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Analysis of the injury-severity outcomes of maritime accidents using a zero-inflated ordered probit model

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ABSTRACT

This study provides an empirical analysis of the injury severity outcomes of maritime accidents by exploring the influential factors for two underlying injury severity states: the injury-free state and the injury-prone state. The former may reflect the generation mechanism of accidents with limited potential to result in injury outcomes, whereas, the latter may represent injury severity when the accident falls into the injury-prone category. To account for the possible presence of these two underlying regimes, a zero-inflated ordered probit (ZIOP) model is employed using injury-severity data extracted from 1,128 maritime accident investigation reports between 2000 and 2019. The results indicate that on one hand, capsizing/sinking, hull/machinery damage and other accident type, adverse sea state, poor education background and short period of holding the present rank are more likely to be injury-prone. On the other hand, gross tonnage and water depth, distance from the coast, flag state of convenience, and accident type impact the likelihood of severe injuries if the accident is in the injury-prone category. The marginal effect analysis highlights some interesting effects caused by sea state, ship manning and gross tonnage, as well as accident type and location. The results of Akaike's information criteria (AIC), Bayesian information criteria (BIC) and Vuong's test show that the ZIOP model outperforms the traditional ordered probit model and can serve as an alternative to study the injury severity of maritime accidents.

1. Introduction

Considering that over 80% of global trade by volume and more than 70% by value is handled by shipping (Huang et al., 2021; UNCTAD, 2021), the safety of shipping activities is critical to the global economy (Puisa, 2018; Tian et al., 2020; Wang et al., 2022b). However, maritime accidents with serious consequences still occur from time to time (Fang et al., 2022). According to the report of Allianz Global Corporate & Specialty (AGCS, 2021), 49 total shipping losses of over 100 GT were reported in 2020. In addition to the large number of total losses, the number of injuries and fatalities in maritime accidents also stays at a high level (Callesen et al., 2021). The 2,837 maritime accidents and incidents reported by the EU Member States to the European Maritime Safety Agency (EMSA, 2021) in 2020 resulted in 38 fatalities and 675 injuries. A total of 196 deaths or missing were also reported in 138 water traffic accidents that occurred in China waterways in 2020 (MOT, 2021).

Therefore, a fully understanding of the determinants of the severity of maritime accidents is of great importance for the avoidance or reduction of maritime accident consequences. A number of studies (Çakır et al., 2021; Callesen et al., 2021; Puisa, 2021; Wang et al., 2021, 2022a; Wang and Yang, 2018; Zaccone and Martelli, 2020) have been conducted to investigate the causal factors that influence the results of accident severity, based on a large data set of maritime accidents occurring over a specific period of time. It was found in these studies that accidents with no-injury outcomes were widely observed in accident data sets. However, the high proportion of no-injury outcomes does not mean an improvement in maritime traffic safety (Kimera and Nangolo, 2022). A portion of the zero-injury observations may relate to very small accidents where specific conditions and contributing factors are unlikely to result in injury-involved outcomes. In this context, the mechanism of

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no-injury accidents and that of injury-involved accidents, should be considered simultaneously when identifying the determinants of the injury severity of maritime accidents (Christensen et al., 2022).

Several statistical methods, such as the zero-inflated Poisson (ZIP) model (Wang et al., 2003), the zero-inflated negative binomial (ZINB) model (Weng et al., 2018) and the tobit model (Hou et al., 2020), have been developed to accommodate the possibility of excessive amount of zero injury observations in accident datasets. These models mainly explain the existence of injury-free and injury-prone states based on accident frequency and accident incidence analysis, respectively. However, within the context of injury-severity study, the possibility of these two distinct states has not been fully explored at a sufficiently disaggregated level. To account for the possible presence of these two underlying regimes in maritime accidents, a ZIOP model is employed to identify the factors that influence the injury severity of maritime accidents by estimating both binary probit and ordered probit models simultaneously. To test the statistical advantages of the proposed approach, a traditional ordered probit model is also built and the results of the two models are compared.

2. Literature review

The severity of maritime accidents is generally expressed by a discrete set of categories describing property loss, casualties and environmental pollution. In terms of injury severity alone, these categories include no injury, minor injury, incapacitating injury and fatality. In recent years, a number of studies have been conducted to investigate the mechanism of maritime accidents, and to evaluate the influence of risk factors on the severity of maritime accidents. A series of statistical models have been developed, which can be broadly divided into nonparametric models (Fan et al., 2020a; Uğurlu et al., 2018) and regression models (Montewka et al., 2012, 2022).

2.1. Nonparametric models

Nonparametric models are widely used in maritime accident studies because of their excellent ability of exploring the most significant influencing factors and achieving impressive goodness-of-fit. Afenyo et al. (2017) proposed a methodology for the analysis of Arctic shipping accidents using Bayesian networks and identified the most significant contributing factors for various consequences. Bayesian networks were also employed by Wang and Yang (2018) and Fan et al. (2020b) to develop a risk analysis method for the analysis of the severity of water traffic accidents and a prevention strategy for maritime accidents, respectively. Ung (2018, 2019) developed a logical safety structure of oil tanker accidents based on fault tree analysis to evaluate the contribution of human errors to the grounding and collision accidents of oil tankers. Chen et al. (2019) developed an improved entropy weight-TOPSIS model to identify the influencing factors of total shipping loss accidents. Jin et al. (2019) evaluated the probability of oil tanker accidents by four machine learning methods, and proposed a risk assessment system which is jointly measured by the probabilities and consequences of accidents. Uğurlu et al. (2020) estimated the occurrence of fishing vessel accidents under different conditions using Bayesian networks and chi-square methods. Cakir et al. (2021) analysed 1,468 cases of ship-involved accidents to predict the severity of oil spills in possible ship accidents by a combined model of decision tree and data-driven Bayesian networks. Yildiz et al. (2021) applied the modified Human Factor Analysis and Classification System for Passenger Vessel collisions (HFACS-PV) to identify human and organizational factors influencing contact, grounding and sinking accidents.

