue (SAR) services and safety of small vessels in small island developing states in the Pacific region and focusing on Papua New Guinea (PNG).

Habibi, D., Rafiei, M., Chehrei, A., Shayan, Z., & Tafaqodi, S. (2018). Comparison of Survival Models for Analyzing Prognostic Factors in Gastric Cancer Patients. *Asian Pacific journal of cancer prevention: APJCP*, *19* (3), 749–753. https://doi.org/-10.22034/APJCP.2018.19.3.749.

Hetherington, C., Flin, R., & Mearns, K., 2006. Safety in shipping: The human element. *Journal of Safety Research*, 37 (4), 401-411.

Hosseini Teshnizi, S., & Taghi Ayatollahi, S. M. (2017). Comparison of Cox Regression and Parametric Models: Application for Assessment of Survival of Pediatric Cases of Acute Leukemia in Southern Iran. *Asian Pacific journal of cancer prevention: APJCP*, *18* (4), 981–985. https://doi.org/10.22034/APJCP.2017.18.4.981.

IMO, 2010. *Code of the International Standards and Recommended Practices for a Safety Investigation into a Marine Casualty or Marine Incident (Casualty Investigation Code)*. https://www.imo.org/en/OurWork/MSAS/Pages/Casualties.aspx. - International Maritime Organization.

IMO, 1997. FSA Trial Application to High-Speed Passenger Catamaran Vessel. London: International Maritime Organization, MSC68/14/2.

IMO GISIS (2024). http://gisis.imo.org.

Jaremin, B., & Kotulak, E., 2004. Mortality in the Polish small-scale fishing industry. *Occupational Medicine*, 54 (4), 258–260.

Jiang, M., Lu, J., Yang, Z., & Li, J., 2020. Risk analysis of maritime accidents along the main route of the Maritime Silk Road: A Bayesian network approach. *Maritime Policy and Management*. ISSN 0308-8839.

Jin, D., & Thunberg, E., 2005. An analysis of fishing vessel accidents in fishing areas off the northeastern United States. *Safety Science*, 43 (8), 523–540.

Jin D. (2014). The determinants of fishing vessel accident severity. *Accident; analysis and prevention*, *66*, 1–7. https://doi.org/10.1016/j.aap.2014.01.001.

Knapp, S., & Franses, P. H., 2007. A global view on port state control: econometric analysis of the effects of inspection patterns. *Transportation Research Part E: Logistics and Transportation Review*, 45 (4), 638-652.

Laursen, L. H., Hansen, H. L., & Jensen, O. C., 2008. Fatal occupational accidents in Danish fishing vessels 1989–2005. *International Journal of Injury Control and Safety Promotion*, 15 (2), 109–117.

Lee, S. H., Kim, H., & Kwon, S. (2024). Fishing Vessel Risk and Safety Analysis: A Bibliometric Analysis, Clusters Review and Future Research Directions. *Applied Sciences*, *14*(22), 10439. https://doi.org/10.3390/app142210439.

Li, G., Gao, K., Weng, J., & Qu, X. (2024). Deciphering spatial heterogeneity of maritime accidents considering impact scale variations. *Maritime Policy & Management*, *52* (2), 309–333. https://doi.org/10.1080/03088839.2024.2347893

Li, J, Bian, S, Zeng, A, Wang, C, Pang, B, Liu, W, Lu, C., 2021. Human Pose Regression with Residual Log-likelihood Estimation. http://openaccess.thecvf.com/content/ICCV2021/html/Li_Human_Pose_Regression_With_Residual_Log-Likelihood_Estimation_ICCV_2021_paper.html.

Li, K., Kevin, W., Wonham, J., & Jon, S., 1999. A method for estimating world maritime employment. *Transportation Research Part E: Logistics and Transportation Review, 35 (1).*

Li, K.X. and Wonham, J. (1999). Who is safe and who is at risk: a study of 20-year-record on accident total loss in different flags. Maritime Policy & Management, vol. 26 issue 2, Pages 137-144. https://doi.org/10.1080/030888399286961.

Li, K. X., & Zheng, H., 2015. Maritime accidents and vessel traffic: An empirical study using AIS data. *Accident Analysis & Prevention*, 76, 20-28.

Li, K. X., Yin, J., & Fan, L., 2014. Ship safety index. *Transportation Research Part A: Policy and Practice*, 66, 75–87.

Lloyd, J., 2021. The dangers of maritime accidents: An analysis of risks and safety measures. *Journal of Maritime Studies*, 33 (2), 112-130.

