Reliability Engineering and System Safety 274 (2026) 112423

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

# Temporal instability analysis of fatal commercial fishing vessel incidents: A correlated random-parameter model with heterogeneity in means

Yun Ye [a,b,c], Mingzheng Liu [d], Fanyu Meng [e], S.C. Wong [e], Xiaowei Gao [f,*], Zaili Yang [g]

[a] Faculty of Maritime and Transportation, Ningbo University, Ningbo, China
[b] Collaborative Innovation Center of Modern Urban Traffic Technologies, Southeast University, Nanjing, China
[c] SpaceTimeLab, Department of Civil, Environmental, and Geomatic Engineering, University College London, London, UK
[d] Shipping Research Centre, PolyU Business School, The Hong Kong Polytechnic University, Hong Kong, China
[e] Department of Civil Engineering, The University of Hong Kong, Hong Kong, China
[f] Department of Earth Science & Engineering, Imperial College London, London, UK
[g] Liverpool Logistics, Offshore and Marine Research Institute, Liverpool John Moores University, Liverpool, UK

ARTICLE INFO

*Keywords:*
Commercial fishing vessel incidents
Temporal instability
Marginal effects
Correlated random parameters
Unobserved heterogeneity
Maritime risk

ABSTRACT

Fatal commercial fishing vessel incidents remain a critical global safety challenge, yet empirical understanding of their underlying determinants is limited by strong unobserved heterogeneity, correlated risk mechanisms, and temporal instability in covariate effects. This study examines how the influence of contributory factors has changed over time using 23 years of data from the U.S. Commercial Fishing Incident Database. A correlated random-parameter logit model with heterogeneity in means is developed to capture unobserved heterogeneity, parameter correlation, and context-dependent variability in risk effects. Temporal instability is assessed through both global and pairwise likelihood ratio tests across five sub-periods. The results demonstrate significant temporal non-stationarity. Weather-related conditions and the absence of a mayday call consistently increase fatality risk across multiple periods. In earlier years, capsizing events and human factors were more influential, reflecting the prominent role of vessel stability and crew performance in early-stage incident outcomes. The use of an EPIRB to send a mayday signal appears as a random parameter in several periods, and its effect varies with ship age, weather conditions, and struck events, indicating that latent operational and behavioral factors shape its effectiveness. Overall, the proposed model achieves superior statistical fitting, improved interpretability, and richer behavioral insights compared with fixed-parameter or standard random-parameter models. The findings highlight the need for time-sensitive and risk-adaptive safety interventions, with recommendations to strengthen communication reliability, emergency preparedness, and context-specific safety management in the commercial fishing sector.

## 1. Introduction

The commercial fishing and seafood industry represents a vital component of cultural heritage, a key source of nutritious protein, and an important driver of the global economy. In 2022, the combined commercial and recreational fisheries in the United States (U.S.) generated approximately US$321 billion in sales and supported nearly 2.3 million jobs [1]. However, commercial fishing remains one of the most hazardous occupations worldwide, characterized by demanding physical labor, long working hours, harsh weather conditions, and high operational risks. In 2019, the work-related fatality rates of commercial fishermen in the U.S. were 40 times higher than the national average, with nearly half of all fatalities resulting from vessel disasters, imposing substantial human and economic costs [2]. Understanding the underlying risk factors contributing to fatal commercial fishing vessel incidents is crucial for developing effective safety management and prevention strategies.

In the last few decades, extensive empirical research has investigated safety outcomes in commercial fishing operations, consistently identifying vessel disasters, human factors, environmental hazards, and vessel characteristics as key contributors to fatalities and injuries [3–12]. Early evidence from the U.S., which has some of the most comprehensive incident records worldwide, shows that capsizing and sinking are among the most lethal accident types, with elevated risks associated with

* Corresponding author.
*E-mail address:* x.gao24@imperial.ac.uk (X. Gao).

https://doi.org/10.1016/j.ress.2026.112423
Received 7 December 2025; Received in revised form 17 January 2026; Accepted 12 February 2026
Available online 14 February 2026
0951-8320/

adverse weather conditions, vessel size, vessel age, and operational context [3–6]. Fleet-level analyses further indicate that vessel disasters and falls overboard have remained the dominant contributors to commercial fishing fatalities over extended periods, despite targeted safety improvements in specific fleets [7,8]. These findings underscore the persistent and multifaceted nature of fatal risks in commercial fishing vessel operations.

Although these efforts have provided valuable empirical evidence and insights into commercial fishing vessel incidents, most studies have relied primarily on descriptive analyses or conventional statistical modeling approaches. Such methods often neglect unobserved heterogeneity, parameter correlation, and context-dependent variability in risk effects. Moreover, while several studies have examined temporal changes in the statistical patterns of commercial fishing vessel incidents, the temporal instability of covariate effects remains insufficiently explored.

To address these challenges, this study investigates the temporal instability of factors influencing fatal commercial fishing vessel incidents using the U.S. Commercial Fishing Incident Database (CFID) .[1] In addition, a correlated random-parameter logit model with heterogeneity in means is developed to account for unobserved heterogeneity. The primary contributions of this study are as follows:

- A temporal instability assessment based on rigorous likelihood ratio tests is conducted to evaluate model transferability across different time periods and reveal how contributory factors associated with fatal commercial fishing incidents evolve over time.
- A correlated random-parameter model with heterogeneity in means is introduced for commercial fishing incident analysis. This advanced specification enhances the modeling of unobserved heterogeneity, delivers strong statistical performance, and provides highly interpretable marginal effects, thereby avoiding potential biases and misleading conclusions.
- The advantages of the proposed model are demonstrated through a comprehensive comparison with multiple random-parameter specifications, including fixed-parameter models, standard random-parameter models, correlated random-parameter models, and correlated random-parameter models with heterogeneity in means.

The remainder of this paper is organized as follows. Section 2 reviews related studies. Section 3 describes the commercial fishing vessel incident dataset and related variables. Section 4 introduces the correlated random-parameter logit model with heterogeneity in means for modeling the severity of fishing vessel incidents, along with the temporal instability assessment method. Section 5 presents and interprets the modeling results. Section 6 discusses the study's findings and implications, and Section 7 concludes the paper.

## 2. Literature review

### 2.1. Empirical evidence on commercial fishing vessel incidents across regions

Extensive empirical research across regions has highlighted vessel disasters, human factors, environmental hazards, and vessel characteristics as central determinants of fatalities and injuries. Early studies from the U.S. have provided some of the most detailed evidence. Using U.S. Coast Guard data, Jin et al. [4,5] and Jin and Thunberg [6] showed that capsizing and sinking are the most lethal accident types, with accident likelihood increasing for high wind speeds, medium-sized vessels, and operations closer to shore. Follow-up analyses demonstrated that severity is exacerbated by loss of stability, vessel age, strong daytime winds, and offshore distance [3]. At the fleet level, Lincoln and Lucas [7] documented over 500 U.S. commercial-fishing fatalities during 2000–2009, largely driven by vessel disasters and falls overboard. Lucas and Case [8] further reported that despite some improvements in specific fleets, particularly scallop fisheries, the U.S. industry continued to experience extremely high fatality rates through 2014.

Similar safety challenges have been observed in the United Kingdom (U.K). Wang et al. [9] identified machinery failures and foundering as the leading causes of vessel accidents in the 1990s, disproportionately affecting small vessels with inadequate maintenance and safety management. A long-term review by Roberts et al. [13] found that U.K. fishing-vessel fatalities from 1948 to 2008 were overwhelmingly associated with vessel foundering, with persistently high mortality linked to unstable or unseaworthy vessels. Complementing these technical and environmental contributors, Lazakis et al. [14] emphasized the central role of human factors, showing that non-compliance, poor equipment use, inadequate design, and limited crew competence remained pervasive contributors to both accidents and near misses over a period of nearly two decades. Xu et al. [11] reviewed casualties and losses involving fishing vessels in the U.K. from 2013 to 2020 and found that loss of control was the primary cause of casualties. They further reported that flooding/foundering and grounding/stranding were the main contributors to vessel losses for fishing vessels less than 24 m and more than 24 m in length, respectively. In addition, small fishing vessels below 15 m in length accounted for the majority of casualties and losses.

Beyond the U.K. and U.S., evidence underscores the global consistency of these mechanisms. In Indonesia, Choiron et al. [10] found that fishing-vessel accidents were most commonly associated with drowning, fires, and crew injuries, primarily driven by human error, adverse weather, and technical failures. Kim et al. [15] similarly noted that the South Korean industry continues to face severe risks linked to vessel condition, human factors, inadequate lookout practices, and communication problems. In Denmark, Rasmussen and Ahsan [16] reported substantial reductions in fatalities between 1998 and 2016; however, slip-and-fall and crushing incidents remained prevalent, especially among inexperienced fishermen. Complementing these country-specific analyses, Uğurlu et al. [12] used over 6000 global accidents (2009–2018) to show strong associations between accident severity and vessel length, vessel age, and accident type, reinforcing the importance of vessel-specific and operational factors in determining life-loss and vessel-loss outcomes.

### 2.2. Methodological approaches to commercial fishing vessel safety analysis

From a methodological perspective, although numerous studies have examined commercial fishing vessel incidents, most of them have relied on descriptive analyses [9,13–16] and thus have limited analytical depth. In recent years, data-driven approaches, including Bayesian networks [12,17,18], association rule mining [19–21], and machine learning methods [17,22], have increasingly gained attention in maritime accident analysis. However, these approaches often face interpretability limitations, as they mainly capture factor co-occurrence patterns or identify contributing factors and their relative importance, without explicitly modelling the underlying relationships between variables. In contrast, several studies have adopted statistical modeling techniques that provide stronger theoretical foundations, transparent functional forms, and interpretable marginal effects, such as logistic regression [6], probit regression [3], ordered logistic regression [23], ordered probit regression [24], and negative binomial regression [4,25].

However, a major challenge of traditional statistical modeling approaches used in studies of commercial fishing vessel incidents is the presence of unobserved heterogeneity, as many safety-related factors are

[1] Note that "incident" and "accident" have distinct meanings in safety science. Consistent with the CFID, we use the term "incident" throughout this study. When discussing prior studies, we retain the original terminology used by the respective authors for accuracy and proper attribution.

unmeasured, leading to variation in the safety effects of observed variables [26]. Such unobserved heterogeneity can confound parameter estimates and result in biased or even misleading conclusions [27]. Numerous road traffic safety studies have demonstrated that random-parameter models offer better statistical fit and richer behavioral insights than traditional approaches [28–30]. Motivated by this, several recent maritime studies have incorporated random parameters to allow certain coefficients to vary across observations according to predefined probability distributions. For instance, Weng et al. [31] modeled grounding, accident location, visibility, and navigational status as random parameters when estimating marine accident property-damage costs using a generalized *F* distribution model.

Despite these advances, the standard random-parameter framework adopted in most maritime safety studies assumes that the mean of each random parameter is constant across observations, a restrictive assumption that may produce incorrect marginal effects [32]. A more appropriate strategy is to allow the mean of each random parameter to vary with observable factors, thereby capturing heterogeneity in means [26,32,33]. For instance, Ye et al. [34] proposed a flexible four-parameter generalized beta of the second kind distribution to better characterize the skewed and heavy-tailed nature of fishing vessel accident losses, and Ye et al. [35] developed a Bayesian random-parameter quantile regression with heterogeneity in means to capture varying covariate effects across loss quantiles.

In addition, standard random-parameter models typically assume independence across random-parameter distributions, thereby ignoring potential correlations among different sources of unobserved heterogeneity. In practice, correlations may naturally arise due to complex interactions among latent characteristics [26,27]. To address this, correlated random-parameter models have been increasingly adopted and shown to outperform their uncorrelated counterparts [26,28,29,36–41]. However, the correlated random-parameter approach remains largely unexplored in the context of fishing vessel or broader marine accident analyses.

A further methodological limitation involves the temporal instability of covariate effects. Most maritime safety studies have aggregated multi-year data into a single pooled dataset, implicitly assuming that the influence of contributing factors remains stable over time. Yet, growing evidence from road traffic safety research shows that the significance and magnitude of risk factors may change substantially across time periods [39,40,42,43], and failing to account for such instability can lead to inaccurate or misleading policy implications [44]. More recently, several studies have employed partially constrained models to explicitly allow parameters and their distributions to evolve across time rather than imposing cross-period restrictions [45–47]. With a few exceptions [34,48], temporal instability has not been adequately examined in maritime safety studies in general or fishing vessel safety research specifically.

To address these gaps, this study employs advanced correlated random-parameter models with heterogeneity in means and explicit assessments of temporal instability to account for unobserved heterogeneity, correlated risk mechanisms, and temporal instability in covariate effects, thereby offering richer behavioral insights and a more nuanced understanding of the underlying risk mechanisms governing commercial fishing vessel incidents.

## 3. Data preparation

The CFID is a national database managed by the National Institute for Occupational Safety and Health in the U.S [49]. It records fatalities and vessel disasters that occurred in the U.S. fishing industry between 2000 and 2022, categorized into five periods: 2000–2002, 2003–2007, 2008–2012, 2013–2017, and 2018–2022. The original dataset comprises 3559 person-level observations of incidents, including diving injuries/illnesses, falls overboard, onboard injuries/illnesses, onshore injuries/illnesses, and vessel casualties.

In this study, we focus exclusively on vessel casualty-related incidents to examine the factors influencing fatal vessel events during navigation and their temporal instability. By aggregating individual-level records to the vessel level based on vessel ID and incident time, a total of 1068 vessel casualty observations were obtained. The original dataset contains 157 variables; however, many exhibit a high proportion of missing values. Following established practice in the literature, the variables with more than 50 % missing values are removed from the analysis [50–53]. An exception is made for key categorical covariates (e.g., response-/communication-related factors) that are essentially important to support the study of this kind in the literature, for which "Unknown" is retained as an explicit category and represented using one-hot encoding, allowing the potential informational content of missing or uncertain reporting to be explicitly modeled [54]. To minimize noise and enhance model performance, feature selection was conducted to reduce dimensionality. Detailed descriptions of the selected explanatory variables are presented in Table 1. Distributions of explanatory variables over the five time periods are summarized in Table A1.

There were 192, 220, 268, 286, and 102 observations of commercial fishing vessel incidents in 2000–2002, 2003–2007, 2008–2012, 2013–2017, and 2018–2022, respectively. The dependent variable is the incidental outcome (i.e., fatal versus non-fatal outcome), which allows for precise identification of high-risk incident patterns and supports data-driven policy formulation aimed at enhancing maritime safety. The distribution of fatal commercial fishing vessel incidents in the U.S. over the 23-year period (2000–2022), along with their relative percentages, is presented in Fig. 1.

## 4. Methods

This study employs correlated random-parameter logit models with heterogeneity in means to discover potential heterogeneity and assess temporal instabilities in fatal commercial fishing vessel incidents in the U.S. The framework of the methodology section is shown in Fig. 2.

### 4.1. Feature selection

A systematic feature selection procedure was applied to enhance model interpretability and avoid multicollinearity [40]. First, features with near-zero variance (variance $< 0.01$) were removed to eliminate non-informative variables. Then, highly correlated features were excluded based on pairwise correlation analysis to reduce redundancy among predictors.