2.2. Regression models

Although nonparametric models are well known for mining determinants of accident severity or improving the goodness-of-fit, these models are difficult to account for the quantitative effects of all variables. In this context, many researchers turn to the use of regression models to study the severity of maritime accidents. These regression models used can be categorised into unordered-response models and ordered-response models according to the ordering of response considered.

2.2.1. Unordered-response models

The first category of regression models is known as unordered-response models, such as a binary logit model, a multinomial logit model, and a probit model. The natural ordering of dependent variables is not considered in these models. In the study of Jin et al. (2002) and Jin and Thunberg (2005), the fishing vessel accident probability for fishing areas off the North-eastern United States was modelled using a logit regression method. Knapp et al. (2011) analysed a dataset of 3.2 million observations from 20,729 individual vessels in the North Atlantic and Arctic regions from 1979 to 2007, to measure the effect of significant wave height and wind strength on the probability of casualty by binary logistic regression. Heij and Knapp (2015) applied logit models to analyse the effect of oceanographic conditions like wind strength and wave height on the risk of shipping incidents. Bye and Aalberg, 2018 conducted a statistical analysis of maritime accident data and AIS data in Norwegian waters, and investigated conditions that are associated with groundings and collisions using a multivariate logistic regression model. In order to find out the causes of drowning and high risk of incidents at sea, Pitman et al. (2019) applied a Poisson model to analyse 6 years' rescue data of the Royal National Lifeboat Institution.

In terms of injury severity analysis, Jin et al. (2001) estimated the total losses and crew injuries in commercial fishing vessel accidents using probit and negative binomial regression methods. The results indicated that the severity of crew injuries in fishing vessels was directly proportional to the loss of stability and sinking of the vessel. Talley et al. (2006) analysed the determinants for the total loss, injuries and deaths/missing in passenger vessel accidents using tobit, negative binomial and Poisson regression techniques. Yip (2008) applied the negative binomial regression technique to identify the determinants of the injuries and casualties caused by ship accidents in Hong Kong waters. Talley (2009) used a probit regression model to investigate the determinants that affect the probability of non-accident injuries to persons onboard a ship of a given shipping line.

2.2.2. Ordered-response models

Another category of regression models in accident severity studies is known as ordered-response models, which treat accident severity as an ordered dependent variable. Ordered logistic models and ordered probit models are the mostly utilized categories of ordered-response models in previous studies. Chin and Debnath (2009) derived an ordered probit regression model to study the perceived collision risks, and calibrated the regression model by comparing the results with the risks perceived by Singapore port pilots. Wang et al. (2021) developed an ordered logistic regression model to investigate the relationship between the influencing factors and the severity of maritime accidents based on the data extracted from maritime accident investigation reports in the period of 2010–2019. In terms of injury severity analysis, Talley et al. (2008) investigated determinants of the injury severities of accidents of three types of cruise vessels utilizing tobit regression and ordered probit approaches. Jin (2014) developed an ordered probit model to estimate the severity of crew injuries in fishing vessel accidents, and the results suggested that crew injury severity was positively related to the loss of vessel stability and sinking. Yip et al. (2015) investigated determinants of passenger vessel accident injuries using Poisson regression and analysed the relationship between passenger injuries and crew injuries.

However, it is worth noting that there may be no fatalities or injuries in many maritime accidents, and the methods mentioned above are not suitable to accommodate the possibility of an excessive amount of zero observations in accident datasets. Therefore, ordered-response models have been improved by many researchers from different perspectives to solve this problem. Weng and Yang (2015) predicted the probability of fatal shipping accidents and corresponding mortalities using a zero-truncated binomial regression model. The results indicate that the zero-truncated binomial regression model was a better fit for solving the problem than conventional Poisson and negative binomial models. Weng et al. (2018) developed a ZINB model based on the maximum likelihood regression tree to predict the mortality of shipping accidents and examine the factors influencing the loss of human life in shipping accidents. Chang and Park (2019) estimated the impact of vessel speed reduction on vessel damages and casualties by ZINB regression and panel negative binomial regression.

Past research (Jiang et al., 2013) in statistical modelling of accident data has shown that the generation mechanism underpinning the injury-free and injury-prone accidents may differ. However, the above zero-inflated models seldom consider the possibility that the zeros can arise from two distinct sources. A ZIOP model, developed by Harris and Zhao (2007), uses a mixture distribution for the non-injury category, where the proportion of zeros that come from different sources may be controlled by one group of explanatory variables and the effects of explanatory variables are allowed to vary across response classes. The model allows one set of parameter coefficients for the first category while all more severe categories share a common set of coefficients. The advantage is that the mixture form ensures that the probabilities are strictly positive so that the model is logically consistent. Moreover, the model is computationally easier to implement and simpler to interpret due to fewer parameters as it is improved upon the standard ordered probit formulation.

Inspired by these advantages, the ZIOP model was adopted to study the effect of factors on injury severity in maritime accidents. Although adoption of this approach may be justified by the fact that this mixture model improves the resulting fit, the researchers attempt to rationalize this approach by claiming that the large proportion of the zeros may come from two distinct populations. The first population is the group of injury-free accidents, which are defined as accidents or incidents that cannot result in an injury. Although this is an artificial construction, it might be hypothesized that these would be oil spill accidents or mechanical failures that may not result in any type of reportable injury. The second population is the group of accidents causing harm to seafarers which are referred to as injury-prone accidents. Factors such as accident type, ship size and sea state may be associated with injury severity. By explicitly considering both populations in the model, it will produce a superior model fit and less bias in the analysis of accidents and their influencing factors.