Luo, M., & Shin, S. H., 2016. Half-century research developments in maritime accidents: Future directions. *Accident Analysis and Prevention*.

MAIB, 2008. Annual Statistical Report of the Marine Accident Investigation Boards. Available at: www.amem.at Retrieved on 22/10/2016.

MAIB., 1997. Accident Investigation Branch: Annual Report 1997. Department of the Environment, Transport and the Regions, UK. / Accident Analysis and Prevention 37 (2005) 1019–1024.

Mansyur, M., Sagitasari, R., Wangge, G., Sulistomo, A.B., & Kekalih, A., 2021. Long working hours, poor sleep quality, and work-family conflict: determinant factors of fatigue among Indonesian tugboat crewmembers. *BMC Public Health, 21* (1), 1832, 10.1186/s12889-021-11883-6.

Maritime Injury Center (2024). Maritime Accidents and Injuries Overview. Accessed on 16 March 2025 from https://www.maritimeinjurycenter.com/accidents-and-injuries/.

Maternova, A., 2023. *Maritime accident analysis and safety improvement strategies*. Nautical Research Press.

Mikelis, N. E., 2008. A statistical overview of ship recycling. *WMU Journal of Maritime Affairs, 7* (1), 227-239.

Miles, J., 2005. Tolerance and Variance Inflation Factor. Encyclopedia of Statistics in Behavioral Science.

Mansyur, M., Sagitasari, R., Wangge, G., Sulistomo, A.B., & Kekalih, A. (2021). Long working hours, poor sleep quality, and work-family conflict: determinant factors of fatigue among Indonesian tugboat crewmembers. *BMC Public Health, 21* (1), 1832, 10.1186/s12889-021-11883-6.

National Transportation Safety Board (2016). Fire aboard Roll-on/Roll-off Passenger Vessel Caribbean Fantasy Atlantic Ocean, 2 Miles Northwest of San Juan, Puerto Rico. Accessed on 13 March 2025 from https://www.ntsb.gov/investigations/AccidentReports/Reports/MAR1801.pdf.

National Transportation Safety Board (2015). Sinking of US Cargo Vessel SS El Faro Atlantic Ocean, Northeast of Acklins and Crooked Island, Bahamas. Accessed on 13 March 2025 from https://www.ntsb.gov/investigations/AccidentReports/Reports/MAR1701.pdf.

Nwokedi, T.C., Ndikom, O.B., Nnadi, K.U., Onyemechi, C. (2023). Modeling shipping accidents economic loss and the compensation in Nigeria. Maritime Technology and Research, Vol. 5 No. 2. https://doi.org/10.33175/mtr.2023.260960.

Obafemi, A. A., Okeke, P. O., & Adeyinka, A. T., 2016. Economic impact of maritime accidents in West Africa: A case study of the Gulf of Guinea. *Journal of Transportation Research*, 7 (4), 78-89.

OECD (2024). Management of hazardous substances in port areas. Accessed on 15 March 2025 from https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/09/management-of-hazardous-substances-in-port-areas_3a2acc76/5d09ac8a-en.pdf.

Okechukwu, I., 2014. Maritime disasters and their socio-economic impact in Nigeria. *Journal of Maritime and Transportation Studies*, 6 (2), 45-58.

O'brien, R. M., 2007. A Caution Regarding Rules of Thumb for Variance Inflation Factors. Quality and Quantity; 4: 673-690.

O'Neil, T.L., 2000. Port traffic risks: A Study of accidents in Hong Kong waters. *Transportation Research Part E, 44* (5), 921-931.

Oyewole, S. (2023). Piracy and the Challenges of Nigeria's Maritime Domain. Democracy and Development: Journal of West Africa Affairs, 7 (1): 58-69.

Ozguc, O., 2019. Structural damage of ship-FPSO collisions. *Journal of Marine Engineering and Technology, 18* (1), 1-35.

Peters, J. (2017). The international ocean transport industry in crisis. The World Bank, Washington, DC, 41.

Roberts, S. E., 2004. Occupational mortality in British commercial fishing, 1976–95. *Occupational and Environmental Medicine, 61* (1), 16–23.

Rothblum, A.M., Wheal, D., Withington, S., Shappell, S.A., Wiegmann, D.A., Boehm, W., & Chaderjin, M., 2002. Human factors in incident investigation and analysis. Excerpts from proceedings of the 2^{nd} international Workshop on Human Factors in Offshore Operations (HFW200). Houston, TX.