Subsequently, an elastic net–regularized logistic regression approach was employed to further identify the most influential variables [55]. The elastic net combines the penalties of lasso (L1) and ridge (L2) regression, achieving both variable selection and coefficient shrinkage [56]. For logistic regression, the coefficients $\beta$ are estimated by minimizing the penalized negative log-likelihood function:

$$\widehat{\beta} = \underset{\beta}{\operatorname{argmin}}\{-\frac{1}{N}\sum_{i=1}^{N}[y_i\log(\pi_i) + (1-y_i)\log(1-\pi_i)] \\ +\lambda\left[(1-\alpha)\frac{\|\beta\|_2^2}{2} + \alpha\|\beta\|_1\right]\} \tag{1}$$

where $\pi_i = \exp(\beta\mathbf{X}_i)/[1+\exp(\beta\mathbf{X}_i)]$ is the predicted probability of a fatal incident, $\lambda$ controls the overall penalty strength, and $\alpha \in [0,1]$ determines the balance between the L1 and L2 penalties. The L1 component promotes sparsity by driving less relevant coefficients to zero, thereby performing automatic feature selection, whereas the L2 component helps stabilize estimates in the presence of multicollinearity. This hybrid regularization enables the model to retain groups of correlated variables while reducing overfitting and improving generalization. Finally, a stepwise regression procedure was applied to further refine the

**Table 1**
Descriptions of explanatory variables.

| Name | Description | Mean/ Per. | SD | Min | Max |
|---|---|---|---|---|---|
| **Light condition** | | | | | |
| Daylight | Yes = 1, No = 0 | 30.99 % | — | — | — |
| Night | Yes = 1, No = 0 | 23.22 % | — | — | — |
| Twilight | Yes = 1, No = 0 | 12.73 % | — | — | — |
| Unknown | Yes = 1, No = 0 | 33.05 % | — | — | — |
| **Mayday method** | | | | | |
| Radio | Yes = 1, No = 0 | 44.57 % | — | — | — |
| Cell phone | Yes = 1, No = 0 | 9.46 % | — | — | — |
| Witness | Yes = 1, No = 0 | 15.07 % | — | — | — |
| EPIRB | Yes = 1, No = 0 | 8.24 % | — | — | — |
| Other | Yes = 1, No = 0 | 8.43 % | — | — | — |
| None | Yes = 1, No = 0 | 14.23 % | — | — | — |
| **Weather related** | Yes = 1, No = 0 | 29.49 % | — | — | — |
| **Number of responses** | | | | | |
| None | Yes = 1, No = 0 | 0.28 % | — | — | — |
| One | Yes = 1, No = 0 | 7.68 % | — | — | — |
| Two or more | Yes = 1, No = 0 | 7.77 % | — | — | — |
| Unknown | Yes = 1, No = 0 | 84.27 % | — | — | — |
| **Vessel activity** | | | | | |
| Fishing | Yes = 1, No = 0 | 30.62 % | — | — | — |
| Transit inbound | Yes = 1, No = 0 | 33.24 % | — | — | — |
| Transit outbound | Yes = 1, No = 0 | 15.36 % | — | — | — |
| Anchored | Yes = 1, No = 0 | 4.96 % | — | — | — |
| Moored | Yes = 1, No = 0 | 2.43 % | — | — | — |
| Other | Yes = 1, No = 0 | 13.39 % | — | — | — |
| **Vessel type** | | | | | |
| Catcher | Yes = 1, No = 0 | 87.45 % | — | — | — |
| Catcher and processor | Yes = 1, No = 0 | 0.47 % | — | — | — |
| Set net skiff/ seine skiff | Yes = 1, No = 0 | 2.53 % | — | — | — |
| Dive boat | Yes = 1, No = 0 | 0.66 % | — | — | — |
| Tender | Yes = 1, No = 0 | 3.75 % | — | — | — |
| Other | Yes = 1, No = 0 | 5.14 % | — | — | — |
| **Fishery type** | | | | | |
| Shellfish | Yes = 1, No = 0 | 37.17 % | — | — | — |
| Groundfish | Yes = 1, No = 0 | 18.45 % | — | — | — |
| Pelagic fish | Yes = 1, No = 0 | 34.18 % | — | — | — |
| Other | Yes = 1, No = 0 | 10.20 % | — | — | — |
| **Gear type** | | | | | |
| Trawl | Yes = 1, No = 0 | 21.44 % | — | — | — |
| Pot and trap | Yes = 1, No = 0 | 18.82 % | — | — | — |
| Longline | Yes = 1, No = 0 | 9.18 % | — | — | — |
| Drift gillnet/set gillnet | Yes = 1, No = 0 | 10.30 % | — | — | — |
| Seine | Yes = 1, No = 0 | 8.33 % | — | — | — |
| Other | Yes = 1, No = 0 | 31.93 % | — | — | — |
| **EPIRB present** | | | | | |
| With | Yes = 1, No = 0 | 40.64 % | — | — | — |

**Table 1** (*continued*)

| Name | Description | Mean/ Per. | SD | Min | Max |
|---|---|---|---|---|---|
| Without | Yes = 1, No = 0 | 10.77 % | — | — | — |
| Unknown | Yes = 1, No = 0 | 48.59 % | — | — | — |
| **First event** | | | | | |
| Struck | Yes = 1, No = 0 | 29.40 % | — | — | — |
| Fire/explosion | Yes = 1, No = 0 | 13.76 % | — | — | — |
| Flooding | Yes = 1, No = 0 | 22.94 % | — | — | — |
| Instability | Yes = 1, No = 0 | 11.42 % | — | — | — |
| Function failure | Yes = 1, No = 0 | 9.08 % | — | — | — |
| Collision | Yes = 1, No = 0 | 7.77 % | — | — | — |
| Other | Yes = 1, No = 0 | 5.63 % | — | — | — |
| **Final event** | | | | | |
| Burned | Yes = 1, No = 0 | 4.12 % | — | — | — |
| Capsized | Yes = 1, No = 0 | 10.49 % | — | — | — |
| Grounded | Yes = 1, No = 0 | 17.04 % | — | — | — |
| Sinking | Yes = 1, No = 0 | 66.01 % | — | — | — |
| Other | Yes = 1, No = 0 | 2.34 % | — | — | — |
| **Human factor** | | | | | |
| Navigational error | Yes = 1, No = 0 | 10.96 % | — | — | — |
| Asleep or fatigue | Yes = 1, No = 0 | 8.52 % | — | — | — |
| None | Yes = 1, No = 0 | 53.93 % | — | — | — |
| Other | Yes = 1, No = 0 | 7.58 % | — | — | — |
| Unknown | Yes = 1, No = 0 | 19.01 % | — | — | — |
| **Hull type** | | | | | |
| Fiber glass | Yes = 1, No = 0 | 37.45 % | — | — | — |
| Steel | Yes = 1, No = 0 | 23.78 % | — | — | — |
| Wood | Yes = 1, No = 0 | 27.06 % | — | — | — |
| Other | Yes = 1, No = 0 | 11.71 % | — | — | — |
| **USCG region** | Pacific area = 1, Atlantic area = 0 | 61.70 % | — | — | — |
| **People onboard** | Number of people onboard | 2.87 | 2.54 | 1.00 | 47.00 |
| **Ship age** | Age of ship in years | 35.59 | 17.23 | 0.00 | 103.00 |

Per. = percentage; SD = standard deviation; EPIRB = emergency position-indicating radio beacon; USCG = United States Coast Guard.

model for the final analysis. This multistage selection process ensured that the retained variables contribute meaningfully to the prediction while maintaining model robustness and interpretability.

These selected features were then incorporated as explanatory variables in the correlated random-parameter logit models with heterogeneity in means for subsequent analysis.

### 4.2. Correlated random-parameter model with heterogeneity in means

In this study, the incident outcome variable in the CFID is binary; i.e., a fatal versus non-fatal outcome. Given the dichotomous nature of the outcome, logit regression models are used. Let $Y_i$ be the discrete outcome for incident $i$, where $Y_i = 1$ if the incident is fatal and $Y_i = 0$ if it is non-fatal. The probability of $Y_i = 1$, conditional on the observation-level independent variables, is formulated as [57]

$$P_i = \int \frac{\exp[\beta \mathbf{X}_i]}{1 + \exp[\beta \mathbf{X}_i]} f(\beta|\varphi) d\beta \tag{2}$$

where $\mathbf{X}_i$ is the vector of observed explanatory variables for incident $i$, $\beta$

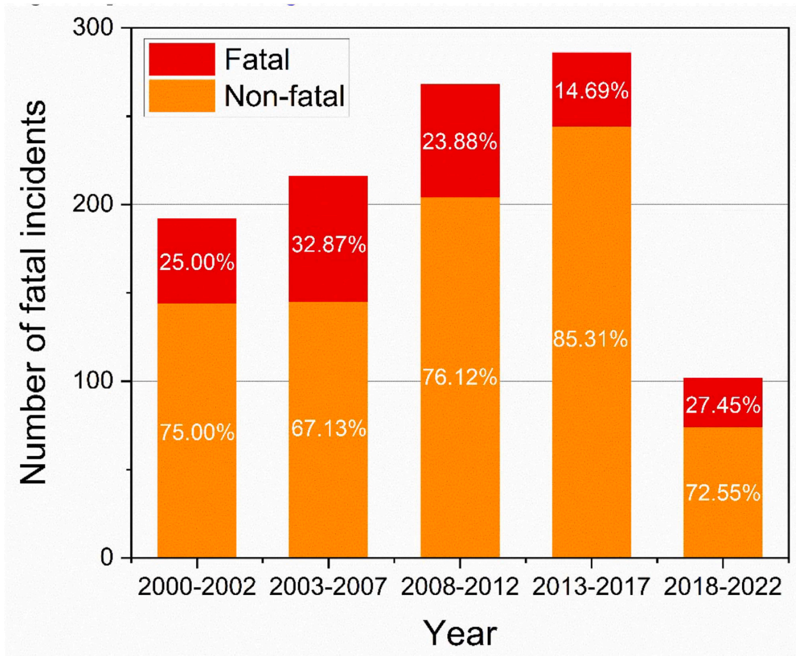


**Fig. 1.** Variation in the number of commercial fishing vessel incidents across time periods.

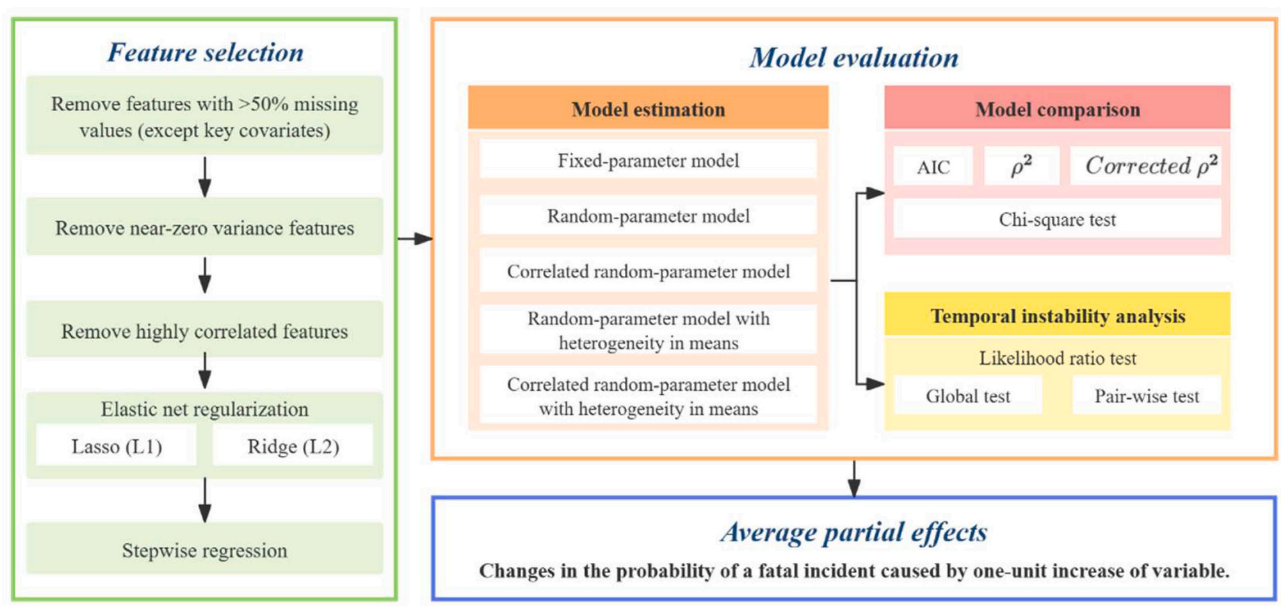


**Fig. 2.** Modeling framework.

is the vector of estimable coefficients, and $f(\beta|\varphi)$ is the density function of the random distribution of $\beta$,defined by the vector of parameters $\varphi$. To enable the capture of the heterogeneity of the means of random parameters, the random-parameter logit model is formulated as [34,35,39]

$$\beta_i = b + \eta Z_i + \Gamma\delta_i \tag{3}$$

where $b$ is the constant component of the random parameter, $Z_i$ is the vector of explanatory variables that account for heterogeneity in the means of random parameters, and $\eta$ represents the corresponding estimable coefficients. $\delta_i$ is an error term with zero mean and an identity variance–covariance matrix, and $\Gamma$ is a symmetric Cholesky matrix associated with the random parameters. The covariance matrix of the random parameters is formulated as

$$\mathbf{V} = \Gamma\Gamma' \tag{4}$$

where the diagonal elements of $\mathbf{V}$ equal the variances of the random parameters, and the covariance matrix is specified as a diagonal matrix in traditional uncorrelated random-parameter modeling, meaning that all off-diagonal elements are zero. Recent correlated random-parameter modeling approaches further extend this framework by allowing the off-diagonal elements of the Cholesky matrix to be non-zero and estimated, thereby capturing possible correlations among the random parameters [29,40,41]. Therefore, the standard deviations of the correlated random parameters are derived as

$$\sigma_k = \sqrt{\sigma_{jj}^2 + \sigma_{jj-1}^2 + \sigma_{jj-2}^2 + \ldots + \sigma_{jj}^2} \tag{5}$$

where $\sigma_k$ is the standard deviation of random parameter $k$, $\sigma_{j,j}$ represents the diagonal elements in the matrix $\Gamma$, and $\sigma_{j,j-1}^2, \ldots, \sigma_{j,1}^2$ denote the off-diagonal elements in the matrix $\Gamma$ corresponding to the random parameter $k$. The standard error of the standard deviation is calculated as

$$SE_{\sigma_k} = \frac{S_{\sigma_{ki}}}{\sqrt{N}} \tag{6}$$

where $\sigma_k$ is the standard deviation of random parameter $k$, and $S_{\sigma_{ki}}$ is the standard deviation of the observation-specific $\sigma_{ki}$. $N$ is the number of observations. The t-statistic $t_{\sigma_k}$ is calculated to test the significance of the estimated standard deviations of correlated random parameters:

$$t_{\sigma_k} = \frac{\sigma_k}{SE_{\sigma_k}} \tag{7}$$

The estimated correlation between the random parameters $\beta_p$ and $\beta'_p$ is formulated as [37]

$$Cor(\beta_p, \beta'_p) = \frac{Cov(\beta_p, \beta'_p)}{\sigma_p \sigma'_p} \tag{8}$$

where $Cov(\beta_p, \beta'_p)$ is the covariance between the two random parameters in the off-diagonal elements of the covariance matrix, and $\sigma_p$ and $\sigma'_p$ are the standard deviations of the random parameters.

All random-parameter models in this study are estimated using the simulated maximum likelihood with 1000 Halton draws to ensure reliable and stable parameter estimation [58].

### 4.3. Model evaluation and comparison

The Akaike information criterion (AIC), McFadden's $\rho^2$, and corrected McFadden's $\rho^2$ statistic are used to evaluate the goodness-of-fit of the estimated models [57,59]:

$$AIC = -2LL(\beta) + 2K \tag{9}$$

$$\rho^2 = 1 - \frac{LL(\beta)}{LL(0)}, \text{Corrected}\rho^2 = 1 - \frac{LL(\beta) - K}{LL(0)} \tag{10}$$

where $K$ is the number of estimated parameters, $LL(0)$ is the log-likelihood of the null model, and $LL(\beta)$ is the log-likelihood of the model at convergence. A model with a lower AIC value, higher McFadden's $\rho^2$ and corrected McFadden's $\rho^2$ has better performance.

Moreover, a chi-square ($\chi^2$) test is conducted for model comparison. The $\chi^2$ statistic is formulated as [57]

$$\chi^2 = -2[LL(\beta_A) - LL(\beta_B)] \tag{11}$$

where $LL(\beta_A)$ and $LL(\beta_B)$ are the log-likelihood values at convergence for model A and the competing model B, respectively. The $\chi^2$ statistic follows a chi-square distribution with the number of degrees of freedom equal to the difference in the number of parameters between model A and model B.

### 4.4. Temporal instability and transferability test

To assess the temporal instability of commercial fishing vessel incidents, two types of likelihood ratio tests (global test and pairwise test) are conducted in this study [57]. The first global test evaluates the significance of temporal stability by comparing an aggregated all-years model with separate models estimated for different year ranges [33,34,42,60]:

$$\begin{aligned}\chi^2 = &-2[LL(\beta_{2000-2022}) - LL(\beta_{2000-2002}) - LL(\beta_{2003-2007}) \\ &- LL(\beta_{2008-2012}) - LL(\beta_{2013-2017}) - LL(\beta_{2018-2022})]\end{aligned} \tag{12}$$

where $LL(\beta_{2000-2022})$ denotes the log-likelihood at convergence of the model estimated using all incident data from 2000 to 2022. Similarly, $LL(\beta_{2000-2002})$, $LL(\beta_{2003-2007})$, $LL(\beta_{2008-2012})$, $LL(\beta_{2013-2017})$, and $LL(\beta_{2018-2022})$ represent the log-likelihood values for models estimated separately for each sub-period.

Additionally, to further examine temporal stability between two specific time periods $t_1$ and $t_2$, another pairwise transferability test is conducted:

$$\chi^2 = -2\left[LL(\beta_{t_2 t_1}) - LL(\beta_{t_1})\right] \tag{13}$$

where $LL(\beta_{t_2 t_1})$ is the log-likelihood at convergence of the model estimated using the parameters derived from period $t_2$ and using data from period $t_1$. $LL(\beta_{t_1})$ is the log-likelihood at convergence based on the data from period $t_1$, with parameters no longer restricted to being time period $t_2$'s converged parameters as is the case for $LL(\beta_{t_2 t_1})$. Conversely, stability in the opposite direction is also tested. Therefore, two likelihood ratio test outcomes are obtained for each pair of models. The null hypothesis of the likelihood ratio test states that the parameters across the models are identical.

### 4.5. Partial effects analysis

In this study, partial effects analysis is conducted to better interpret the effects of explanatory variables on the probability of a fatal incident, a method that has been widely adopted in previous research [38,61]. For each explanatory variable, the partial effect represents the marginal change in the outcome probability with respect to a one-unit change in the variable, while keeping other factors constant [57]. For a continuous explanatory variable, the partial effect of the probability of a fatal incident is calculated as the partial derivative of the estimated probability with respect to that variable:

$$PE_{ik} = \frac{\partial \pi_i}{\partial X_{ik}} \tag{14}$$

where $PE_{ik}$ denotes the partial effect for variable $k$ of observation $i$, $X_{ik}$ represents the value of the corresponding continuous variable, and $\pi_i$ is the predicted probability of the fatal outcome.

For binary explanatory variables, the partial effect is computed as the discrete change in the predicted probability when the variable changes from 0 to 1:

$$PE_{ik}^{(d)} = \overline{\pi}_i(X_{ik} = 1) - \overline{\pi}_i(X_{ik} = 0) \tag{15}$$

The final reported partial effect for each variable is the sample mean of these individual effects across all observations, referred to as the average partial effect (APE), which provides a solid theoretical foundation for the interpretability of the model results.