3. Methodology

3.1. ZIOP model

The ZIOP model can be considered as a mixture of a binary probit regression model and an ordered probit model. Binary probit regression is used to determine whether the accident is injury-free or injury-prone, while ordered probit regression is used to determine the severity of injury-prone accidents through the ordered probit mechanism which is described by Cameron and Trivedi (1998). The overall structure of the ZIOP is sketched in Fig. 1.

The parameters in these two parts are estimated simultaneously in a ZIOP model. Assume that s denotes a binary variable indicating injury-free ($s = 0$) and injury-prone ($s = 1$). s is related to a latent variable γ^*, which represents the propensity of injury involvement. The mapping between s and γ^* follows the following criteria:

$$\begin{cases} s = 0, & if \quad \gamma^* \leq 0 \\ s = 1, & if \quad \gamma^* > 0 \end{cases} \tag{1}$$

The latent variable γ^* can be obtained by Eq. (2):

$$\gamma^* = x\beta^T + \varepsilon \tag{2}$$

where $x = \{x_1, x_2, \cdots, x_n\}$ represents a vector of variables identifying injury propensity, $\beta = \{\beta_1, \beta_2, \cdots, \beta_n\}$ is the corresponding vector of parameters to be estimated, and ε is the error term which follows a standard normal distribution.

The probability of a maritime accident being injury-prone is then given as:

$$P(s = 1|x) = P(\gamma^* > 0|x) = \varphi\left(x\beta^T\right) \tag{3}$$

where $\varphi(\cdot)$ is the cumulative probability distribution function of a standard normal distribution. Conditional on $s = 1$, the observed injury level $\widetilde{y} = \{\widetilde{y}_1, \cdots, \widetilde{y}_j, \cdots, \widetilde{y}_J\}$ can be connected to a latent variable y^* through the ordered probit regression function:

$$y^* = z\alpha^T + \delta \tag{4}$$

where $z = \{z_1, \cdots, z_i, \cdots, z_n\}$ represents explanatory variables influencing injury level in an injury-prone accident; $\alpha = \{\alpha_1, \cdots, \alpha_i, \cdots, \alpha_n\}$ is a set of unknown coefficients for variables influencing injury level; and δ is a standard-normally distributed error term that is not correlated with ε. The mapping between $\widetilde{y}$ and y^* is obtained by Eq. (5).

$$\widetilde{y}(y^*) = \begin{cases} 0 & if \quad y^* \leq 0 \\ j & if \quad \mu_{j-1} < y^* \leq \mu_j \qquad (j = 1, 2, \cdots, J-1) \\ J & if \quad y^* > \mu_{J-1} \end{cases} \tag{5}$$

where μ_j is the threshold of each injury level, which is subjected to the constraint $\mu_0 < \mu_1 < \mu_2 < \cdots < \mu_{J-1}$. J is the number of maritime accident injury levels. In addition, it is assumed that $\mu_1 = 0$.

Note that zero injury level is also allowed in the ordered probit part, therefore separate explanatory variables can be used in both binary probit and ordered probit sections. Conditional on $s = 1$, the probability of each injury level in the ordered probit section is expressed as follows:

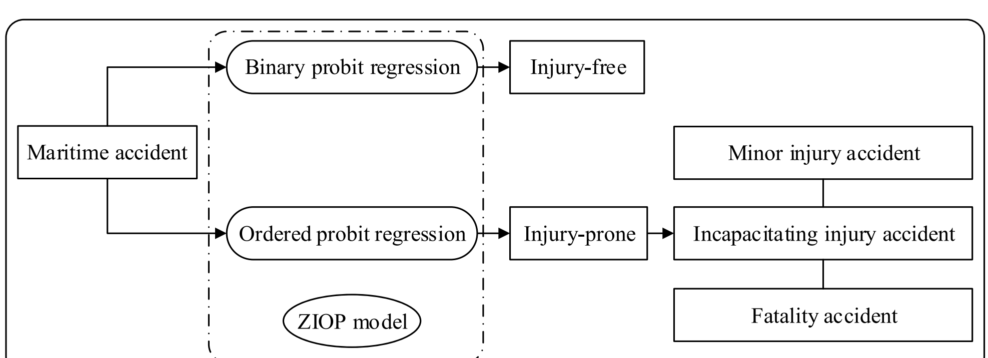

Fig. 1. The sketch of the ZIOP model.

$$P(\tilde{y}) = \begin{cases} P(\tilde{y}=0) = \varphi(-z^T\alpha) \\ P(\tilde{y}=j) = \varphi(\mu_j - z^T\alpha) - \varphi(\mu_{j-1} - z^T\alpha) \quad , (j=1,2,\cdots,J-1) \\ P(\tilde{y}=J) = 1 - \varphi(\mu_{J-1} - z^T\alpha) \end{cases} \tag{6}$$

The modelling for injury-free accident and injury-prone accident can be combined using the following equation:

$$y = s\tilde{y} \tag{7}$$

To observe the outcome of $y = 0$, it requires either that $s = 0$ (injury-free) or jointly that $s = 1$ and that $\tilde{y} = 0$ (injury-prone but no injury involved). To observe a positive y, the ZIOP regression requires jointly that the accident is injury-prone ($s = 1$) and that the accident happened to be injury-involved ($\tilde{y} > 0$). Under the assumption that ε and μ identically and independently follow standard normal distributions, the full probabilities for observed y are given by Eq. (8).

$$P(y) = \begin{cases} P(y=0|x,z) = P(s=0|x) + P(s=1|x) \times P(\tilde{y}=0|z,s=1) \\ P(y=j|x,z) = P(s=1|x) \times P(\tilde{y}=j|z,s=1), (j=1,2,\cdots,J) \end{cases} \tag{8}$$