Rothblum, A. M., 2000. Human error and marine safety. National Safety Council Congress and Expo, Orlando, FL.

Schellhammer, V., 2014 Annual report on maritime casualty investigation. Federal bureau of maritime casualty.

Shin, S., 2017. Analyzing the Evolution of Ship Accident Research, Recurrent Accidents and Ship's Lifespan April, 2017 The Hong Kong Polytechnic University Department of Logistics and Maritime Studies.

Smith, J., & Jones, A., 2015. Maritime accidents and their economic consequences: An analysis of recent case studies. *Journal of Maritime Economics and Policy*, 23 (4), 345-367.

Talley, W. K. (1999a). Determinants of Ship Accident Seaworthiness. *Marit Econ Logist* **1**, 1–14. https://doi.org/10.1057-/ijme.1999.9

Talley, W. K., (1999b). The safety of sea transport: determinants of crew injuries. Applied Economics, 31 (11), 1365–1372.

Thompson, CG, Kim, RS, Aloe, AM, Becker, BJ., 2017. Extracting the Variance Inflation Factor and Other Multicollinearity Diagnostics from Typical Regression Results. Basic and Applied Social Psychology; 39, 2: 1-10.

Transportation Safety Board of Canada (2023). Marine transportation occurrences in 2023. Accessed on 12 March 2025 from https://www.bst.gc.ca/eng/stats/marine/2023/ssem-ssmo--2023.html

Uberti, W., 2001. Operation safe return: A nontraditional approach to improving commercial fishing vessel safety. *Proceedings of the Marine Safety Council, 58* (2), 35.

Uğurlu, Ö.;Yıldız, S.; Loughney, S. and Wang, J., 2018. Modified human factor analysis and classification system for passenger vessel accidents (HFACS-PV). Ocean Engineering, 161: 47-61.

Ukoji, V., & Ukoji, M., 2015. *Maritime accident analysis and safety measures*. Oceanic Research Press.

United States Coast Guard (2023). Flag State Control In The United States. Accessed on 13 March 2025 from https://www.dco.uscg.mil/Portals/9/DCO%20Documents/5p/CG-5PC/CG-CVC/CVC1/AnnualRpt/2023%20Flagstate%20Annual%20-Report.pdf.

Vanem, Erik, and Michael, 2008. "Maritime accident risk assessment, applicability of formal safety assessment (FSA) to the maritime transport sector." *Reliability Engineering & System Safety* 93.8 (2008): 1153-1163.

Wang, Y., & Fu, S. (2022). Framework for Process Analysis of Maritime Accidents Caused by the Unsafe Acts of Seafarers: A Case Study of Ship Collision. *Journal of Marine Science and Engineering*, *10* (11), 1793. https://doi.org/10.3390/jmse1011-1793.

Wang, J., Zhou, K., Xing, W., Li, H., & Yang, Z., 2023. Applications, evolutions, and challenges of drones in maritime transport. *Journal of Marine Science and Engineering, 11* (11), 2056.

Wang, J., Zhou, Y., Zhuang, L., Shi, L., Zhang, S. (2023). A model of maritime accidents prediction based on multi-factor time series analysis. Journal of Marine Engineering & Technology, Volume 22 issue 3. https://doi.org/10.1080/20464177.20-23.2167269.

Wang, J., Wang, M., Shi, S., Fu, M., & Zhu, M., 2021. Critical risk factors in ship fire accidents. *Maritime Policy & Management, 48* (6), 895-913.

Wang, T.;Wu, Q.;A. Diaconeasa, M.;Yan, X. and Mosleh, A., 2020. On the use of the hybrid causal logic methodology in ship collision risk assessment. Journal of Marine Science and Engineering, 8 (7): 485.

Wang, J., Pillay, A., Kwon, Y. S., Wall, A. D., & Loughran, C. G., 2005. An analysis of fishing vessel accidents. *Accident Analysis & Prevention, 37* (6), 1019-1024.

Weng, J., & Li, G., 2019. Exploring shipping accident contributory factors using association rules. *Journal of Transportation Safety & Security, 11* (1), 36-57.

Wired Science (2025). A Tanker Collision Threatens One of the UK's Most Important Coast Lines. Accessed on 16 March 2025 from https://www.wired.com/story/how-north-sea-tanker-collision-could-affect-one-of-britains-most-important-coastline-s/.

Zhao Z, Liang B, Wang X, Lu W., 2017. Remaining useful life prediction of Aircraft engine based on degradation pattern learning. Reliability Engineering and System Safety; 164:74–83.