## 5. Results

### 5.1. Feature selection

In the elastic net–regularized logistic regression approach, two hyperparameters ($\lambda$ and $\alpha$) are tuned to reduce feature dimensionality while maintaining model performance. In this study, we fix the L1 and L2 penalties by setting $\alpha = 0.5$. The regularization strength $\lambda$ is selected via 5-fold cross-validation, using the area under the receiver operating characteristic curve (AUC) as the selection criterion. Fig. 3 plots AUC against $\ln(\lambda)$. Using this curve, we choose $\lambda = 33$, which retains 29 features and achieves an AUC of 0.8302 on the validation folds. Fig. 4 presents the correlation matrix of the selected features, indicating generally weak inter-feature correlations. Subsequently, the stepwise

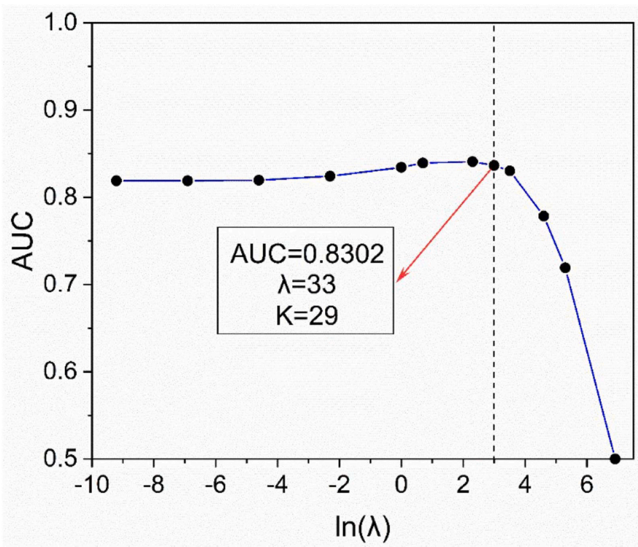


**Fig. 3.** Feature selection based on elastic net logistic regression ($\alpha = 0.5$).

approach is adopted to further select significant variables for each model.

### 5.2. Overview of model evaluation

For all time periods, several logit models were developed: the fixed-parameter model (FPM), random-parameter model (RPM), correlated random-parameter model (CRPM), random-parameter model with heterogeneity in means (RPMHM), and correlated random-parameter model with heterogeneity in means (CRPMHM). A parameter was considered random only if both its mean and standard deviation were statistically significant. Moreover, the CRPM and CRPMHM were estimated only when at least two random parameters were identified. The correlations among explanatory variables were examined to confirm that all correlation coefficients were below 0.6 [40]. During model estimation, a stepwise regression procedure was adopted to exclude nonsignificant variables. Parameters significant at the 90 % confidence level were retained to maintain consistency in variable definitions, as these variables still explained part of the random error in the dependent variable, despite their marginal statistical significance [40].

To evaluate and compare all estimated models, McFadden's $\rho^2$, corrected McFadden's $\rho^2$, AIC, and likelihood ratio tests were conducted [33,61], as summarized in Table 2. The results indicate that models

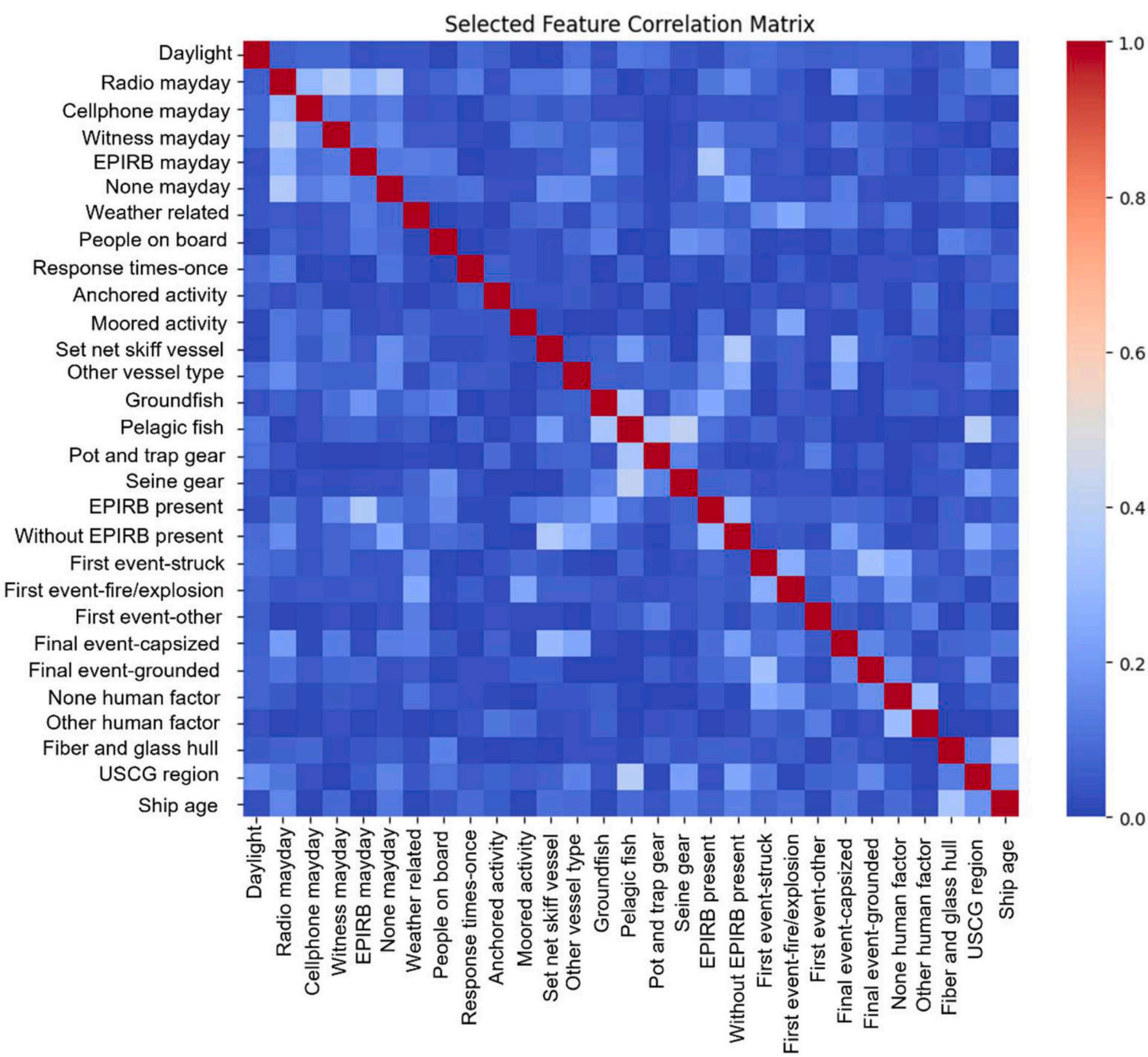


**Fig. 4.** Correlation matrix of selected features.

accounting for unobserved heterogeneity (RPMHM and CRPMHM) performed significantly better than their simpler counterparts. However, the improvement of the CRPMHM over the RPMHM was not statistically significant at the 90 % confidence level based on the likelihood ratio test—44.017 % and 40.591 % for the 2000–2002 and 2003–2007 models, respectively.

Similarly, for the 2013–2017 model, the RPMHM did not exhibit a statistically significant improvement over the FPM (89.423 %), and for the 2018–2022 model, the RPM did not significantly outperform the FPM (71.596 %). In terms of McFadden's $\rho^2$, model performance followed a consistent ranking across all time periods: CRPMHM > RPMHM > CRPM > RPM > FPM, reflecting the increasing explanatory power of more advanced model specifications.

With respect to the corrected McFadden's $\rho^2$ and AIC, the RPMHM and CRPMHM models exhibited only marginal differences, with the RPMHM slightly outperforming the CRPMHM in the 2000–2002 and 2003–2007 periods. For 2013–2017, the RPMHM again performed marginally better than the FPM, whereas for 2018–2022, the FPM achieved a slightly lower AIC value. Despite these minor variations, the key parameters estimated across comparable models (e.g., the RPMHM and CRPMHM for 2000–2007, the FPM and RPMHM for 2013–2017, and the FPM and RPM for 2018–2022) were largely consistent in terms of statistical significance, coefficient direction, and the number of fixed, random, and heterogeneous parameters.

Overall, a balance between model complexity and explanatory power is desirable. For instance, although the CRPMHM model is more complex, it can capture correlations between random parameters and provide deeper behavioral insights. Consequently, this study reports the CRPMHM results for the 2000–2002 and 2003–2007 periods, the RPMHM results for the 2013–2017 period, and the RPM results for the 2008–2012 and 2018–2022 periods. This selection offers relevant agencies practical flexibility in applying the model outcomes to policy and operational contexts [28,41,61].

### 5.3. Model estimation results

The model estimation results for 2000–2002, 2003–2007, 2008–2012, 2013–2017, and 2018–2022 are presented in Tables 3, 5, 7, 8, and 9, respectively, along with the corresponding average partial effects. The Cholesky matrix of correlated random parameters for 2000–2002 and 2003–2007 are presented in Tables 4 and 6.

For 2000–2002, five models—namely an FPM, RPM, CRPM, RPMHM, and CRPMHM—were developed, with all random parameters assumed to follow a normal distribution. Overall, the direction and magnitude of the effects of the explanatory variables were consistent across models. According to the CRPMHM model, several key variables were identified as significant determinants of the fatal incident probability among commercial fishing vessels. Incidents reported by *witnesses* ($\beta = 2.539$, APE $= 0.109$) or with *mayday method – none* ($\beta = 6.229$, APE $= 0.321$) exhibited markedly higher fatality probabilities, reflecting the crucial role of rapid and reliable communication in an emergency response. *Weather-related* incidents ($\beta = 4.673$, APE $= 0.223$) and *vessel activity – anchored* ($\beta = 4.900$, APE $= 0.231$) were associated with an increased likelihood of fatalities, likely due to limited maneuverability and harsher operating environments. Similarly, an increase in the *number of people onboard* slightly raised fatality risk ($\beta = 0.460$, APE $= 0.021$), consistent with greater exposure and evacuation complexity. In contrast, *pelagic fisheries* ($\beta = -2.781$, APE $= -0.115$), *fire/explosion as the first event* ($\beta = -3.582$, APE $= -0.132$), *grounding as the final event* ($\beta = -2.374$, APE $= -0.093$), and the absence of *human error* ($\beta = -4.693$, APE $= -0.193$) all significantly reduced fatality probabilities, suggesting safer operating conditions, earlier evacuation opportunities, and the critical influence of human factors on incident outcomes. Although the presence of an EPIRB device ($\beta = 4.722$, APE $= 0.215$) appeared positively associated with fatalities, this likely reflects reporting bias, as EPIRBs are typically activated in more severe incidents. Overall, these

**Table 2**
Model fit statistics and likelihood ratio test results for comparing model superiority.

| | 2000–2002 | | | | | 2003–2007 | | | | | 2008–2012 | | 2013–2017 | | | 2018–2022 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | FPM | RPM | CRPM | RPMHM | CRPMHM | FPM | RPM | CRPM | RPMHM | CRPMHM | FPM | RPM | FPM | RPM | RPMHM | FPM | RPM |
| Number of estimated parameters | 13 | 15 | 16 | 16 | 17 | 14 | 16 | 17 | 18 | 19 | 14 | 15 | 10 | 11 | 12 | 8 | 9 |
| Log likelihood at zero | −107.968 | −107.968 | −107.968 | −107.968 | −107.968 | −141.160 | −141.160 | −141.160 | −141.160 | −141.160 | −147.320 | −147.320 | −119.322 | −119.322 | −119.322 | −59.945 | −59.945 |
| Log likelihood at convergence | −43.216 | −40.413 | −40.384 | −36.506 | −36.336 | −60.179 | −52.303 | −52.283 | −48.670 | −48.528 | −78.428 | −76.065 | −83.487 | −82.818 | −81.240 | −31.319 | −30.742 |
| McFadden's $\rho^2$ | 0.600 | 0.626 | 0.626 | 0.662 | 0.663 | 0.574 | 0.629 | 0.630 | 0.655 | 0.656 | 0.468 | 0.484 | 0.300 | 0.306 | 0.319 | 0.478 | 0.487 |
| Corrected McFadden's $\rho^2$ | 0.479 | 0.487 | 0.478 | 0.514 | 0.506 | 0.475 | 0.516 | 0.509 | 0.528 | 0.522 | 0.373 | 0.382 | 0.217 | 0.214 | 0.219 | 0.344 | 0.337 |
| AIC | 112.4 | 110.8 | 112.8 | 105.0 | 106.7 | 148.4 | 136.6 | 138.6 | 133.3 | 135.1 | 184.9 | 182.1 | 187.0 | 187.6 | 186.5 | 78.6 | 79.5 |
| Likelihood ratio test | | | | | | | | | | | | | | | | | |
| | FPM vs. CRPMHM | RPM vs. CRPMHM | CRPM vs. CRPMHM | RPMHM vs. CRPMHM | | FPM vs. CRPMHM | RPM vs. CRPMHM | CRPM vs. CRPMHM | RPMHM vs. CRPMHM | | FPM vs. RPM | | FPM vs. RPMHM | RPM vs. RPMHM | | FPM vs. RPM | |
| Degrees of freedom | 4 | 2 | 1 | 1 | | 5 | 3 | 2 | 1 | | 1 | | 2 | 1 | | 1 | |
| Resulting $\chi^2$ | 13.760 | 8.154 | 8.096 | 0.340 | | 23.302 | 7.550 | 7.510 | 0.284 | | 4.726 | | 4.494 | 3.156 | | 1.154 | |
| Level of confidence | 99.190 % | 98.304 % | 99.556 % | 44.017 % | | 99.970 % | 94.371 % | 97.660 % | 40.591 % | | 97.029 % | | 89.428 % | 92.434 % | | 71.596 % | |
| Superior model | CRPMHM | CRPMHM | CRPMHM | — | | CRPMHM | CRPMHM | CRPMHM | — | | RPM | | — | RPMHM | | — | |

**Table 3**
Estimation results of logit models for fatal commercial fishing vessel incidents during 2000–2002.

| Variable | FPM | | RPM | | CRPM | | RPMHM | | CRPMHM | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | APE | Coefficient | APE | Coefficient | APE | Coefficient | APE | Coefficient | APE |
| Intercept | −1.590* | — | −1.278 | — | −1.436* | — | −1.144 | — | −1.322 | — |
| Mayday method – radio | −2.075** | −0.138 | −4.209*** | −0.208 | −3.943*** | −0.200 | −8.132*** | −0.274 | −7.874*** | −0.269 |
| *Standard deviation* | — | — | 5.806*** | — | 6.375*** | — | 4.481*** | — | 5.262*** | |
| Mayday method – witness | 1.631* | 0.117 | 2.329** | 0.130 | 2.341** | 0.133 | 2.475** | 0.107 | 2.539** | 0.109 |
| Mayday method – none | 4.959*** | 0.411 | 5.760*** | 0.374 | 5.786*** | 0.381 | 6.024*** | 0.310 | 6.229*** | 0.321 |
| Weather related | 3.251*** | 0.265 | 4.360*** | 0.266 | 4.286*** | 0.267 | 4.572*** | 0.221 | 4.673*** | 0.223 |
| People onboard | 0.408*** | 0.029 | 0.452*** | 0.025 | 0.493*** | 0.028 | 0.421*** | 0.019 | 0.460*** | 0.021 |
| Vessel activity – anchored | 2.572** | 0.201 | 4.160*** | 0.250 | 4.067*** | 0.249 | 4.680*** | 0.221 | 4.900*** | 0.231 |
| Fishery type – pelagic fish | −2.527*** | −0.159 | −2.762** | −0.136 | −2.786** | −0.141 | −2.678** | −0.112 | −2.781** | −0.115 |
| With EPIRB present | 3.380*** | 0.250 | 4.484*** | 0.242 | 4.476*** | 0.248 | 4.567*** | 0.211 | 4.722*** | 0.215 |
| First event – fire/explosion | −3.299** | −0.174 | −3.439 | −0.150 | −3.439 | −0.151 | −3.465 | −0.130 | −3.582* | −0.132 |
| Final event – grounded | −2.174** | −0.134 | −2.378** | −0.114 | −2.336** | −0.115 | −2.367** | −0.094 | −2.374** | −0.093 |
| Human factor – none | −2.481*** | −0.165 | −3.906*** | −0.197 | −3.834*** | −0.197 | −4.565*** | −0.188 | −4.693*** | −0.193 |
| Ship age | −0.056*** | −0.004 | −0.082*** | −0.005 | −0.081*** | −0.115 | −0.082*** | −0.004 | −0.082*** | −0.004 |
| *Standard deviation* | — | — | 0.034** | — | 0.035** | — | 0.031** | — | 0.037** | — |
| **Heterogeneity in means** | | | | | | | | | | |
| **Mayday method – radio** | | | | | | | | | | |
| Human factor – none | — | — | — | — | — | — | 6.727*** | — | 6.645*** | |
| No. of observations | 192 | | 192 | | 192 | | 192 | | 192 | |
| Degrees of freedom | 13 | | 15 | | 16 | | 16 | | 17 | |
| Log likelihood at zero | −107.968 | | −107.968 | | −107.968 | | −107.968 | | −107.968 | |
| Log likelihood at convergence | −43.216 | | −40.413 | | −40.384 | | −36.506 | | −36.336 | |
| McFadden's $\rho^2$ | 0.600 | | 0.626 | | 0.626 | | 0.662 | | 0.663 | |
| Corrected McFadden's $\rho^2$ | 0.479 | | 0.487 | | 0.478 | | 0.514 | | 0.508 | |
| AIC | 112.4 | | 110.8 | | 112.8 | | 105.0 | | 106.7 | |

*:$p < 0.10$; **:$p < 0.05$; ***: $p < 0.01$; APE: average partial effects.