It can be observed from Eq. (8) that the binary probit regression part is included to account for the excess zero observations. In other words, the probability of no injury in the model is the sum of the probability of accidents being injury-free and the probability of accidents being no-injury given an injury-prone accident. The parameters of the full model can be estimated using the maximum likelihood criteria. The log-likelihood function is given by Eq. (9).

$$l(\theta) = \sum_{i=1}^{n} \sum_{j=0}^{J} h_{ij} \ln[P(y=j|x,z,\theta)] \tag{9}$$

where θ is the parameter to be estimated; the indicator function h_{ij} is:

$$h_{ij} = \begin{cases} 1, & \textit{if the observation } i \textit{ is level } j \\ 0, & \textit{otherwise} \end{cases} \quad (i=1,2,\cdots,n; j=1,2,\cdots,J) \tag{10}$$

The unconditional probability of positive injury (i.e. injury severity levels 1 and 2) is also a combination of the probability of being injury-prone and the conditional probability of each injury level.

3.2. Marginal effects

As the estimated parameters of the ZIOP model can only reflect the influence trend of each factor on the injury severity of maritime accidents, it cannot evaluate the variation of the probability of a certain injury severity with the change of each factor. Therefore, the marginal effect of each significant variable is calculated after estimating the model parameters. In this study, one may be interested in the marginal effect of each variable on the probability of not being injured ($P(s=0)$), on the probability of a certain injury level given the accident is injury-prone ($P(\tilde{y}=j|s=1)$), or on the overall probability of each injury level ($P(y=j)$).

The marginal effect value herein refers to the change in probability of a variable changing by one unit on the injury severity of a certain maritime accident when holding all other variables fixed (Harris and Zhao, 2007). The marginal effect value can be calculated by Eq. (11).

$$M_{x_k}^{P(y)} = \frac{1}{n}\sum_{i=1}^{n}(P(y|x_{ik}=1) - P(y|x_{ik}=0)) \tag{11}$$

where x_{ik} is the value of the k_{th} independent variable in the i_{th} accident; $P(y|x_{ik}=1)$ is the probability that the injury severity level of the i_{th} accident is y, with x_{ik} assigned to 1 and holding other variables fixed; $P(y|x_{ik}=0)$ is the probability that the injury severity level of the i_{th} accident is y, with x_{ik} assigned to 0 and holding other variables fixed. Since each variable in each accident has a marginal effect value on a certain injury severity level, $M_{x_k}^{P(y)}$ in this study represents the average marginal effect of the k_{th} independent variable changing by one unit on the accident injury severity level y.

3.3. Model comparison

As the traditional ordered probit (OP) model has often been applied to the analysis of injury severity data, it may be useful to compare the fit of the ZIOP model against the traditional OP model. Therefore, the traditional OP model will also be built with all factors included. AIC (Akaike, 1973) and BIC (Sawa, 1978) will be employed to compare these two models. The model with smaller AIC and BIC among all competing models is deemed to be the better model (Akaike, 1973; Sawa, 1978).

Vuong's test (Vuong, 1989) will also be employed as it can outperform AIC in comparing models from different regression series. The likelihood ratio m_i can be calculated by Eq. (12).

$$m_i = \log\left(\frac{P_1(y_i)}{P_2(y_i)}\right) \tag{12}$$

where $P_1(y_i)$ and $P_2(y_i)$ are the estimated probabilities of the observed injury severity level i using model 1 and model 2, respectively.

The Vuong statistic, V, is computed to test whether the two models are significantly different in predicting the observed injury severity level or not, which can be calculated by Eq. (13).

$$V = \frac{\sqrt{n}\left(\frac{1}{n}\sum_{i=1}^{n} m_i\right)}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(m_i - \bar{m})^2}} \tag{13}$$

where n is the sample size. The Vuong statistic V is an asymptotically standard normal distribution. If the absolute value of V is larger than 1.96 (95% confidence level), the test result will support the selection of one model over the other (Washington et al., 2020). More specifically, if $V > 1.96$, the first model has a better model fitness than the second one. If $V < -1.96$, the second model is preferred. Values between -1.96 and 1.96 would mean that the test is inconclusive.

4. Data

To illustrate the potential of the proposed zero-inflated approach in maritime accident injury severity analysis, a large amount of injury data is analysed, which is extracted from maritime accident investigation reports of various investigation agencies, including the Transportation Safety Board of Canada (TSB), Marine Accident Investigation Branch of the United Kingdom (MAIB), Australian Transport Safety Bureau (ATSB), National Transportation Safety Board of the United States (NTSB), Federal Bureau of Maritime Casualty Investigation of Germany (BSU), China Maritime Safety Administration (MSA) and Japan Transport Safety Board (JTSB). The dataset includes information on 1,128 maritime accidents that occurred in the period of 2000–2019, which includes accident-specific information (date; time and location of the accident; accident types; injury severity), crew-specific characteristics (education background; sea experience; period of holding the present rank (PHPR); physical & mental health; communication ability), ship-specific characteristics (ship types; ship age; gross tonnage; flag state), and environment-specific information (visibility; wind; sea state; water depth; water width; ship traffic density). The number and sources of accidents of each type are shown in Table 1. It should be noted that each collision accident involves at least 2 ships, and the injury outcomes of each ship involved are counted separately for the calculation of injury severity. Therefore, a total of 1,294 ships were counted according to this principle, which will be used in empirical analysis.

To avoid variable covariance problems, the Pearson correlation parameters between different variables are calculated to examine which factor may covariate with other factors. Variables that are closely linked to other variables are combined into one group before included into the model. After a number of rounds of attempt, it is found that there is no

Table 1
The number and sources of each type accident.