**Table 4**
Diagonal and off-diagonal elements of the Cholesky matrix, t-stat [in brackets], and correlation coefficients (in parentheses) of the correlated random parameters for the CRPMHM during 2000–2002.

| | Mayday method – radio | Ship age |
|---|---|---|
| Mayday method – radio | 5.262 [3.41] (1.000) | 0.037 [2.28] (0.998) |
| Ship age | 0.037 [2.28] (0.998) | 0.002 [0.14] (1.000) |

results indicate that communication efficiency, human factors, and environmental conditions jointly shape the fatality risk in commercial fishing vessel incidents during this period.

The distributions of random parameters are shown in Fig. 5. The CRPMHM results reveal that *ship age* was a statistically significant random parameter, with a mean of −0.082, a standard deviation of 0.037, and an APE of −0.004. This indicates that approximately 98.67 % of old ships were more likely to be involved in non-fatal incidents, and that, on average, the probability of fatal incidents decreased by 0.4 % with each additional year of ship age (Fig. 5(a)). Moreover, *mayday method – radio* exhibited significantly heterogeneous effects on fatal commercial fishing vessel incidents, interacting with the variable *human factor – none*. As illustrated in Fig. 5(b) and Fig. 5(c), for incidents involving and not involving human error, the mean values of the random parameter for *mayday method – radio* were −7.874 and −1.229, respectively, indicating that approximately 93.27 % and 59.23 % of vessels using the radio mayday method were associated with non-fatal incidents.

Table 4 presents the diagonal and off-diagonal elements of the Cholesky matrix, as well as the correlation coefficients of the random parameters in the CRPMHM for the 2000–2002 period. The correlation coefficients represent the interactions between pairs of random parameters, with positive coefficients indicating a homogeneous effect and negative coefficients indicating an opposite influence. The diagonal element for mayday method – radio shows a statistically significant t-statistic (> 1.96), confirming the robustness of its random effect. In contrast, the diagonal element for ship age is not statistically significant, suggesting limited independent heterogeneity in this parameter. However, the off-diagonal element shows a significant positive correlation between the random components of ship age and mayday method – radio. This indicates that although the random variation in ship age itself is minor, it co-varies significantly with the heterogeneity in the effect of radio-based distress communication. In other words, vessels for which the safety-enhancing impact of the radio mayday method is stronger also tend to exhibit a slightly greater reduction in fatality risk as ship age increases. This pattern suggests a homogeneous relationship, indicating that underlying operational and technical factors, such as crew experience, vessel maintenance, and communication efficiency, jointly influence these two variables in a consistent direction.

For 2003–2007, another five models—namely an FPM, RPM, CRPM, RPMHM, and CRPMHM—were developed under the assumption of normally distributed random parameters. The estimation results reveal that the direction and magnitude of most explanatory variables were generally consistent across models. According to the CRPMHM results, several key factors significantly influenced the probability of fatal incidents among commercial fishing vessels. Incidents reported by *mayday method* – witnesses ($\beta$ = 3.864, APE = 0.258) or with *mayday method* – none ($\beta$ = 4.994, APE = 0.400) exhibited substantially higher fatality probabilities, emphasizing the vital role of timely distress communication. In addition, weather-related incidents ($\beta$ = 3.243, APE = 0.207) and capsizing as the final event ($\beta$ = 2.706, APE = 0.180) were associated with increased fatality risks, reflecting the severe physical conditions and limited survivability in such situations. In contrast, operations within groundfish fisheries ($\beta$ = −2.333, APE = −0.116) and during the daylight condition ($\beta$ = −1.849, APE = −0.085) were significantly associated with lower fatality probabilities, suggesting safer working environments and better visibility. Similarly, incidents without human error ($\beta$ = –1.527, APE = –0.090) exhibited a lower likelihood of fatality, further confirming the predominant influence of human factors on incident outcomes. The variable with EPIRB present ($\beta$ = 2.917, APE = 0.152) was again positively related to fatal incidents, likely reflecting a reporting or activation bias, as EPIRBs are typically triggered during more severe emergencies. These findings collectively suggest that

**Table 5**
Estimation results of logit models for fatal commercial fishing vessel incidents during 2003–2007.

| Variable | FPM | | RPM | | CRPM | | RPMHM | | CRPMHM | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | APE | Coefficient | APE | Coefficient | APE | Coefficient | APE | Coefficient | APE |
| Intercept | −1.252 | — | −1.278 | — | −1.279 | — | −0.955 | — | −0.971 | — |
| Daylight | −1.500* | −0.113 | −1.750* | −0.099 | −1.745* | −0.099 | −1.860* | −0.086 | −1.849* | −0.085 |
| Mayday method – witness | 2.926*** | 0.280 | 3.833*** | 0.288 | 3.829*** | 0.288 | 3.882*** | 0.265 | 3.864** | 0.258 |
| Mayday method – EPIRB | 1.539** | 0.145 | 2.167** | 0.159 | 2.175** | 0.161 | −7.209** | −0.290 | −8.622** | −0.302 |
| *Standard deviation* | | | 4.602*** | — | 4.485*** | — | 6.035** | — | 6.805* | — |
| Mayday method – none | 4.126*** | 0.451 | 5.107*** | 0.443 | 5.090*** | 0.442 | 5.021*** | 0.413 | 4.994*** | 0.400 |
| Weather related | 2.595*** | 0.259 | 3.348*** | 0.257 | 3.345*** | 0.257 | 3.245*** | 0.207 | 3.243*** | 0.207 |
| Fishery type – groundfish | −1.060* | −0.086 | −2.475** | −0.149 | −2.420** | −0.147 | −2.397** | −0.120 | −2.333** | −0.116 |
| *Standard deviation* | | | 5.997*** | — | 5.890*** | — | 6.376*** | — | 6.173*** | — |
| Gear type – seine | −5.751*** | −0.332 | −7.867*** | −0.342 | −7.835*** | −0.342 | −7.734*** | −0.272 | −7.697*** | −0.272 |
| With EPIRB present | 1.650*** | 0.141 | 2.784*** | 0.175 | 2.769*** | 0.175 | 2.932*** | 0.153 | 2.917** | 0.152 |
| First event – struck | −2.498*** | −0.202 | −3.574*** | −0.222 | −3.587*** | −0.223 | −3.756*** | −0.194 | −3.778*** | −0.194 |
| Final event – capsized | 1.631** | 0.157 | 2.447** | 0.186 | 2.442** | 0.186 | 2.680** | 0.180 | 2.706** | 0.180 |
| Human factor – other | 2.036* | 0.191 | 1.942 | 0.138 | 2.053 | 0.146 | 1.341 | 0.080 | 1.519 | 0.091 |
| Human factor – none | −1.322** | −0.117 | −1.642*** | −0.113 | −1.635*** | −0.112 | −1.557*** | −0.092 | −1.527** | −0.090 |
| Ship age | −0.028* | −0.002 | −0.047** | −0.003 | −0.047** | −0.003 | −0.061** | −0.003 | −0.061** | −0.003 |
| **Heterogeneity in means** | | | | | | | | | | |
| **Mayday method – EPIRB** | | | | | | | | | | |
| Weather related | — | — | — | — | — | — | 7.804*** | — | 10.112* | — |
| Ship age | — | — | — | — | — | — | 0.198** | — | 0.223** | — |
| No. of observations | 220 | | 220 | | 220 | | 220 | | 220 | |
| Degrees of freedom | 14 | | 16 | | 17 | | 18 | | 19 | |
| Log likelihood at zero | −141.160 | | −141.160 | | −141.160 | | −141.160 | | −141.160 | |
| Log likelihood at convergence | −60.179 | | −52.303 | | −52.283 | | −48.670 | | −48.528 | |
| McFadden's $\rho^2$ | 0.574 | | 0.629 | | 0.630 | | 0.655 | | 0.656 | |
| Corrected McFadden's $\rho^2$ | 0.475 | | 0.516 | | 0.509 | | 0.528 | | 0.522 | |
| AIC | 148.4 | | 136.6 | | 138.6 | | 133.3 | | 135.1 | |

*:$p < 0.10$; **:$p < 0.05$; ***: $p < 0.01$; APE: average partial effects.

**Table 6**
Diagonal and off-diagonal elements of the Cholesky matrix, t-stat [in brackets], and correlation coefficients (in parentheses) of the correlated random parameters for the CRPMHM during 2003–2007.

| | Mayday method – EPIRB | Fishery type – groundfish |
|---|---|---|
| Mayday method – EPIRB | 6.805 [1.89] (1.000) | 4.333 [2.98] (0.702) |
| Fishery type – groundfish | 4.333 [2.98] (0.702) | 4.397 [3.07] (1.000) |

environmental conditions, human performance, and communication efficiency remained the dominant determinants of fatality risk in fishing vessel incidents during this period.

The distributions of random parameters are shown in Fig. 6. The CRPMHM results reveal that fishery type – groundfish was a statistically significant random parameter, with a mean of −2.333, a standard deviation of 6.173, and an APE of −0.116. This indicates that approximately 64.73 % of vessels engaged in groundfish fisheries were more likely to be involved in non-fatal incidents, and, on average, the probability of fatal incidents was 11.6 % less than that for non-groundfish fishery types (Fig. 6(a)). In addition, mayday method – EPIRB exhibited significantly heterogeneous effects on fatal commercial fishing vessel incidents, interacting with weather-related and ship age variables. As illustrated in Fig. 6(b–e), for non-weather-related and weather-related incidents involving vessels aged 0 years, the mean values of the random parameter for mayday method – EPIRB were −8.622 (6.805) and 1.490 (6.805), respectively, indicating that approximately 89.74 % and 41.33 % of vessels using the EPIRB mayday method were associated with non-fatal incidents. However, for vessels aged 100 years, the mean values were 13.678 (6.805) and 23.790 (6.805) under non-weather-related and weather-related conditions, respectively, indicating that approximately 97.78 % and 99.98 % of such vessels were associated with fatal incidents. Specifically, the protective effect of EPIRB communication diminished under adverse weather conditions and for older vessels, reflecting the combined influence of environmental severity and vessel condition on emergency response efficiency.

As shown in Table 6, the diagonal elements of mayday method – EPIRB and fishery type – groundfish confirm the presence of statistically significant random heterogeneity, whereas the off-diagonal elements indicate a strong positive correlation between their random components. This positive correlation suggests that vessels benefiting more from the safety-enhancing effects of EPIRB communication also tend to have a higher likelihood of non-fatal outcomes within groundfish fisheries. Such a homogeneous relationship indicates that the unobserved

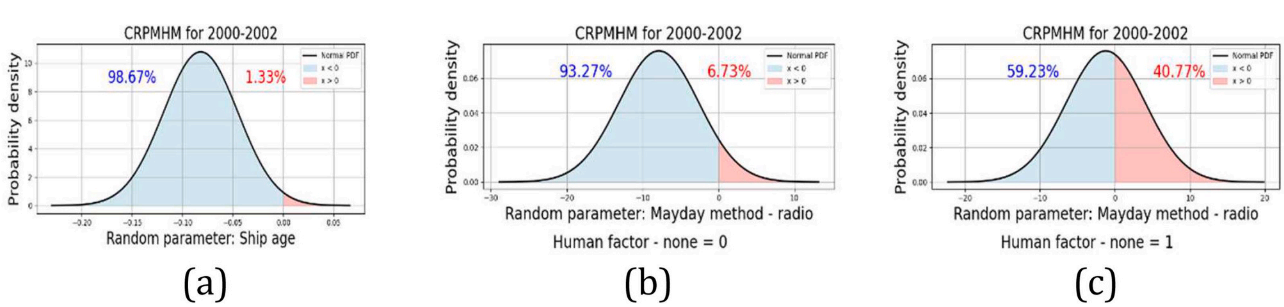


**Fig. 5.** Distributions of random parameters of the CRPMHM for 2000–2002.

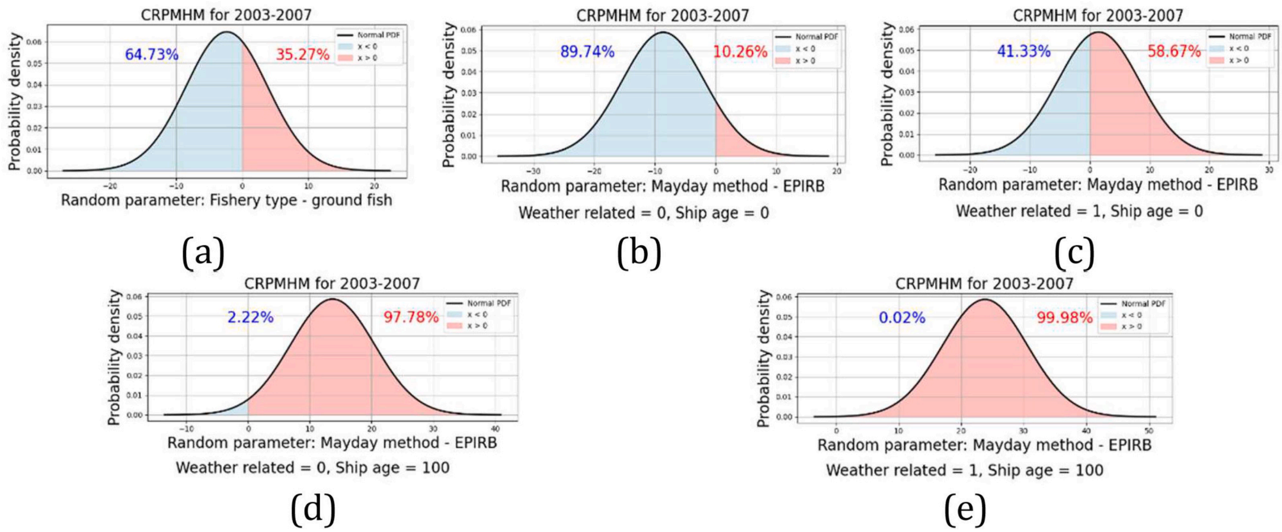


**Fig. 6.** Distributions of random parameters of the CRPMHM for 2003–2007.

characteristics represented by these two variables, such as advanced equipment, coordinated crew communication, and effective operational routines, interact synergistically to reduce the risk of a fatal incident.

For 2008–2012, two models—namely an FPM and RPM—were developed, with all random parameters assumed to follow a normal distribution. Overall, the direction and magnitude of the coefficients were consistent across the two models. The RPM demonstrated slightly better goodness-of-fit than the FPM, as reflected by a higher McFadden's $\rho^2$ and a lower AIC, suggesting that accounting for unobserved heterogeneity improved the explanatory power of the modeling.

The RPM results (Table 7) reveal several key variables as significant determinants of fatal incident probability among commercial fishing vessels. Incidents with *mayday method* – *witness* ($\beta$ = 2.323, APE = 0.271), *mayday method* – none ($\beta$ = 3.397, APE = 0.437), or *mayday method* – EPIRB ($\beta$ = 3.919, APE = 0.509) exhibited substantially higher fatality probabilities, highlighting the importance of prompt and reliable communication during emergencies. The elevated fatality probability associated with using an *EPIRB* may reflect activation bias, as EPIRBs are generally triggered in more severe events.

In terms of vessel and operational characteristics, the number of people onboard ($\beta$ = 0.393, APE = 0.037) was positively associated with fatality risk, reflecting increased exposure and evacuation complexity. In addition, vessels categorized as other types ($\beta$ = 2.676, APE = 0.321) and those using pot and trap gear ($\beta$ = 0.784, APE = 0.078) showed elevated fatality risks. The presence of an EPIRB device on board ($\beta$ = −1.131, APE = −0.100) significantly reduced the fatality likelihood, suggesting that the availability of such safety equipment has a preventive effect even if the equipment is not activated during an incident.

Incident progression variables also had notable effects. Incidents involving first event – other ($\beta$ = 3.326, APE = 0.414) or final event – capsized ($\beta$ = 1.421, APE = 0.160) were associated with increased fatality probabilities, whereas final event – grounded ($\beta$ = −1.928, APE = −0.157) reduced the fatality likelihood, likely due to better opportunities for early evacuation and rescue. Ship age ($\beta$ = −0.042, APE = –0.004) exhibited a small but significant negative effect, indicating that older vessels—possibly operated more cautiously or under more stable conditions—were slightly less prone to fatal outcomes.

Moreover, the RPM identified hull type – fiber glass as a statistically significant random parameter (mean = −0.795, SD = 2.859, APE = −0.116). As illustrated in Fig. 7, approximately 67.17 % of fiber-glass vessels had negative effects, corresponding to a lower probability of fatal incidents, whereas 32.83 % had positive effects, indicating a higher fatality risk. This substantial heterogeneity implies that the safety performance of fiber-glass hulls varies widely, potentially influenced by differences in structural integrity, maintenance practices, or exposure to

**Table 7**
Estimation results of logit models for fatal commercial fishing vessel incidents during 2008–2012.

| Variable | FPM | | RPM | |
|---|---|---|---|---|
| | Coefficient | APE | Coefficient | APE |
| Intercept | −2.193*** | — | −1.724** | — |
| Mayday method – witness | 2.709*** | 0.308 | 2.323*** | 0.271 |
| Mayday method – EPIRB | 4.221*** | 0.525 | 3.919*** | 0.509 |
| Mayday method – none | 3.607*** | 0.445 | 3.397*** | 0.437 |
| People onboard | 0.413*** | 0.037 | 0.393** | 0.037 |
| Vessel type – other | 2.735*** | 0.311 | 2.676*** | 0.321 |
| Gear type – pot and trap | 0.881* | 0.083 | 0.784* | 0.078 |
| Gear type – seine | −2.263* | −0.159 | −2.097 | −0.153 |
| With EPIRB present | −1.178** | −0.100 | −1.131** | −0.100 |
| First event – other | 3.517*** | 0.418 | 3.326** | 0.414 |
| Final event – capsized | 1.135* | 0.116 | 1.421** | 0.160 |
| Final event – grounded | −1.742** | −0.141 | −1.928*** | −0.157 |
| Hull type – fiber glass | −0.795* | −0.070 | −1.271** | −0.116 |
| *Standard deviation* | — | — | 2.859*** | — |
| Ship age | −0.042** | −0.004 | −0.042** | −0.004 |
| No. of observations | 268 | | 268 | |
| Degrees of freedom | 14 | | 15 | |
| Log likelihood at zero | −147.320 | | −147.320 | |
| Log likelihood at convergence | −78.428 | | −76.065 | |
| McFadden's $\rho^2$ | 0.468 | | 0.484 | |
| Corrected McFadden's $\rho^2$ | 0.373 | | 0.382 | |
| AIC | 184.9 | | 182.1 | |

*:$p < 0.10$; **:$p < 0.05$; ***: $p < 0.01$; APE: average partial effects.