Accident types	Investigation Agencies							Total
	TSB	MAIB	ATSB	NTSB	BSU	MSA	JTSB	
Collision	37	65	70	41	52	29	32	326
Grounding	23	44	62	21	24	21	12	207
Fire/explosion	11	23	43	18	10	20	8	133
Contact	15	25	50	13	20	12	7	142
Sinking	12	27	47	21	15	25	10	157
Equipment failure	26	34	28	23	26	24	15	176
Other	13	42	33	17	17	18	13	153
Total	137	260	333	154	164	149	97	1294

variable covariance problem if some changes on grouping are made. The definitions and descriptive statistics of the variables are shown in Table 2.

The injury-severity outcomes in this study are classified into four categories (Fountas and Anastasopoulos, 2018): no injury, minor injury, incapacitating injury, and fatality. Consistent with previous studies (Fountas and Anastasopoulos, 2017; Jiang et al., 2013), the reported injury-severity outcome is defined as the injury severity level of the most severely injured person in the accident. The number of accidents per injury severity outcome is presented in Fig. 2 in the form of a histogram. It is clearly indicated in Fig. 2 that more than half of the accidents to be analysed in this study (approximately 55.8%) resulted in no injury, which shows significant clustering in zero injury observations. In this context, it supports the use of a ZIOP framework, which can address the excessive amount of zero observations, for identifying the determinants of the injury severity outcomes of maritime accidents.

5. Results and discussions

5.1. Parameter estimates

In this section, the OP procedure and ZIOP procedure in the Statistical software for data science (STATA, 15.0; Texas: Stata Corp LLC) are applied to estimate the parameters of the variables for the OP model and ZIOP model, respectively. A series of OP models and ZIOP models are established and the parameters are estimated using Eqs. (1)–(10). The variables for the ZIOP model are selected by the following steps. In the first step, the ZIOP model is fitted for the first time. Variables that are significant at the 90% confidence level in the traditional OP model are selected as candidate variables for the first process of the ZIOP model. All the individual variables considered in this study are selected as the candidates in the second process. In the second step, the variables that are not significant in both processes of the first fitting of the ZIOP model are removed and the ZIOP model is fitted again. Finally, the variables in the final ZIOP model are significant in either or both processes of the second fitting of the ZIOP model, which include accident type, location, gross tonnage, flag state, ship manning, water depth, visibility, sea state, PHPR, and education background.

In the analysis of each ZIOP model, for categorical variables, grade “1” (i.e. collision and cargo ship) is chosen as the reference, for binary variables, grade “0” (i.e. otherwise) is chosen as the reference. Holding all other explanatory variables constant, parameter estimates provide the change in the level of injury severity compared to a reference attribute. Parameter estimates larger than 0 indicate that a particular cluster of a variable results in a higher injury severity level, and vice versa.

As shown in Table 3, the ZIOP model shows significant effects of accident type on injury severity in maritime accidents. This study only shows the influencing factors whose influence is statistically significant ($p < 0.1$) in first or second process. In the first process, the coefficients for capsizing/sinking, hull/machinery damage and other accident types are significantly positive while that for stranding/grounding is negative, indicating that, in comparison to collision, the former accident types are more likely to be injury-prone and the latter one is less likely to be injury-prone. The finding of injury propensity is to some extent consistent with some previous studies (Wang et al., 2021; Yip et al., 2015), which indicate that a large number of crew injuries are expected if a vessel is involved in a capsizing/sinking accident. In the second process, the coefficients for contact, hull/machinery damage and other accident types are positive, which instead indicate that conditional on being injury-prone, these accident types are more likely to be associated with a higher level of injury severity in comparison to collision. The effect of hull/machinery damage, however, is not consistent with the result reported by Jin (2014). This discrepancy may be caused by the fact that the research of Jin (2014) only focused on fishing vessel accident severity. It should also be noted that stranding/grounding is only significant in the injury propensity process, and the negative coefficient indicates that stranding/grounding is less likely to lead to injury-prone consequences, but made no difference on the conditional injury severity as compared to collision ($p = 0.957$). Similar situations appear for contact and capsizing/sinking.

Among other variables, gross tonnage, water depth and PHPR are significant in both the injury propensity and injury severity processes. Ships larger than 500 t and with water depth larger than 1.5 draught are associated with a significantly lower probability of injury-prone accidents, but lead to more severe injuries conditional on being in the injury-prone category. The less injury-prone finding is to some extent consistent with the result reported by Talley (2009), but contrary to the finding of Chang and Park (2019)and Talley et al. (2006). Seafarers holding the present rank for less than 3 years are associated with a significantly higher probability of injury-prone accidents, but make no difference on the injury severity conditional on being in the injury-prone category. The finding of injury propensity is to some extent consistent with the result reported by Wang et al. (2021), which indicates that seafarers with less sea experience are more likely to be involved in accidents of serious consequences.

Ship manning that meets the requirements is associated with a significantly lower probability of injury-prone accidents, but make no difference on the conditional injury severity as compared to one that does not meet the requirements. It is quite understandable that the crew’s workloads will increase if the ship is undermanned, which may lead to more fatigue for the crew and more injury-prone accidents. Poor visibility is also found to be associated with a significantly lower probability of injury-prone accidents, but made no difference on the conditional injury severity as compared to good visibility. The lower probability of being injury-prone can be explained by the fact that the seafarers are usually more cautious in poor visibility. Adverse sea state, however, is associated with a significantly higher probability of injury-prone accidents, but made no difference on the conditional injury severity as compared to good sea state. The finding on the conditional injury severity is not consistent with some previous studies (Weng and Yang, 2015; Weng et al., 2018). The reason may be that the latter only focused on mortalities, which are just modelled in terms of an injury severity level in this study. Seafarers with a poor education background are associated with a higher likelihood of injury-prone accidents as compared to those with a good education background, but do not show

Table 2
Variable definitions and descriptive statistics.