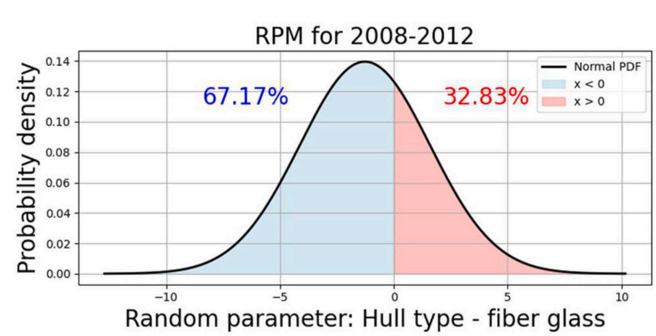


**Fig. 7.** Distributions of random parameters of the RPM for 2008–2012.

adverse operating conditions.

Overall, the 2008–2012 results underscore that communication reliability, vessel characteristics, and incident dynamics jointly shape the fatality risk of commercial fishing vessels. The introduction of random parameters effectively captures unobserved behavioral and technical heterogeneity, enhancing the model's capacity to represent real-world variations in vessel safety performance.

For 2013–2017, three models—namely an FPM, RPM, and RPMHM—were developed, with all random parameters assumed to follow a normal distribution. The overall direction and magnitude of the explanatory variables remained consistent across models. The RPMHM provided the best model fit, as reflected by the highest McFadden's $\rho^2$ and the lowest AIC, indicating that accounting for heterogeneity in means improved explanatory power. However, the improvement over the FPM was not statistically significant at the 90 % confidence level, suggesting that unobserved heterogeneity had only a moderate influence on this period's incident patterns.

The RPMHM results (Table 8) reveal several factors as significant determinants of fatality risk. Incidents involving mayday method – witness ($\beta = 0.768$, APE = 0.103) exhibited higher fatality probabilities, highlighting the critical role of timely distress communication. Environmental and operational variables also had notable impacts. *Weather-related* incidents ($\beta = 0.855$, APE = 0.112) significantly increased the fatality risk, indicating that adverse weather conditions heighten vulnerability during emergencies. In addition, vessels operating without an EPIRB device ($\beta = 1.684$, APE = 0.278) were more prone to fatal outcomes, emphasizing the importance of safety equipment availability.

In contrast, certain incident sequence characteristics were associated with reduced fatality risk. Incidents initiated by first event – struck ($\beta = -1.112$, APE = −0.122) had significantly lower fatality probabilities, possibly due to earlier detection or improved response opportunities in these circumstances.

The RPMHM identified mayday method – EPIRB as a significant random parameter (mean = 1.230, SD = 1.888, APE = 0.185) with heterogeneity in means. As shown in Fig. 8, this parameter exhibited notable variability depending on the first event – struck variable. When first event – struck = *0*, approximately 74.26 % of vessels using the EPIRB mayday signaling method were associated with fatal incidents, whereas 25.74 % were associated with non-fatal incidents (Fig. 8(a)). In contrast, when first event – struck = *1*, 96.45 % of vessels using the EPIRB mayday signaling method were linked to fatal outcomes (Fig. 8 (b)). This strong heterogeneity suggests that the effectiveness of EPIRB-based distress communication is context dependent; i.e., although beneficial for certain incident types, an EPIRB is less effective in struck scenarios where rapid impact progression limits the time for activation or rescue.

Overall, the 2013–2017 results indicate that communication reliability, environmental constraints, and incident dynamics jointly determine the likelihood of fatal outcomes. The inclusion of heterogeneity in means within the RPMHM effectively captures contextual variability—particularly the interaction between mayday method – EPIRB and struck-related incidents—thereby providing a more nuanced understanding of the mechanisms underlying fatal commercial fishing vessel incidents during this period.

For 2018–2022, two models—an FPM and RPM—were developed assuming that random parameters followed a normal distribution. The direction and magnitude of coefficients were consistent across the two models. The RPM results (Table 9) reveal several key variables as significant determinants of fatal incident probability. Incidents without a mayday call ($\beta = 1.781$, APE = 0.190) exhibited substantially higher fatality probabilities, confirming that the absence of emergency communication critically impedes timely rescue. Similarly, weather-related incidents ($\beta = 2.676$, APE = 0.293) significantly increased the likelihood of fatalities, likely due to reduced visibility, rough sea states, and constrained maneuverability under adverse weather conditions.

Vessel operation and equipment characteristics also played important roles. Incidents involving gear type – pot and trap ($\beta = 1.235$, APE = 0.127) were associated with higher fatality probabilities, which may reflect entanglement hazards or limited escape routes during emergencies. The absence of an EPIRB device ($\beta = 5.033$, APE = 0.548) had the strongest positive association with fatal outcomes, underscoring the essential role of emergency locator transmitters in facilitating prompt search and rescue responses.

The RPM identified *number of* responses – once as a statistically significant random parameter (mean = −3.539, SD = 3.092, APE = −0.340). As illustrated in Fig. 9, approximately 87.38 % of vessels had negative effects, corresponding to a lower probability of fatal incidents, whereas 12.62 % exhibited positive effects, indicating elevated risk. This heterogeneity implies that although emergency responses generally reduce fatality likelihood, a small subset of vessels still experienced fatal

**Table 8**
Estimation results of logit models for fatal commercial fishing vessel incidents during 2013–2017.

| Variable | FPM | | RPM | | RPMHM | |
|---|---|---|---|---|---|---|
| | Coefficient | APE | Coefficient | APE | Coefficient | APE |
| Intercept | −2.938*** | — | −2.087*** | — | −2.032*** | — |
| Mayday method – witness | 1.080** | 0.108* | 0.784** | 0.106 | 0.768* | 0.103 |
| Mayday method – EPIRB | 2.712*** | 0.379 | 1.891*** | 0.314 | 1.230** | 0.185 |
| *Standard deviation* | — | — | 3.160** | — | 1.888** | — |
| Mayday method – none | 1.175* | 0.125 | 0.851 | 0.120 | 0.826 | 0.116 |
| Weather related | 1.119** | 0.109 | 0.898** | 0.120 | 0.855** | 0.112 |
| Vessel activity – moored | 3.023** | 0.430 | 2.363** | 0.404 | 2.246 | 0.385 |
| Vessel type – other | 1.308* | 0.147 | 0.972 | 0.143 | 0.987 | 0.145 |
| No EPIRB present | 2.333*** | 0.317 | 1.682*** | 0.276 | 1.684*** | 0.278 |
| First event – struck | −1.039** | −0.084 | −0.962** | −0.110 | −1.112** | −0.122 |
| First event – fire/explosion | −2.650** | −0.143 | −2.084 | −0.171 | −1.982 | −0.161 |
| **Heterogeneity in means** | | | | | | |
| **Mayday method – EPIRB** | | | | | | |
| First event – struck | — | — | — | — | 2.179** | — |
| No. of observations | 286 | | 286 | | 286 | |
| Degrees of freedom | 10 | | 11 | | 12 | |
| Log likelihood at zero | −119.322 | | −119.322 | | −119.322 | |
| Log likelihood at convergence | −83.487 | | −82.818 | | −81.240 | |
| McFadden's $\rho^2$ | 0.300 | | 0.306 | | 0.319 | |
| Corrected McFadden's $\rho^2$ | 0.217 | | 0.214 | | 0.219 | |
| AIC | 187.0 | | 187.6 | | 186.5 | |

*:$p < 0.10$; **:$p < 0.05$; ***: $p < 0.01$; APE: average partial effects.

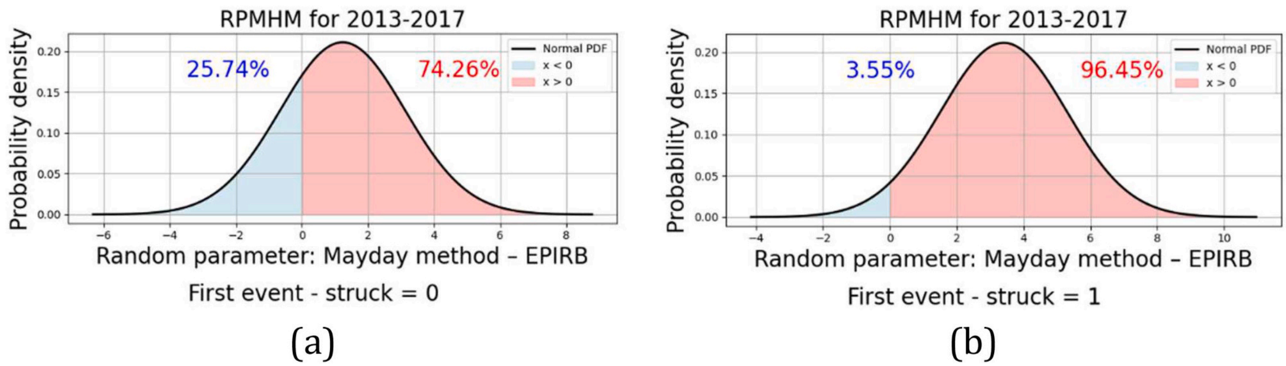


**Fig. 8.** Distributions of random parameters of the RPMHM for 2013–2017.

**Table 9**
Estimation results of logit models for fatal commercial fishing vessel incidents during 2018–2022.

| Variable | FPM | | RPM | |
|---|---|---|---|---|
| | Coefficient | APE | Coefficient | APE |
| Intercept | −1.420** | — | −1.216** | — |
| Mayday method – none | 2.188** | 0.245 | 1.781** | 0.190 |
| Weather related | 3.148*** | 0.361 | 2.676*** | 0.293 |
| Number of responses – one | −2.840*** | −0.290 | −3.539*** | −0.340 |
| *Standard deviation* | — | — | 3.092** | — |
| Gear type – pot and trap | 1.361* | 0.141 | 1.235* | 0.127 |
| No EPIRB present | 4.811*** | 0.554 | 5.033** | 0.548 |
| First event – struck | −1.869* | −0.165 | −1.807** | −0.161 |
| Hull type – fiber and glass | −1.325* | −0.122 | −0.989 | −0.094 |
| No. of observations | 102 | | 102 | |
| Degrees of freedom | 8 | | 9 | |
| Log likelihood at zero | −59.945 | | −59.945 | |
| Log likelihood at convergence | −31.319 | | −30.742 | |
| McFadden's $\rho^2$ | 0.478 | | 0.487 | |
| Corrected McFadden's $\rho^2$ | 0.344 | | 0.337 | |
| AIC | 78.6 | | 79.5 | |

*:$p < 0.10$; **:$p < 0.05$; ***: $p < 0.01$; APE: average partial effects.

outcomes despite timely action, possibly due to severe incident circumstances or insufficient response coordination.

Overall, the 2018–2022 results highlight the decisive influence of emergency preparedness, weather conditions, and response timeliness on fatality risk in commercial fishing vessel incidents. The presence of significant random heterogeneity in number of responses – one emphasizes that even in rapid-response scenarios, differences in vessel capability, crew coordination, and incident severity continue to shape survival outcomes in modern fishing operations.

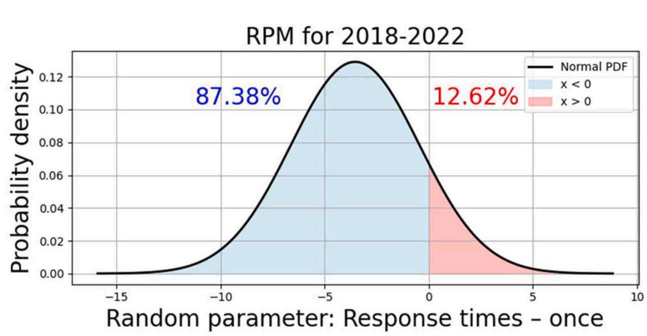


**Fig. 9.** Distributions of random parameters of the RPM for 2018–2022.

### 5.4. Temporal instability assessment

To assess the temporal instability of fatal commercial fishing vessel incidents, two types of transferability tests were conducted: a global test and a pairwise test.

In the global test, the calculated $\chi^2$ value was 81.734 with 36 degrees of freedom, which equals the total number of estimated parameters across all separate models minus the number of parameters in the all-years combined model. The result rejects the null hypothesis that the parameters of the all-years model and the separate models are equal, with 99 % confidence ($P(\chi^2 \leq 81.734) = 99.998\%$).

In the pairwise test, the null hypothesis states that model estimates are temporally stable between two specific periods. The results are presented in Table 10. Fourteen out of twenty pairwise tests show temporal instability that is statistically significant at the 95 % confidence level or higher. Exceptions occur for the $t_2/t_1$ comparisons between 2000 and 2002/2013–2017, 2000–2002/2018–2022, 2003–2007/2013–2017, 2003–2007/2018–2022, 2008–2012/2018–2022, and 2013–2017/2018–2022, which exhibit confidence levels below 95 %. However, the reverse tests for these model pairs produce results exceeding the 99 % confidence level. These results indicate that the null hypothesis of temporal stability can be rejected, confirming the presence of temporal instability across different time periods.

The two types of transferability tests together provide strong evidence that the parameters of fatal commercial fishing vessel incident models developed using CFID data are temporally unstable.

Table 11 presents the results of the temporal stability evaluation of the explanatory variables associated with fatal commercial fishing vessel incidents, following comprehensive experimental testing. The APEs of explanatory variables with significant effects on fatal commercial fishing vessel incidents for more than two periods are presented in Fig. 10. The results reveal that no explanatory variable maintained a stable influence throughout all five periods from 2000 to 2022. Only one variable, mayday method – witness, remained temporally stable across four consecutive periods (2000–2017), consistently showing a positive effect on fatality likelihood. Two variables, mayday method – none (2000–2013) and ship age (2003–2017), demonstrated stability over three consecutive periods. In addition, seven variables—namely mayday method – EPIRB (2008–2017), weather related (2000–2007 and 2013–2022), with EPIRB present (2000–2007), no EPIRB present (2013–2022), first event – struck (2013–2022), final event – capsized (2003–2012), and human factor – none (2000–2007)—exhibited stability across two consecutive periods.

It is noted that a parameter was regarded as temporally stable across consecutive periods only if it was statistically significant and maintained a consistent directional effect on the fatal outcome of commercial fishing vessel incidents. For instance, mayday method – EPIRB was significant over three consecutive periods (2003–2017); however, although it had a positive effect on the fatality probability during 2008–2017, it exhibited

**Table 10**
Pairwise transferability test results (number of degrees of freedom in parentheses and confidence level in brackets).

| $t_1$ | $t_2$ | | | | |
|---|---|---|---|---|---|
| | 2000–2002 (Model) | 2003–2007 (Model) | 2008–2012 (Model) | 2013–2017 (Model) | 2018–2022 (Model) |
| 2000–2002 (Data) | — | 31.644 (19) [> 96.57 %] | 43.400 (15) [> 99.99 %] | 64.232 (12) [> 99.99 %] | 87.198 (7) [> 99.99 %] |
| 2003–2007 (Data) | 58.772 (17) [> 99.99 %] | — | 61.624 (15) [> 99.99 %] | 56.090 (12) [> 99.99 %] | 80.238 (7) [> 99.99 %] |
| 2008–2012 (Data) | 38.710 (17) [> 99.80 %] | 31.922 (19) [> 96.81 %] | — | 34.568 (12) [> 99.95 %] | 100.016 (7) [> 99.99 %] |
| 2013–2017 (Data) | 14.818 (17) [> 39.14 %] | 17.502 (19) [> 44.41 %] | 29.862 (15) [> 98.76 %] | — | 32.016 (9) [> 99.98 %] |
| 2018–2022 (Data) | 5.358 (17) [> 0.34 %] | 9.766 (19) [> 4.15 %] | 19.46 (15) [> 80.64 %] | 8.36 (12) [> 24.36 %] | — |

Note: Several variables were excluded due to collinearity.

**Table 11**
Temporal stability assessment of explanatory variables.

| Variable | Temporally unstable | Temporally stable | | | |
|---|---|---|---|---|---|
| | | 5 consecutive periods | 4 consecutive periods | 3 consecutive periods | 2 consecutive periods |
| **Light condition** | | | | | |
| Daylight | √ | | | | |
| **Mayday method** | | | | | |
| Radio | √ | | | | |
| Witness | | | √ | | |
| EPIRB | | | | | √ |
| None | | | | √ | |
| **Weather related** | | | | | √ |
| **Number of responses** | | | | | |
| One | √ | | | | |
| **Vessel activity** | | | | | |
| Anchored | √ | | | | |
| **Vessel type** | | | | | |
| Other | √ | | | | |
| **Fishery type** | | | | | |
| Groundfish | √ | | | | |
| Pelagic fish | √ | | | | |
| **Gear type** | | | | | |
| Pot and trap | √ | | | | |
| Seine | √ | | | | |
| **EPIRB present** | | | | | |
| With | | | | | √ |
| Without | | | | | √ |
| **First event** | | | | | |
| Struck | | | | | √ |
| Fire/explosion | √ | | | | |
| Other | √ | | | | |
| **Final event** | | | | | |
| Capsized | | | | | √ |
| Grounded | √ | | | | |
| **Human factor** | | | | | |
| None | | | | | √ |
| **Hull type** | | | | | |
| Fiber glass | √ | | | | |
| **People on board** | √ | | | | |
| **Ship age** | | | | √ | |

a random effect with a negative average partial effect during 2003–2007, indicating stability only over two consecutive periods.

Overall, most explanatory variables were found to be temporally unstable, with their significance and directional effects varying substantially across the five investigated time periods (2000–2022). This suggests that either the parameters were not significant in some periods or their relationships with fatal outcomes changed over time, implying strong temporal non-stationarity in the behavioral, operational, and environmental determinants of fatal commercial fishing vessel incidents.

## 6. Disscussion

### 6.1. Temporal instability

The temporal instability revealed in this study provides important insights into the dynamic nature of risk factors associated with fatal commercial fishing vessel incidents. The results indicate that relationships between explanatory variables and fatal outcomes evolve over time rather than remaining fixed. Such instability suggests that the behavioral and operational mechanisms underlying maritime safety are influenced by changing technologies, regulations, environmental conditions, and human decision-making. These findings imply that aggregating multi-year maritime incident data, as done in many previous studies [3,23,25,62,63], may obscure dynamic behavioral and operational changes and lead to biased or outdated interpretations of risk.

Several factors may contribute to the observed temporal instability [44]. First, technological progress, including improvements in electronic distress signaling (e.g., the adoption of EPIRB systems), vessel navigation, and safety equipment, has gradually altered the mechanisms through which incidents occur and are managed. Parameters that were once positively associated with fatal outcomes may have become less

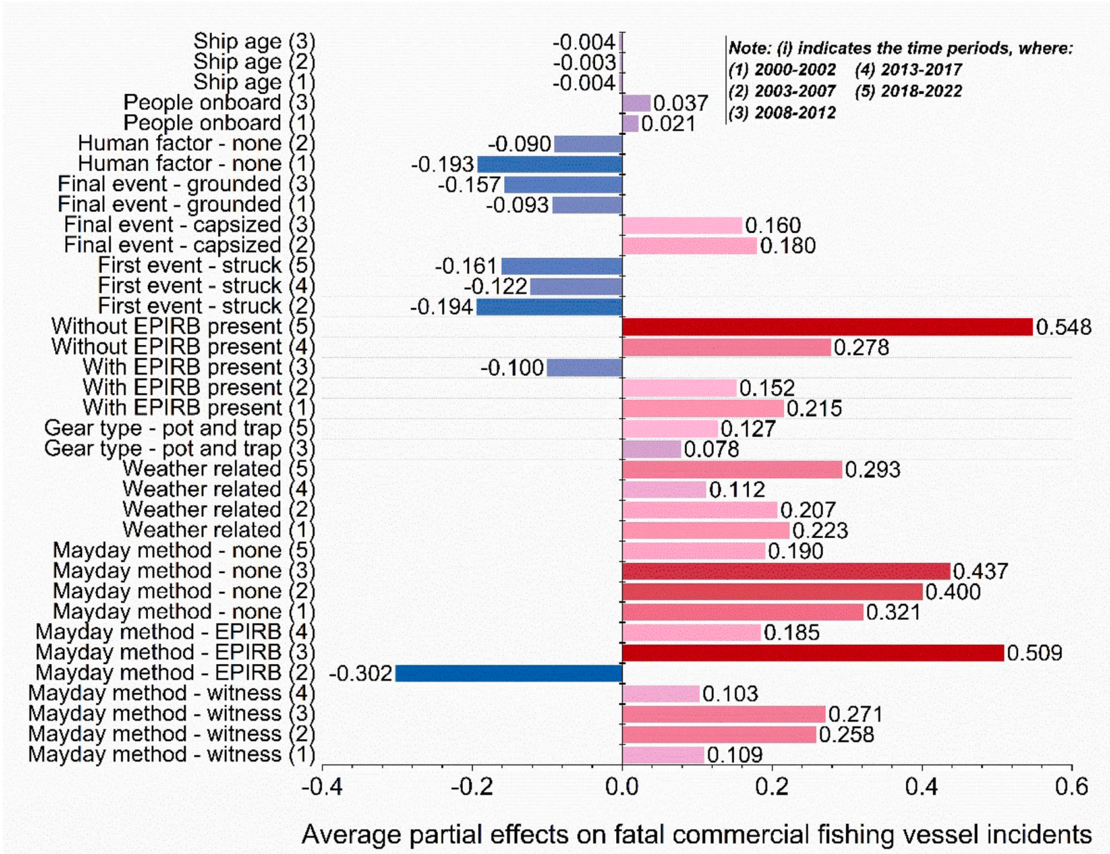


**Fig. 10.** APEs of explanatory factors with significant effects over two periods.

influential (e.g., weather related) due to enhanced detection, faster responses, and better rescue efficiency.

Second, regulatory and institutional changes in the fishing industry may have affected how risk factors manifest in different periods. For instance, around 2003, the U.S. Coast Guard and the Federal Communications Commission mandated a transition from legacy 121.5 MHz analog EPIRBs to more reliable 406 MHz digital systems, fundamentally altering distress alerting capabilities and compliance practices across the fleet [64]. These policy evolutions may account for shifts over time in the statistical significance and direction of certain variables, such as mayday communication methods or EPIRB presence.

Third, human and cognitive factors are likely to play important roles. Crew experience, safety awareness, and risk-taking tendencies can evolve with generational replacement, economic pressure, and workload intensity. Variations in these unobserved behavioral dimensions can introduce time-dependent heterogeneity in how environmental and technical conditions translate into fatal outcomes.

Fourth, macroeconomic and environmental contexts may underlie temporal shifts. Economic downturns or market competition can lead to intensified fishing efforts, extended operational hours, or cost cuttings in maintenance, which may temporarily elevate fatality risks. Likewise, climate-induced changes in weather patterns and fishing ground accessibility can modify exposure conditions and the effectiveness of safety measures.

Overall, these findings highlight that fatal commercial fishing vessel incidents are highly dynamic systems influenced by intertwined human, environmental, and institutional processes. Ignoring temporal instability and estimating a single static model over long-time spans would mask crucial structural changes and potentially mislead safety management strategies.

From a policy perspective, incorporating temporal instability into maritime safety analysis enables more adaptive and targeted interventions. Period-specific modeling can help identify when and under what conditions specific risk factors become most critical, such as in the examples of declining EPIRB effectiveness due to emergent risks under changing weather regimes. Regular model re-estimation using updated data can thus guide data-driven inspection prioritization, dynamic training programs, and the timely revision of safety regulations.

### 6.2. Random parameters

Several parameters were identified as random and normally distributed across the five time periods, indicating that the effects of certain explanatory variables on fatal commercial fishing vessel incidents vary across vessels and contexts. The presence of random parameters highlights unobserved heterogeneity in the behavioral, technical, and operational mechanisms influencing fatality risks, which cannot be fully captured by observed variables alone.

During the early periods (2000–2002 and 2003–2007), multiple random parameters were detected, suggesting substantial heterogeneity when safety technologies and operational practices were less standardized. In the 2000–2002 model, mayday method – radio and ship age were random parameters, reflecting considerable variation in the safety performance of vessels depending on communication equipment reliability, crew competence, and vessel condition. Similarly, in the 2003–2007 model, mayday method – EPIRB and fishery type – groundfish were identified as random, revealing that the reliability of EPIRB-based distress communication and the risk exposure of groundfish fisheries varied widely among vessels due to differing environmental and technical conditions.

In contrast, the later periods (2008–2022) exhibited fewer random parameters, indicating a reduction in overall heterogeneity as technological and regulatory systems matured. For 2008–2012, only *hull type – fiber glass* was random, which may be attributable to variations in hull construction quality, maintenance practices, and operational exposure. These factors are not explicitly captured in the available data but are known to vary considerably across fiberglass fishing vessels. In 2013–2017, *mayday method – EPIRB* remained random, but its variability became more conditional and context-specific (as discussed in Section 5.3). In 2018–2022, *number of responses – one* was identified as a random parameter, showing that even when response actions were rapid, their effectiveness in preventing fatalities varied significantly across vessels due to operational coordination, response capability, or incident severity.

### 6.3. Correlation among random parameters

In addition to individual random effects, significant correlations between random parameters were observed in the models for 2000–2002 and 2003–2007, providing further insight into the joint influence of unobserved mechanisms.

For 2000–2002, the CRPMHM revealed a strong positive correlation between *mayday method – radio* and *ship age*. This pattern does not imply a direct functional interaction between radio use and vessel aging, but more likely reflects shared unobserved attributes, such as differences in fleet organization, reporting practices, or equipment configurations, which simultaneously influence communication effectiveness and the operational impact of vessel age on fatality risk.

For 2003–2007, a similarly positive correlation was found between *mayday method – EPIRB* and *fishery type – groundfish*. This correlation does not imply that groundfish operations inherently derive greater safety benefits from EPIRB use, but rather may reflect shared unobserved operational or institutional characteristics. For example, certain groundfish fleets may operate in more standardized fishing grounds, follow more structured operating routines, or exhibit more consistent reporting practices. These latent attributes, which are not explicitly captured in the data, may jointly influence both the likelihood of EPIRB use and its associated safety effect.

The existence of correlated random parameters underscores that risk factors in fatal vessel incidents are not independent but interconnected through shared latent processes, such as safety culture, equipment reliability, or management practices. Ignoring these correlations would lead to biased variance estimates and overlook the co-dependency between technical and human safety mechanisms. The correlation structure thus provides an important complement to random-effect modeling, offering a more holistic understanding of how safety technologies and vessel characteristics interact to influence fatality risk.

### 6.4. Heterogeneity in means of random parameters

Beyond the presence of random and correlated random parameters, several models revealed heterogeneity in means, indicating that the average effects of random parameters vary systematically as a function of other observed variables. While random parameters represent unstructured heterogeneity arising from unobserved differences across vessels and incidents, heterogeneity in means captures structured heterogeneity by allowing the mean of a random parameter to vary with contextual factors such as environmental conditions, vessel characteristics, or human factors.

In the earliest period (2000–2002), the effect of *mayday method – radio* exhibited significant heterogeneity in means as a function of *human factor – none*. This pattern indicates that the estimated impact of radio-based distress communication varies systematically depending on whether human factors were involved during emergencies. The findings suggest that the role of radio communication is shaped by the broader operational context associated with human-related circumstances, which may influence response timeliness and distress handling processes.

For 2003–2007, heterogeneity in means was identified for the *mayday method – EPIRB* parameter, conditional on *weather-related* conditions and *ship age*. The interaction with weather conditions indicates that EPIRB distress signaling effectiveness varied markedly between fair and adverse weather scenarios. In stormy or high-sea conditions, even a well-functioning EPIRB might fail to prevent fatalities due to delayed signal transmission, damaged equipment, or rescue inaccessibility. The interaction with ship age further implies that the protective role of the EPIRB mayday diminishes for older vessels, which were generally less robust structurally and more vulnerable under stress. These findings highlight that the benefits of safety technologies like EPIRB are not uniform but contingent upon vessel condition and environmental stressors.

During the 2013–2017 period, *mayday method – EPIRB* again exhibited significant heterogeneity in means, this time conditioned by *first event – struck*. The positive interaction coefficient indicates that the effectiveness of EPIRB distress communication diminished in struck-type incidents. Struck events typically unfold rapidly, leaving little time for crew members to activate distress signals before the situation escalates. This finding reinforces the notion that technology-driven safety mechanisms are constrained by the physical and temporal dynamics of incident progression.

The recurring appearance of *mayday method – EPIRB* in heterogeneity structures across multiple periods underscores its evolving and context-dependent nature. While EPIRB systems represent an essential technological safeguard, their real-world effectiveness depends on timing, activation reliability, environmental interference, and crew readiness. Such systematic variations in the mean effect reflect the adaptive complexity of safety systems within dynamic maritime environments.

In summary, heterogeneity in means extends the explanatory power of the random-parameter framework by uncovering structured dependencies between behavioral, technical, and environmental factors. It reveals that the influence of key safety-related variables, particularly distress communication systems, cannot be generalized across all conditions but instead varies predictably with contextual circumstances. Incorporating heterogeneity in means thus provides a richer and more realistic representation of maritime risk processes, enabling more targeted safety interventions.

From a practical standpoint, these findings suggest that safety management strategies should move beyond technology deployment toward contextual optimization. The protective effect of EPIRB communication was found to weaken for older vessels and under adverse weather conditions, and targeted improvements are thus necessary to enhance its reliability in such contexts. For instance, regular functionality checks, simplified activation procedures, and enhanced automatic triggering systems could help mitigate the reduced effectiveness of EPIRBs in these high-risk scenarios. Likewise, integrating human-factor training with equipment maintenance can help address the interaction effects observed between communication reliability and operational error. Recognizing and responding to such structured heterogeneity is expected to strengthen the resilience of maritime safety systems and reduce fatality risks across diverse vessel operations.

### 6.5. Explanatory variables

#### 6.5.1. Environmental characteristics

Light conditions and weather consistently influence fatality risk in marine and fishing-vessel incidents. Several studies have shown that poor visibility and adverse weather substantially increase the likelihood of fatalities because they degrade situational awareness, hinder maneuverability, and delay search-and-rescue operations ([63,65]; Bye and Aalberge, 2018; [66]). In addition, the early-period model in this study (2003–2007) revealed marginally significant protective effects of daylight, consistent with findings that marine navigational accidents are often associated with low visibility [63,65,67]. This result probably arises because daytime operations permit better detection and faster emergency responses.

Interestingly, some studies have reported contradictory results. For instance, Wang et al. [23] found that the severity of accidents under good visibility conditions was 1.779 times higher than under poor visibility, whereas Weng and Li [21] suggested that both severe and minor accidents are more likely to occur in good visibility. This contradiction may be explained by the fact that ships tend to travel at higher speeds in good visibility, and watchkeepers on the bridge or nearby vessels may become less vigilant [23]. Consequently, potential hazards may be overlooked more easily under clear conditions. Therefore, the effect of light conditions probably varies depending on situational and behavioral factors. In this study, the light condition did not show significant effects during the other periods investigated.

Conversely, the variable “weather related” retained a positive and significant effect across nearly all periods, reinforcing earlier evidence that adverse weather conditions reduce a ship’s maneuvering capability and amplify casualty severity [63,66,68–70]. Such conditions can cause a range of vessel and equipment failures, including loss of stability (e.g., surf-riding, broaching-to, synchronous or parametric rolling), physical impacts (e.g., slamming or shipping seas), and mechanical stress (e.g., propeller racing or torque-induced engine strain) [71].

With advances in marine technology, many commercial routing systems now assist navigators by applying preset limits for wind or wave conditions to plot optimal routes and avoid the worst weather [72]. However, the observed persistence but varying magnitude of weather effects suggests that although vessel technology and crew training have gradually improved, weather-related operational risk has not been fully eliminated. For commercial fishing vessels, mariners should therefore identify and assess potentially hazardous conditions using modern weather-forecasting services. Moreover, adopting probabilistic and risk-based monitoring approaches would enable early intervention in hazardous situations and support timely responses to weather-related emergencies.

#### 6.5.2. Operating activities and fishery attributes

Vessel activity, fishery type, and gear type capture exposure patterns and operational hazards. Anchored vessels during 2000–2002 were associated with higher fatality probabilities, consistent with limited maneuverability and greater vulnerability to sudden environmental changes [73,74]. In the early periods, groundfish fisheries (e.g., halibut, pollock, sole, and black cod) and pelagic fisheries (e.g., salmon, sardine, and tuna) exhibited negative average partial effects on fatal incidents. In addition, Kincl et al. [75] found that groundfish fisheries experienced the highest number of incidents, though these mostly resulted in nonfatal injuries. In contrast, consistent with previous research [76], the positive effects of pot-and-trap gear in later years reflect mechanical entanglement and restricted-escape hazards identified in previous analyses of fishery incidents. Notably, vessel activity, fishery type, and gear type were significant in only a few periods, indicating strong temporal instability. This variability is expected, as operational activities and fishery attributes evolve over time alongside advances in vessel technology, the modernization of fleets, and changes in regulatory oversight.

#### 6.5.3. Vessel characteristics and equipment

Physical and technological attributes, such as vessel type, hull type, EPIRB presence, and ship age, govern both structural resilience and emergency response capability. Previous studies have demonstrated that hull integrity and equipment reliability are key latent factors contributing to casualty escalation [62]. The significant random effect observed for fiberglass hulls during 2008–2012 indicates substantial unobserved heterogeneity among vessels with this hull type. This heterogeneity likely reflects differences in construction characteristics, operating environments, or maintenance practices.

The shifting effect of EPIRB presence illustrates a classic activation-bias reversal: early devices were installed mainly on high-risk vessels and activated only during severe events, whereas widespread adoption and automatic triggering later transformed EPIRBs into a preventive asset. In addition, Hansen et al. [77] found that although EPIRBs have proven to be effective in practice, their influence on survival rates remains limited, highlighting the importance of complementary safety measures and crew training.