Variable description		Mean	Std. Dev.	Min	Max
Injury severity	0 for no injury 1 for minor injury 2 for incapacitating injury 3 for fatality	1.073	1.321	0	3
Accident-specific characteristics					
Season	1 if Spring 2 if Summer 3 if Autumn 4 if Winter	2.436	1.131	1	4
Time	1 if the accident occurred during daytime (the period from the local time of sunrise to the time of sunset) 0 otherwise	0.582	0.493	0	1
Location	1 if the accident occurred near the coast (less than 12 nm), 0 otherwise	0.912	0.284	0	1
Accident type	1: collision 2: stranding/grounding 3: fire/explosion 4: contact 5: capsizing/sinking 6: hull/machinery damage 7. other	3.576	2.131	1	7
Ship-specific characteristics					
Ship type	1: cargo ship 2: passenger ship 3: fishing vessel 4: tug and port traffic boat	2.371	0.941	1	4
Ship age	1 if the ship age is less than 10 years, 0 otherwise	0.381	0.486	0	1
Gross tonnage	1 if the gross tonnage is larger than 500 t, 0 otherwise	0.641	0.48	0	1
Flag state	1 if the ship's flag state is country of flag of convenience[a], 0 otherwise	0.258	0.438	0	1
Ship manning	1 if the ship manning meets requirements, 0 otherwise	0.94	0.237	0	1
Environment-specific characteristics					
Water depth	1 if the depth-draught ratio is larger than 1.5, 0 otherwise	0.6	0.49	0	1
Water width	1 if the ratio of water width and ship length is larger than 2, 0 otherwise	0.664	0.473	0	1
Visibility	1 if the visibility is poor (visibility <2 nm), 0 otherwise	0.368	0.482	0	1
Wind	1 if the wind force is larger than Beaufort wind scale 7, 0 otherwise	0.105	0.307	0	1
Sea state	1 if the sea state is larger than Beaufort wave scale 5, 0 otherwise	0.067	0.251	0	1
Traffic density	1 if the traffic density is low, 0 otherwise	0.471	0.499	0	1
Seafarer-specific characteristics					
Sea experience	1 if the sea experience is less than 5 years, 0 otherwise	0.162	0.368	0	1
PHPR	1 if PHPR is less than 3 years, 0 otherwise	0.838	0.368	0	1
physical and mental health	1 if the seafarer is not physically or mentally healthy, 0 otherwise	0.141	0.349	0	1
Education background	1 if seafarer's education background is not good, 0 otherwise	0.114	0.318	0	1
Communication ability	1 if there is communication problem with others, 0 otherwise	0.025	0.155	0	1

[a] The list of countries of flag of convenience (FOC) refers to those who have declared FOCs by the ITF (International Transport Workers' Federation)'s fair practices committee, https://www.itfglobal.org/en/sector/seafarers/flags-of-convenience.

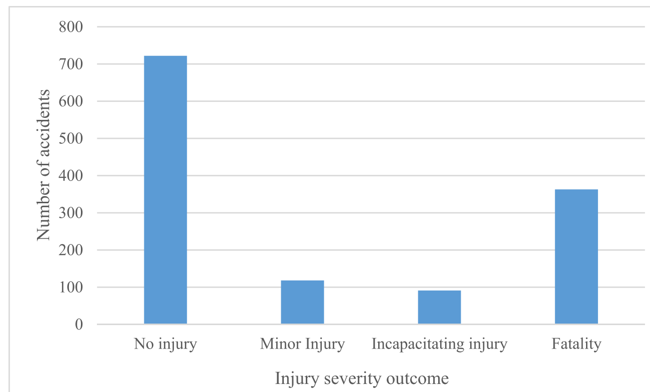

Fig. 2. Number of accidents per injury-severity outcome.

any significant difference on the conditional injury severity. Usually, seafarers with a poor education background are more likely to cause some injury accidents as they are not familiar with some operations, but they do not cause very serious accidents as they may be more careful in their work.

Compared with those that occurred far away from the coast, accidents that occurred near the coast are found not significant in injury propensity prediction, but are associated with the higher injury severity level conditional on being in the injury-prone group. The result is to some extent consistent with some previous studies (Weng and Yang, 2015; Weng et al., 2018) which indicate that the probability of fatal accidents is likely to increase for accidents occurring far away from the coast. It is undeniable that it is much more difficult to carry out search and rescue if the accident occurs far away from the coast. Ships of flag of convenience are also found not significant in injury propensity prediction, but are significantly associated with the higher injury severity level conditional on being in the injury-prone group. The reason may be that some open registry countries do not enforce regulations and policy requirements strictly. It also revealed in the study of (Li and Wonham, 1999) that flag of convenience ships were often associated with a high total loss rate due to accidents.

For comparisons, the parameters of the OP model with the same variables are also estimated but will not be illustrated in detail due to the space limitations. The comparison results of the OP model and ZIOP model are presented in Table 4. The AIC value of the ZIOP model is approximately 36 units less than that of the OP model, indicating that the ZIOP model outperformed the OP model. The superiority of the ZIOP model is also confirmed by the result of Vuong's test, which is 3.93, far larger than the critical value 1.96. In conclusion, the ZIOP model has a significant improvement in the overall prediction of injury severity in comparison with the traditional OP model, from the results of AIC, BIC and Vuong's test.

Table 3
Parameter estimates of the ZIOP model.