In this study, ship age showed stable negative effects through 2003–2017, paralleling findings that vessels that have been used for a long time are usually of high quality and have been well maintained [78]. However, other studies have reported contrasting results. For instance, Talley [79] and Tzannatos [80] found that ship age was positively associated with the probability of accidents, suggesting that deterioration and outdated systems might increase operational risk. Eliopoulou et al. [81] further observed that fishing vessels had uniformly low accident frequencies across age groups, suggesting that ship age does not strongly influence accident occurrence for this vessel type. This may be attributed to the operational structure of the fishing sector, where vessel masters are often also the owners, leading to greater familiarity with vessel handling and stronger incentives for maintenance and safe operation. Moreover, the effect of ship age was found to be random during 2000–2002 in this study.

Collectively, the influence of ship age is likely to vary across vessel types, operation environments, and other unobserved factors. Collectively, these results emphasize that safety equipment, maintenance practices, and regulatory modernization jointly shape the temporal dynamics of vessel-specific risk in commercial fishing operations.

#### 6.5.4. Human factors

Crew composition and behavior remain central determinants of incident outcomes [14,82]. The positive association between the number of people onboard and fatality probability in the early periods probably reflects increased exposure and operational interdependence. Fishing vessels with larger crews typically undertake more complex operations, such as multi-gear deployment or high-volume catches, which increase the potential for cascading hazards during emergencies [82]. Moreover, larger crews may also introduce greater coordination during emergencies, and variations in response organization or communication efficiency could influence the likelihood of successful evacuation once an incident occurs.

Consistent with many studies, the negative effect of *human factor – none* indicates that incidents involving human errors, such as navigational mistakes, fatigue, or communication lapses, tend to result in more severe outcomes [10,17,83]. However, other research has found that incidents resulting from unavoidable environmental conditions are more likely to have severe outcomes than those stemming from human factors [4,34]. In this study, both weather-related and human-factor variables exhibited significant associations with fatal fishing vessel incidents.

It is noted that the effects of *people onboard* and *human factor – none* became nonsignificant in the later periods. This reduction in significance may reflect evolving operational practices, improvements in crew training, or gradual strengthening of safety management approaches, rather than the disappearance of human influence in maritime incidents. This temporal moderation aligns with previous findings suggesting that recent improvements in fishermen’s training and growing awareness of safety culture have contributed to a gradual reduction in human-factor-related risks [14].

#### 6.5.5. Incident process

First and final events delineate the physical evolution of an incident and, consequently, its survivability. The consistently negative APEs for *first event – struck* in this study confirm that although such events are frequent, they are more associated with non-fatal outcomes than other first events [3,4], possibly because they typically allow quicker detection and rescue. In contrast, *final event – capsized* exhibited strong positive effects during 2003–2012, supporting prior evidence that capsizing leads to rapid loss of stability and increased immersion hazards [3,62]. *Final event – grounded* remained protective in multiple periods, aligning with global findings that grounding provides a more controllable endpoint with accessible rescue options, often resulting in no or only minor injuries [75].

In terms of temporal patterns within the incident process, *first event – struck* showed significant effects across multiple periods, whereas *final event – capsized* and *final event – grounded* exhibited significance mainly in earlier years. These temporal trends highlight how advancements in vessel design, emergency drills, and search-and-rescue coordination have likely modified the relative lethality of incident sequences over the past two decades.

#### 6.5.6. Emergency communication and response

Communication and response timing are pivotal determinants of survival. Throughout the study, *mayday method – none* maintained strong positive APEs, confirming that delayed or absent distress reporting greatly increases the likelihood of fatalities [84]. Interestingly, *mayday method – witness* also exhibited a consistently positive and significant effect across multiple periods. This does not imply that witness reporting increases fatality risk; rather, fatal incidents are more likely to be reported by external observers, reflecting a reporting pattern in which more severe or rapidly unfolding cases are detected by nearby vessels or shore-based observers. Such cases typically occur when onboard communication systems fail or when crew members are unable to transmit distress signals due to rapid or catastrophic events (e.g., explosions, capsizing, or sudden sinking).

In contrast, *radio mayday, EPIRB,* and *once response time* exhibited complex random effects on fatal commercial fishing vessel incidents, as discussed in earlier sections. Large vessels operating under the Global Maritime Distress and Safety System (GMDSS) can typically be rescued within a short time because their locations are automatically identified by satellite-based EPIRBs. Smaller vessels outside GMDSS coverage—which comprise the majority of the U.S. commercial fishing fleet—often lack mandatory EPIRBs and rely instead on VHF radios or mobile phones, which may be unreliable in offshore or adverse-weather conditions. Moreover, EPIRBs are expensive to purchase and maintain, and their bulky design limits their usability on small vessels [85].

#### 6.5.7. Limitations and future studies

This study is not without limitations. First, the analysis relies on incident data from the United States, which may limit the generalizability of the findings to other regulatory, institutional, and environmental contexts. Future research could incorporate commercial fishing incident datasets from multiple regions to examine potential spatial dependence and cross-regional heterogeneity, thereby providing a more comprehensive understanding of how fatal fishing vessel incidents evolve under different governance structures and operating environments.

Second, although the sample size in this study satisfies the “events per variable” rule [86], it remains relatively modest. Small samples may constrain the reliable estimation of complex model structures and limit statistical power, particularly when assessing heterogeneity and temporal instability. Future studies could leverage larger and more granular datasets, which are better suited to advanced random-parameter and temporal modeling techniques, thereby yielding more robust estimates and richer behavioral insights.

Third, the assessment of temporal instability in this study is subject to both data-driven and methodological constraints. The temporal segmentation is dictated by the predefined time periods in the NIOSH CFID, which vary in length across periods. Unequal temporal aggregation may influence the observed temporal patterns by smoothing short-term variability in longer periods while amplifying noise in shorter ones, thereby complicating strict cross-period comparisons. Moreover, the temporal instability assessment approach adopted in this study does not fully capture continuously evolving random-parameter distributions within a unified estimation framework and implicitly assumes stability in the underlying random-parameter structure. Future research could adopt partially constrained temporal instability assessment approaches, if feasible, to allow the entire random-parameter structure to evolve more flexibly and coherently across time periods.

Finally, future work may further enhance the analytical framework by integrating spatial dependence structures, injury severity levels, and vessel-level operational histories. Incorporating these dimensions would enable a more refined characterization of risk mechanisms and support more targeted and context-sensitive policy interventions for improving safety in the commercial fishing industry.

## 7. Conclusions

This study provides a holistic temporal analysis of fatal commercial fishing vessel incidents in the U.S. using a correlated random-parameter logit model with heterogeneity in means. By integrating advanced econometric modeling with 23 years of CFID data, the study identifies substantial temporal instability in the effects of contributory factors and highlights the importance of capturing unobserved heterogeneity and correlated risk structures in maritime safety research.

The temporal instability assessment, supported by both a global likelihood ratio test and 20 pairwise transferability tests, provides strong evidence that the relationships between covariates and fatality risk are not stable over time. Weather-related conditions and the absence of any mayday communication remain consistently associated with higher fatality risk across multiple periods, confirming the persistent vulnerability of vessels to environmental exposure and delayed emergency responses. In earlier years, capsizing events and human factors exert stronger influences, reflecting the heightened importance of vessel stability and crew performance before regulatory and technological improvements were introduced. In addition, the mayday method using an EPIRB exhibits substantial heterogeneity, appearing as a random parameter in several sub-periods. Its effect varies with ship age, weather conditions, and struck events, suggesting that operational context, activation timing, and vessel characteristics jointly determine the effectiveness of EPIRB-based communication. The correlated random parameters reveal that some risk factors (e.g., *mayday method – radio* and *ship age*) exhibit joint variation driven by shared unobserved characteristics, particularly in the earlier periods. This indicates that latent operational and technological conditions historically exerted a stronger combined influence on fatality risk.

These findings have important policy implications. Safety strategies that assume time-invariant risk relationships may misallocate resources or fail to address emerging hazards. Regulators and industry stakeholders should adopt adaptive and time-responsive measures that strengthen emergency communication, enhance preparedness for adverse weather, improve equipment maintenance, and reduce human-factor vulnerabilities.

## Funding

This research was supported by grants from the National Natural Science Foundation of China (Project No. 72,501,150), Zhejiang Provincial Natural Science Foundation of China (Grant No. LQN25E080011), Ningbo Natural Science Foundation (Grant No. 2024J440), Research Grants Council of the Hong Kong Special Administrative Region, China (Project No. T32–707/22-N), National “111″ Centre on Safety and Intelligent Operation of Sea Bridges (Project No. D21013) and the European Research Council (ERC) under the European Union’s Horizon 2020 research and innovation programme (Grant Agreement No. 864,724). In addition, Prof. S.C. Wong was supported by the Francis S Y Bong Professorship in Engineering. The funders had no role in the study design, data collection and processing, manuscript preparation, or decision to publish.

## CRediT authorship contribution statement

**Yun Ye:** Writing – original draft, Visualization, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Mingzheng Liu:** Writing – review & editing, Formal analysis. **Fanyu Meng:** Writing – review & editing, Methodology. **S.C. Wong:** Writing – review & editing, Funding acquisition. **Xiaowei Gao:** Writing – review & editing, Project administration, Methodology, Conceptualization. **Zaili Yang:** Writing – review & editing, Validation.

## Declaration of competing interest

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

## Appendix

**Table A1**
Descriptions of explanatory variables over five time periods from 2000 to 2022.

| Name | 2000–2002 | | 2003–2007 | | 2008–2012 | | 2013–2017 | | 2018–2022 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean/Per. | SD | Mean/Per. | SD | Mean/Per. | SD | Mean/Per. | SD | Mean/Per. | SD |
| **Light condition** | | | | | | | | | | |
| Daylight | 10.42 % | — | 12.73 % | — | 39.18 % | — | 45.10 % | — | 48.04 % | — |
| Night | 8.33 % | — | 9.55 % | — | 31.72 % | — | 31.47 % | — | 35.29 % | — |
| Twilight | 5.21 % | — | 5.45 % | — | 16.42 % | — | 19.23 % | — | 14.71 % | — |
| Unknown | 76.04 % | — | 72.27 % | — | 12.68 % | — | 4.20 % | — | 1.96 % | — |
| **Mayday method** | | | | | | | | | | |
| Radio | 34.90 % | — | 41.82 % | — | 48.51 % | — | 45.80 % | — | 54.90 % | — |
| Cell phone | 4.17 % | — | 7.27 % | — | 13.81 % | — | 11.19 % | — | 7.84 % | — |
| Witness | 17.19 % | — | 14.09 % | — | 13.81 % | — | 17.48 % | — | 9.80 % | — |
| EPIRB | 5.21 % | — | 10.45 % | — | 7.46 % | — | 7.34 % | — | 13.73 % | — |
| Other | 18.22 % | — | 8.64 % | — | 5.22 % | — | 5.60 % | — | 5.89 % | — |
| None | 20.31 % | — | 17.73 % | — | 11.19 % | — | 12.59 % | — | 7.84 % | — |
| **Weather related** | 29.17 % | — | 38.18 % | — | 24.25 % | — | 26.92 % | — | 32.35 % | — |
| **Number of responses** | | | | | | | | | | |
| None | 0.00 % | — | 0.00 % | — | 0.00 % | — | 0.35 % | — | 1.96 % | — |
| One | 0.00 % | — | 0.00 % | — | 0.00 % | — | 11.19 % | — | 49.02 % | — |
| Two or more | 0.00 % | — | 0.00 % | — | 0.00 % | — | 14.68 % | — | 40.20 % | — |
| Unknown | 100.00 % | — | 100.00 % | — | 100.00 % | — | 73.78 % | — | 8.82 % | — |
| **Vessel activity** | | | | | | | | | | |
| Fishing | 33.33 % | — | 34.55 % | — | 30.60 % | — | 26.57 % | — | 28.43 % | — |
| Transit inbound | 32.81 % | — | 38.18 % | — | 36.19 % | — | 27.97 % | — | 30.39 % | — |
| Transit outbound | 13.02 % | — | 15.45 % | — | 13.43 % | — | 19.23 % | — | 13.73 % | — |
| Anchored | 6.25 % | — | 2.73 % | — | 4.85 % | — | 5.24 % | — | 6.86 % | — |
| Moored | 2.08 % | — | 1.36 % | — | 3.73 % | — | 2.10 % | — | 2.94 % | — |
| Other | 12.51 % | — | 7.73 % | — | 11.20 % | — | 18.89 % | — | 17.65 % | — |
| **Vessel type** | | | | | | | | | | |
| Catcher | 86.98 % | — | 87.73 % | — | 84.70 % | — | 89.16 % | — | 90.20 % | — |
| Catcher and Processor | 1.04 % | — | 0.00 % | — | 0.75 % | — | 0.35 % | — | 0.00 % | — |
| Set net skiff/seine skiff | 3.13 % | — | 3.18 % | — | 3.73 % | — | 0.70 % | — | 1.96 % | — |
| Dive boat | 1.04 % | — | 0.91 % | — | 0.00 % | — | 0.70 % | — | 0.98 % | — |
| Tender | 4.69 % | — | 4.55 % | — | 3.36 % | — | 3.15 % | — | 2.94 % | — |
| Other | 3.12 % | — | 3.63 % | — | 7.46 % | — | 5.94 % | — | 3.92 % | — |
| **Fishery type** | | | | | | | | | | |
| Shellfish | 17.71 % | — | 23.18 % | — | 44.03 % | — | 52.10 % | — | 44.12 % | — |
| Groundfish | 18.75 % | — | 22.73 % | — | 19.40 % | — | 13.64 % | — | 19.61 % | — |
| Pelagic fish | 37.50 % | — | 40.45 % | — | 32.46 % | — | 30.77 % | — | 28.43 % | — |
| Other | 26.04 % | — | 13.64 % | — | 4.11 % | — | 3.49 % | — | 7.84 % | — |
| **Gear type** | | | | | | | | | | |
| Trawl | 13.02 % | — | 10.45 % | — | 25.37 % | — | 27.62 % | — | 33.33 % | — |
| Pot and trap | 12.50 % | — | 16.36 % | — | 21.27 % | — | 23.43 % | — | 16.67 % | — |
| Longline | 9.38 % | — | 12.27 % | — | 8.58 % | — | 8.04 % | — | 6.86 % | — |
| Drift gillnet/set gillnet | 15.63 % | — | 11.36 % | — | 9.33 % | — | 8.74 % | — | 4.90 % | — |
| Seine | 8.85 % | — | 12.73 % | — | 8.96 % | — | 4.90 % | — | 5.88 % | — |
| Other | 40.62 % | — | 36.83 % | — | 26.49 % | — | 27.27 % | — | 32.36 % | — |
| **EPIRB present** | | | | | | | | | | |
| With | 30.21 % | — | 42.73 % | — | 38.81 % | — | 46.15 % | — | 45.10 % | — |
| Without | 9.90 % | — | 6.82 % | — | 19.78 % | — | 8.04 % | — | 4.90 % | — |
| Unknown | 59.89 % | — | 50.45 % | — | 41.41 % | — | 45.81 % | — | 50.00 % | — |
| **First event** | | | | | | | | | | |
| Struck | 25.52 % | — | 34.09 % | — | 28.73 % | — | 32.87 % | — | 18.63 % | — |
| Fire/explosion | 18.22 % | — | 9.55 % | — | 11.94 % | — | 13.99 % | — | 18.63 % | — |
| Flooding | 25.52 % | — | 20.00 % | — | 24.25 % | — | 21.33 % | — | 25.49 % | — |
| Instability | 9.90 % | — | 15.45 % | — | 13.06 % | — | 8.39 % | — | 9.80 % | — |
| Function failure | 7.29 % | — | 8.64 % | — | 8.21 % | — | 11.54 % | — | 8.82 % | — |
| Collision | 9.90 % | — | 6.36 % | — | 8.58 % | — | 6.29 % | — | 8.82 % | — |
| Other | 3.65 % | — | 5.91 % | — | 5.23 % | — | 5.59 % | — | 9.81 % | — |

(*continued on next page*)

**Table A1** (*continued*)

| Name | 2000–2002 | | 2003–2007 | | 2008–2012 | | 2013–2017 | | 2018–2022 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean/Per. | SD | Mean/Per. | SD | Mean/Per. | SD | Mean/Per. | SD | Mean/Per. | SD |
| **Final event** | | | | | | | | | | |
| Burned | 2.60 % | — | 3.64 % | — | 4.10 % | — | 4.55 % | — | 6.86 % | — |
| Capsized | 9.38 % | — | 12.27 % | — | 9.32 % | — | 10.84 % | — | 10.78 % | — |
| Grounded | 18.75 % | — | 16.36 % | — | 16.42 % | — | 21.68 % | — | 3.92 % | — |
| Sinking | 67.19 % | — | 66.82 % | — | 68.66 % | — | 58.74 % | — | 75.49 % | — |
| Other | 2.08 % | — | 0.91 % | — | 1.50 % | — | 4.20 % | — | 2.95 % | — |
| **Human factor** | | | | | | | | | | |
| Navigational error | 10.94 % | — | 8.64 % | — | 14.55 % | — | 10.14 % | — | 8.82 % | — |
| Asleep and fatigue | 5.73 % | — | 13.18 % | — | 5.97 % | — | 9.09 % | — | 8.82 % | — |
| None | 65.63 % | — | 60.45 % | — | 46.27 % | — | 50.70 % | — | 47.06 % | — |
| Other | 4.17 % | — | 5.00 % | — | 6.72 % | — | 10.49 % | — | 13.73 % | — |
| Unknown | 13.53 % | — | 12.73 % | — | 26.49 % | — | 19.58 % | — | 21.57 % | — |
| **Hull type** | | | | | | | | | | |
| Fiber glass | 34.90 % | — | 27.73 % | — | 40.67 % | — | 44.41 % | — | 35.29 % | — |
| Steel | 18.75 % | — | 30.91 % | — | 21.64 % | — | 21.68 % | — | 29.41 % | — |
| Wood | 28.13 % | — | 29.55 % | — | 27.99 % | — | 24.83 % | — | 23.53 % | — |
| Other | 18.22 % | — | 11.81 % | — | 9.70 % | — | 9.08 % | — | 11.77 % | — |
| **USCG region** | 84.38 % | — | 81.36 % | — | 51.87 % | — | 46.15 % | — | 46.08 % | — |
| **People on board** | 2.69 | 2.27 | 2.83 | 1.40 | 2.96 | 3.14 | 2.88 | 3.03 | 2.98 | 1.45 |
| **Ship age** | 31.62 | 18.80 | 34.41 | 17.69 | 35.07 | 17.56 | 37.03 | 14.48 | 42.93 | 17.03 |

Per. = percentage; SD = standard deviation.

## Data availability

Data will be made available on request.

## References


[1] National Marine Fisheries Service. Fisheries economics of the United States, 2022. Retrieved from: https://www.unalaska.gov/sites/default/files/fileattachments/City%20Manager%26%23039%3Bs%20Office/page/927/fisheries_economics_of_the_united_states_2022.pdf; 2024.
[2] National Institute for Occupational Safety and Health. Commercial fishing safety in the United States. Retrieved from: https://www.cdc.gov/niosh/fishing/data-research/regional-summaries/index.html; 2025.
[3] Jin D. The determinants of fishing vessel accident severity. Accid Anal Prev 2014;66:1–7.
[4] Jin D, Kite-Powell H, Talley W. The safety of commercial fishing: determinants of vessel total losses and injuries. J Saf Res 2001;32(2):209–28.
[5] Jin D, Kite-Powell HL, Thunberg E, Solow AR, Talley WK. A model of fishing vessel accident probability. J Saf Res 2002;33(4):497–510.
[6] Jin D, Thunberg E. An analysis of fishing vessel accidents in fishing areas off the northeastern United States. Saf Sci 2005;43(8):523–40.
[7] Lincoln JM, Lucas DL. Occupational fatalities in the United States commercial fishing industry, 2000–2009. J Agromed 2010;15(4):343–50.
[8] Lucas DL, Case SL. Work-related mortality in the US fishing industry during 2000-2014: new findings based on improved workforce exposure estimates. Am J Ind Med 2018;61(1):21–31.
[9] Wang J, Pillay A, Kwon YS, Wall AD, Loughran CG. An analysis of fishing vessel accidents. Accid Anal Prev 2005;37(6):1019–24.
[10] Choiron MA, Setyarini PH, Nurwahyudy A. Fishing vessel safety in Indonesia: a study of accident characteristics and prevention strategies. Int J Saf Secur Eng 2024;14(2):499–511.
[11] Xu T, Liu X, Zhang Z, Li Y. Review of casualties and losses of UK fishing vessels from 2013 to 2020. Int J Occup Saf Ergon 2024;30(1):129–35.
[12] Uğurlu F, Yıldız S, Boran M, Uğurlu Ö, Wang J. Analysis of fishing vessel accidents with Bayesian network and Chi-square methods. Ocean Eng 2020;198:106956.
[13] Roberts SE, Jaremin B, Marlow PB. Human and fishing vessel losses in sea accidents in the UK fishing industry from 1948 to 2008. Int Marit Health 2010;62(3):143–53.
[14] Lazakis I, Kurt RE, Turan O. Contribution of human factors to fishing vessel accidents and near misses in the UK. J Shipp Ocean Eng 2014;4:245–61.
[15] Kim H, Koo K, Lim H, Kwon S, Lee Y. Analysis of fishing vessel accidents and suggestions for safety policy in South Korea from 2018 to 2022. Sustainability 2024;16(9):3537.
[16] Rasmussen HB, Ahsan D. Injuries and fatalities in Danish commercial fishing fleet in 1998–2016. Safety 2018;4(2):13.
[17] Wang F, Du W, Feng H, Ye Y, Grifoll M, Liu G, Zheng P. Identification of risk influential factors for fishing vessel accidents using claims data from fishery mutual insurance association. Sustainability 2023;15(18):13427.
[18] Zhou K, Xing W, Wang J, Li H, Yang Z. A data-driven risk model for maritime casualty analysis: a global perspective. Reliab Eng Syst Saf 2024;244:109925.
[19] ... & Cao Y, Iulia M, Majumdar A, Feng Y, Xin X, Wang X, Yang Z. Investigation of the risk influential factors of maritime accidents: a novel topology and robustness analytical framework. Reliab Eng Syst Saf 2025;254:110636.
[20] Jin L, Li P, Wang Y, Yang Z. Risk analysis of Arctic navigation using text mining (TM) and improved association rule mining (ARM) methods. Reg Stud Mar Sci 2025;81:103990.
[21] Weng J, Li G. Exploring shipping accident contributory factors using association rules. J Transp Saf Secur 2019;11(1):36–57.
[22] Cao W, Wang X, Feng Y, Zhou J, Yang Z. Improving maritime accident severity prediction accuracy: a holistic machine learning framework with data balancing and explainability techniques. Reliab Eng Syst Saf 2026;266:111648.
[23] Wang H, Liu Z, Wang X, Graham T, Wang J. An analysis of factors affecting the severity of marine accidents. Reliab Eng Syst Saf 2021;210:107513.
[24] Wang H, Liu Z, Wang X, Huang D, Cao L, Wang J. Analysis of the injury-severity outcomes of maritime accidents using a zero-inflated ordered probit model. Ocean Eng 2022;258:111796.
[25] Weng J, Ge YE, Han H. Evaluation of shipping accident casualties using zero-inflated negative binomial regression technique. J Navig 2016;69(2):433–48.
[26] Chen Z, Xu W, Qu Y. Investigating factors of crash rates for freeways: a correlated random parameters Tobit model with heterogeneity in means. J Transp Eng A: Syst 2022;148(2):04021116.
[27] Mannering FL, Shankar V, Bhat CR. Unobserved heterogeneity and the statistical analysis of highway accident data. Anal Methods Accid Res 2016;11:1–16.
[28] Ahmed SS, Cohen J, Anastasopoulos PC. A correlated random parameters with heterogeneity in means approach of deer–vehicle collisions and resulting injury-severities. Anal Methods Accid Res 2021;30:100160.
[29] Alrejjal A, Farid A, Ksaibati K. A correlated random parameters approach to investigate large truck rollover crashes on mountainous interstates. Accid Anal Prev 2021;159:106233.
[30] Ye Y, Wong SC, Li YC, Choi KM. Crossing behaviors of drunk pedestrians unfamiliar with local traffic rules. Saf Sci 2023;157:105924.
[31] Weng J, Yang D, Du G. Generalized F distribution model with random parameters for estimating property damage cost in maritime accidents. Marit Policy Manag 2018;45(8):963–78.
[32] Behnood A, Mannering F. The effect of passengers on driver-injury severities in single-vehicle crashes: a random parameters heterogeneity-in-means approach. Anal Methods Accid Res 2017;14:41–53.
[33] Se C, Champahom T, Jomnonkwao S, Karoonsoontawong A, Ratanavaraha V. Temporal stability of factors influencing driver-injury severities in single-vehicle crashes: a correlated random parameters with heterogeneity in means and variances approach. Anal Methods Accid Res 2021;32:100179.
[34] Ye Y, Zheng P, Wang Q, Wong SC, Xu P. Modeling economic loss associated with fishing vessel accidents: a Bayesian random-parameter generalized beta of the second kind model with heterogeneity in means. Anal Methods Accid Res 2025;46:100384.
[35] Ye Y, Zheng P, Xu P, Ren Q, Yan R, Gao X. Varying effects of risk factors on economic losses from fishing vessel accidents: a Bayesian random-parameter quantile regression with heterogeneity in means. Reliab Eng Syst Saf 2026;266:111690.
[36] Adanu EK, Dzinyela R, Jones S. Analysis of crash severity factors under different airbag deployment status using correlated random parameters logit with heterogeneity in means. Next Res 2024;1(2):100039.
[37] Fountas G, Anastasopoulos PC. Analysis of accident injury-severity outcomes: the zero-inflated hierarchical ordered probit model with correlated disturbances. Anal Methods Accid Res 2018;20:30–45.
[38] Graham BS, Powell JL. Identification and estimation of average partial effects in “irregular” correlated random coefficient panel data models. Econometrica 2012;80(5):2105–52.

[39] Hou Q, Huo X, Leng J. A correlated random parameters tobit model to analyze the safety effects and temporal instability of factors affecting crash rates. Accid Anal Prev 2020;134:105326.
[40] Meng F, Sze NN, Song C, Chen T, Zeng Y. Temporal instability of truck volume composition on non-truck-involved crash severity using uncorrelated and correlated grouped random parameters binary logit models with space–time variations. Anal Methods Accid Res 2021;31:100168.
[41] Saeed TU, Hall T, Baroud H, Volovski MJ. Analyzing road crash frequencies with uncorrelated and correlated random-parameters count models: an empirical assessment of multilane highways. Anal Methods Accid Res 2019;23:100101.
[42] Alnawmasi N, Mannering F. A temporal assessment of distracted driving injury severities using alternate unobserved-heterogeneity modeling approaches. Anal Methods Accid Res 2022;34:100216.
[43] Jafari M, Starewich M, Das S, Barua S, Tamakloe R. Temporal stability analysis of crash injury severity in school zones: a mixed logit modeling approach. IATSS Res 2025;49(4):528–43.
[44] Mannering F. Temporal instability and the analysis of highway accident data. Anal Methods Accid Res 2018;17:1–13.
[45] Abdulrazaq MA, Fan WD. Seasonal instability indeterminants of vulnerable road user crashes: a partially temporally constrained modeling approach. Accid Anal Prev 2026;224:108277.
[46] Alnawmasi N, Mannering F. An analysis of day and night bicyclist injury severities in vehicle/bicycle crashes: a comparison of unconstrained and partially constrained temporal modeling approaches. Anal Methods Accid Res 2023;40: 100301.
[47] Wei S, Yang H, Li Y, Xie M, Wang Y. Investigating the impact of temporal instability in smart roadway retrofitting on terrain-related crash injury severity. Accid Anal Prev 2024;207:107757.
[48] Li H, Jiao H, Chen ZS, Lam JSL, Yang Z. COVID crisis-aware maritime risk assessment: a Bayesian network analysis. Reliab Eng Syst Saf 2025:111783.
[49] National Institute for Occupational Safety and Health. Commercial Fishing Incident Database. Retrieved from: https://www.data-liberation-project.org/datasets/niosh-commercial-fishing-incident-database; 2024.
[50] Chalkou K, Steyerberg E, Egger M, Manca A, Pellegrini F, Salanti G. A two-stage prediction model for heterogeneous effects of treatments. Stat Med 2021;40(20): 4362–75.
[51] ... & Goodacre S, Thomas B, Sutton L, Burnsall M, Lee E, Bradburn M, Walter D. Derivation and validation of a clinical severity score for acutely ill adults with suspected COVID-19: the PRIEST observational cohort study. PloS One 2021;16(1): e0245840.
[52] Heymans MW, Twisk JW. Handling missing data in clinical research. J Clin Epidemiol 2022;151:185–8.
[53] ... & Ottenhoff MC, Ramos LA, Potters W, Janssen ML, Hubers D, Hu S, Beudel M. Predicting mortality of individual patients with COVID-19: a multicentre Dutch cohort. BMJ Open 2021;11(7):e047347.
[54] Bonneville EF, Schetelig J, Putter H, de Wreede LC. Handling missing covariate data in clinical studies in haematology. Best Pract Res Clin Haematol 2023;36(2): 101477.
[55] Tay JK, Narasimhan B, Hastie T. Elastic net regularization paths for all generalized linear models. J Stat Softw 2023;106:1–31.
[56] Zou H, Hastie T. Regularization and variable selection via the elastic net. J R Stat Soc B: Stat Methodol 2005;67(2):301–20.
[57] Washington S, Karlaftis MG, Mannering F, Anastasopoulos P. Statistical and econometric methods for transportation data analysis. Chapman and Hall/CRC; 2020.
[58] Bhat CR. Simulation estimation of mixed discrete choice models using randomized and scrambled Halton sequences. Transp Res B: Methodol 2003;37(9):837–55.
[59] Dzinyela R, Alnawmasi N, Adanu EK, Dadashova B, Lord D, Mannering F. A multi-year statistical analysis of driver injury severities in single-vehicle freeway crashes with and without airbags deployed. Anal Methods Accid Res 2024;41:100317.
[60] Zubaidi H, Obaid I, Alnedawi A, Das S, Haque MM. Temporal instability assessment of injury severities of motor vehicle drivers at give-way controlled unsignalized intersections: a random parameters approach with heterogeneity in means and variances. Accid Anal Prev 2021;156:106151.
[61] Wisutwattanasak P, Jomnonkwao S, Se C, Champahom T, Ratanavaraha V. Correlated random parameters model with heterogeneity in means for analysis of factors affecting the perceived value of road accidents and travel time. Accid Anal Prev 2023;183:106992.
[62] Pilatis AN, Pagonis DN, Serris M, Peppa S, Kaltsas G. A statistical analysis of ship accidents (1990–2020) focusing on collision, grounding, hull failure, and resulting hull damage. J Mar Sci Eng 2024;12(1):122.
[63] Weng J, Yang D. Investigation of shipping accident injury severity and mortality. Accid Anal Prev 2015;76:92–101.
[64] National Oceanic and Atmospheric Administration. Termination of 121.5/243 MHz Satellite Alerting. Retrieved from: https://www.federalregister.gov/documents/2001/07/02/01-16575/termination-of-1215243-mhz-satellite-alerting?utm_source=chatgpt.com; 2001.
[65] Chauvin C, Lardjane S, Morel G, Clostermann JP, Langard B. Human and organisational factors in maritime accidents: analysis of collisions at sea using the HFACS. Accid Anal Prev 2013;59:26–37.
[66] Ventikos NP, Papanikolaou AD, Louzis K, Koimtzoglou AJOE. Statistical analysis and critical review of navigational accidents in adverse weather conditions. Ocean Eng 2018;163:502–17.
[67] Bye RJ, Aalberg AL. Maritime navigation accidents and risk indicators: an exploratory statistical analysis using AIS data and accident reports. Reliab Eng Syst Saf 2018;176:174–86.
[68] Rawson A, Brito M, Sabeur Z, Tran-Thanh L. A machine learning approach for monitoring ship safety in extreme weather events. Saf Sci 2021;141:105336.
[69] Rezaee S, Pelot R, Ghasemi A. The effect of extreme weather conditions on commercial fishing activities and vessel incidents in Atlantic Canada. Ocean Coast Manag 2016;130:115–27.
[70] Wu Y, Pelot RP, Hilliard C. The influence of weather conditions on the relative incident rate of fishing vessels. Risk Anal 2009;29(7):985–99.
[71] International Maritime Organization. MSC.1/Circ. 1228 Revised guidance to the Master for avoiding dangerous situations in adverse weather and sea conditions. Retrieved from, https://wwwcdn.imo.org/localresources/en/OurWork/Safety/Documents/Stability/MSC.1-CIRC.1228.pdf; 2007.
[72] StormGeo. Weather routing & voyage optimization. Retrieved from: https://stormgeo.com/shipping/weather-routing-and-voyage-optimization; 2025.
[73] Gao X, Makino H. Analysis of anchoring ships around coastal industrial complex in a natural disaster. J Loss Prev Process Ind 2017;50:355–63.
[74] Gunnu GR, Moan T. Stability assessment of anchor handling vessels during operations. J Mar Sci Technol 2018;23(2):201–27.
[75] Kincl L, Doza S, Nahorniak J, Case S, Vaughan A, Bovbjerg V. Commercial fishing fatalities and injuries described by linked vessel incidents. J Agromed 2023;28(4): 881–9.
[76] Lincoln JE, Lucas D. Commercial Fishing Fatalities – California, Oregon, and Washington, 2000–2006. Wkly Rep: Morb Mortal Wkly Rep (MMWR) 2008;57(16). https://stacks.cdc.gov/view/cdc/183049.
[77] Hansen HL, Jepsen JR, Hermansen K. Factors influencing survival in case of shipwreck and other maritime disasters in the Danish merchant fleet since 1970. Saf Sci 2012;50(7):1589–93.
[78] Li KX, Yin J, Fan L. Ship safety index. Transp Res A: Policy Pract 2014;66:75–87.
[79] Talley W. Vessel damage severity of tanker accidents. Logist Transp Rev 1995;31 (3):191–208.
[80] Tzannatos E. Human element and accidents in Greek shipping. J Navig 2010;63(1): 119–27.
[81] Eliopoulou E, Papanikolaou A, Voulgarellis M. Statistical analysis of ship accidents and review of safety level. Saf Sci 2016;85:282–92.
[82] Obeng F, Domeh V, Khan F, Bose N, Sanli E. Analyzing operational risk for small fishing vessels considering crew effectiveness. Ocean Eng 2022;249:110512.
[83] Uğurlu Ö, Erol S, Başar E. The analysis of life safety and economic loss in marine accidents occurring in the Turkish Straits. Marit Policy Manag 2016;43(3):356–70.
[84] Boshier R. Theoretical perspectives on learning for prevention of fishing vessel accidents. Can J Study Adult Educ 2000;14(2):49–66.
[85] Kim JJ, Hong CH, Kim DJ, Lee BB, Kim JD, Ko KN. The device for generation the distress signal and monitoring system for a Survivor based on WSN. In: 2010 International Conference on Electronics and Information Engineering. 1. IEEE; 2010. V1–81.
[86] Peduzzi P, Concato J, Kemper E, Holford TR, Feinstein AR. A simulation study of the number of events per variable in logistic regression analysis. J Clin Epidemiol 1996;49(12):1373–9.