		Binary probit process			Ordered probit process		
		Coef.	Std. Err.	P	Coef.	Std. Err.	P
Location		0.068	0.167	0.683	1.409	0.754	0.062
Gross tonnage		−0.543	0.097	0.000	2.365	0.629	0.000
Flag state		0.051	0.097	0.598	4.065	0.836	0.000
Ship manning		−0.488	0.174	0.005	−0.666	0.505	0.187
Water depth		−0.300	0.099	0.002	2.284	0.525	0.000
Visibility		−0.183	0.092	0.047	0.153	0.317	0.630
Sea state		0.285	0.168	0.089	6.034	139.351	0.965
PHPR		0.568	0.119	0.000	−1.417	0.772	0.066
Education background		0.235	0.131	0.074	−0.662	0.447	0.139
Accident type	2: stranding/grounding	−0.848	0.154	0.000	7.500	137.971	0.957
	4: contact	−0.181	0.145	0.210	2.124	0.888	0.017
	5: capsizing/sinking	1.250	0.186	0.000	−0.054	0.338	0.873
	6: hull/machinery damage	0.950	0.130	0.000	3.014	0.799	0.000
	7. other	1.375	0.146	0.000	2.253	0.868	0.009
_cons		−1.509	1.010	−1.490	0.135	−3.490	0.471
/cut1					−0.170	0.290	−0.739
/cut2					0.190	0.289	−0.376
/cut3					0.491	0.288	−0.075

Table 4
The performance of OP model and ZIOP model.

	ZIOP model	OP model
No. of observations	1,294	1,294
Log-likelihood	−1135.595	−1169.609
AIC	2339.191	2375.217
BIC	2514.818	2468.196
Vuong's test (ZIOP/OP)	3.93	

5.2. Marginal effects

In order to interpret the impact of various variables on injury severity of maritime accidents, marginal effects are calculated, which are derivatives evaluated at a particular point of the covariate space. In this study, the marginal effects are obtained through evaluating the marginal effects individually for each observation and report the average of all observations. According to Eq. (11), the marginal effects of each variable on the injury severity probabilities computed from ZIOP model are estimated, and the results are listed in Table 5 and Table 6. For comparison, the marginal effects computed from the traditional OP model are also included.

As shown in Table 5, the marginal effects of the ZIOP model and OP model on $P(y = 0)$ are presented. It should be noted that the overall marginal effects for the ZIOP model are decomposed into two parts: the effect on injury-free accidents ($P(s = 0)$), and the effect on no injury conditional on being injury-prone accidents ($P(y = 0|s = 1)$). Some interesting differences from alternative models for some of the variables are found. For example, the ZIOP model shows that large gross tonnage brought about a 16.4% decrease in the probability of injury-free accidents, but a 20% increase in the probability of no injury accidents conditional on being injury-prone. The former marginal effect indicates that ships of large gross tonnage are less likely to be involved in injury-free accidents as compared to those of smaller gross tonnage. However, the latter marginal effect shows that ships of large gross tonnage are associated with accidents of a relatively higher likelihood of no injury compared with smaller ones, conditional on being injury-prone. As mentioned above, the ZIOP model is based on the assumption that zero observations come from two distinct sources. Therefore, it allows flexibility in assigning the overall probability of non-injury outcomes. A small increase (3.6%) on the overall probability of no injury for large gross tonnage is obtained after the offset of the opposite effects of the results. This is smaller than the parameter estimated from the OP model (8.5%). Similar situations are found for the variables of location, flag state, water depth, visibility, sea state and accident types such as stranding/grounding and contact.

However, some opposite conclusions are found for variables of PHPR, education background, and capsizing/sinking. Taking PHPR as an example, a short period of holding the present rank brought about a 9.8% increase in the probability of injury-free accidents, but a 18.2% decrease in the probability of no injury conditional on being injury-prone. The former marginal effect indicates that seafarers with a short period of holding the present rank are more likely to be involved in injury-free accidents as compared to those with a longer period of holding the present rank, while the latter marginal effect shows that seafarers with a short period of holding the present rank are associated with accidents of a relatively lower likelihood of no injury compared with those with a longer period of holding the present rank, conditional on being injury-prone. It is quite understandable that seafarers with a short period of holding the present rank usually tend to be more cautious as they are not very familiar with the present rank, which leads to a low probability of injure prone accidents. It is also because they may be less unfamiliar with the present rank, once injury-prone accidents occur, the probability of injury is often high. In addition, ship manning is found to bring an increase in the probability of both injury-free and injury-prone accidents conditional on being injury-prone, while hull/machinery damage and other accident type bring a decrease in both probabilities.

Table 5
Marginal effects for no injury category.

		OP	ZIOP		
		$P(y = 0)$	$P(s = 0)$	$P(y = 0\|s = 1)$	$P(y = 0)$
Location		−0.072	−0.098	0.019	−0.079
Gross tonnage		0.085	−0.164	0.200	0.036
Flag state		−0.065	−0.282	0.091	−0.191
Ship manning		0.144	0.046	0.108	0.154
Water depth		0.043	−0.158	0.135	−0.023
Visibility		0.046	−0.011	0.051	0.040
Sea state		−0.200	−0.419	0.081	−0.337
PHPR		−0.138	0.098	−0.182	−0.084
Education background		−0.067	0.046	−0.077	−0.031
Accident type	2: stranding/grounding	0.155	−0.220	0.360	0.140
	4: contact	−0.012	−0.193	0.163	−0.030
	5: capsizing/sinking	−0.284	0.009	−0.332	−0.323
	6: hull/machinery damage	−0.413	−0.210	−0.221	−0.431
	7. other	−0.523	−0.196	−0.334	−0.531

Table 6
Marginal effects for minor injury, incapacitating injury and fatality categories.

		Minor injury, P(y = 1)		Incapacitating injury, P(y = 2)		Fatality, P(y = 3)	
		OP	ZIOP	OP	ZIOP	OP	ZIOP
Location		0.005	0.012	0.006	0.010	0.061	0.057
Gross tonnage		−0.006	0.011	−0.007	0.005	−0.072	−0.052
Flag state		0.004	0.032	0.006	0.027	0.055	0.132
Ship manning		−0.009	−0.011	−0.013	−0.014	−0.123	−0.129
Water depth		−0.003	0.014	−0.004	0.009	−0.036	0.001
Visibility		−0.003	−0.001	−0.004	−0.003	−0.039	−0.036
Sea state		0.013	0.050	0.017	0.044	0.17	0.243
PHPR		0.009	−0.004	0.012	0.002	0.117	0.085
Education background		0.004	−0.002	0.006	0.000	0.057	0.033
Accident type	2: stranding/grounding	−0.036	−0.027	−0.03	−0.027	−0.088	−0.086
	4: contact	0.002	0.016	0.002	0.008	0.008	0.006
	5: capsizing/sinking	0.023	−0.008	0.034	0.018	0.228	0.313
	6: hull/machinery damage	0.014	0.028	0.035	0.046	0.365	0.357
	7. other	−0.008	0.002	0.023	0.032	0.508	0.497

The marginal effects on the unconditional probabilities of all three positive injury levels are shown in Table 6. The resulting marginal effects on the unconditional probabilities of each injury level also come from two sources. The ZIOP model in Table 6 reveals that accidents that occurred near the coast, as opposed to those that occurred far away from the coast, are associated with increases of 1.2%, 1.0% and 5.7% in the probability of minor injury, incapacitating injury and fatality, respectively. As a contrast, the conventional OP model shows a monotonically increasing positive effect on the probabilities of three types of injury-prone accidents. Similar marginal effects are found in the ZIOP model for variables of flag state, water depth, sea state and some accident types.

However, the ZIOP model shows opposite effects on ship manning and visibility, which are associated with various extents of decrease in the probability of minor injury, incapacitating injury and fatality, respectively. In addition, compared with small gross tonnage, large gross tonnage is associated with increases of 1.10% and 0.5% in the probability of minor injury and incapacitating injury respectively, but a decrease of 5.20% in the probability of fatality. In contrast, variables of PHPR, education background and capsizing/sinking are associated with various extents of decrease in the probability of minor injury, and an increase in the probability of incapacitating injury and fatality respectively. Due to the space limitations, the marginal effects of other covariates in the ZIOP model, as well as the covariates in the OP model, will not be illustrated in detail.

6. Conclusions

This study aims to investigate the impacts of the contributing factors on the injury severity of maritime accidents. On the basis of maritime accident data collected from 1,128 maritime accident investigation reports, a ZIOP regression model and an OP model, are developed to estimate the effects of influencing factors on the injury severity of maritime accidents.

The results indicate that the injury severity of maritime accidents should be analysed by separating it into two states, namely injury-free state that determines whether a maritime accident will lead to injury, and injury-prone state that determines the injury severity levels. The effects of the variables exhibiting statistically significant influence on injury severity are concluded as follows:

- Large gross tonnage and water depth significantly decrease the likelihood of injury-free accidents, but also notably increase the probability of severe injury conditional on being injury-prone.
- Adverse sea state, poor education background and short period of holding the present rank significantly increase the likelihood of injury prone accidents, but make no difference on the injury severity conditional on being in the injury-prone category.
- Adequate ship manning and poor visibility are associated with a significantly lower probability of injury-free accidents, but make no difference on the injury severity conditional on being in the injury-prone category.
- Being near the coast and flag state of convenience do not bring about significant changes to the probability of being injury-free, but result in more severe injuries conditional on being injury-prone.
- In comparison to collision, stranding/grounding and capsizing/sinking make no changes on the chances to be severely injured conditional on being injury-prone, but the former significantly decreases and the latter increases the likelihood of being injury-prone. However, both make no changes on the likelihood of being injury-prone and increase chances to be severely injured conditional on being injury-prone; the hull/machinery damage and other accident type increase both the likelihood of injury-prone accidents and being severely injured conditional on being injury-prone.

This study provides several contributions to the literature on maritime accident analysis. Firstly, it provides a comprehensive review and analysis related to maritime accidents by focusing on injury severity and its influencing factors. Secondly, it is the first time that the zero-inflated ordered probit model is applied to the study of the injury severity of maritime accidents, which provides a rational way of solving the problem associated with an excessive amount of zero injury observations in maritime accident datasets. The significantly superior statistical fit of the ZIOP model in comparison to that of the conventional OP model is illustrated by the results of AIC, BIC and Vuong's test. Finally, the results of this study provide an insight into the injury severity of maritime accidents, which can be used to assist relevant maritime safety authorities in taking effective measures to reduce the consequences of maritime accidents.

In terms of the limitations and constraints of this study, the following two aspects can be further investigated. Firstly, additional research is needed to improve the flexibility of the ZIOP model by allowing random coefficients or variable thresholds as the model does not allow change in the directionality of effects within the injury-prone accidents. Secondly, due to the incompleteness of the database, a few typical variables, such as organization management and occupational health management, were not accounted for in this study. The analysis of the impacts of management factors on injury severity should be considered in future studies after collecting relevant data.

CRediT authorship contribution statement

Huanxin Wang: Conceptualization, Methodology, Writing – original draft. **Zhengjiang Liu:** Data curation, Project administration. **Xinjian Wang:** Visualization, Writing – review & editing. **Daozheng Huang:** Writing – review & editing. **Liang Cao:** Writing – review & editing. **Jin**

Wang: Writing – review & editing, Visualization, Supervision.

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.

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