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Investigating the Role of the Human Element in Maritime Accidents using Semi-Supervised Hierarchical Methods

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Abstract

Navigation safety is a priority both at European and global level. Despite the important progress made over the years, sea accidents remain a major concern and much work is still needed to enhance maritime safety. Knowing the causes and precursors of past accidents is essential to identify the elements on which to intervene to improve safety and reduce the possibility of an accident to occur again. In this study, 1.079 sea accidents from the International Maritime Organization (IMO) database are analyzed using Semi-supervised Recursively Partitioned Mixture Models in an attempt to identify and categorize causal themes from accident data. Special attention is devoted to the human element, which is widely recognized as a primary or precursory cause in most accidents.

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Keywords: Sea Accidents; Clustering; Sea Safety; Human Factors; Hierarchical Methods

1. Introduction and purpose of the research

The international shipping industry traffics approximately 90% of world trade, involves around 60,000 merchant ships and is manned by over a million seafarers (Allianz Global Corporate and Specialty, 2019). Merchant ships and seafarers operate in a highly dynamic and high-risk environment characterized by a high rate of organizational accidents and maritime disasters (Hansen et al., 2002).

Over the last decades, the shipping industry has implemented several measures to achieve more robust safety management and procedures on vessels. Among the others, SOLAS – International Convention for the Safety of Life at Sea - is widely considered the most important international treaty concerning the safety of merchant ships (IMO, 1999). In 1994, the International Maritime Organization (IMO) added to SOLAS the International Safety Management Code (ISM) whose purpose is to provide an international standard for the safe management and operation of ships and for pollution prevention.

Despite the important progress made over the years, shipping accidents remain a major concern (Chauvin et al., 2013). Causes and cause relations of marine accidents are complex, and many different factors may have a role on

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the cause of an accident. Luo and Shin (2016) classify the major causes of maritime accidents by dividing them as follows: vessel and equipment factors, environmental factors, navigation and operation factors, traffic factors, and human factors. Although the causes of an accident can be various and numerous, it is widely recognized that human factors play a crucial role in most of them. Allianz Global Corporate and Specialty (2019) estimates that 75% to 96% of maritime accidents involve human errors and/or violations. The paper by Hetherington et al. (2006) identifies several human factors influencing safety such as fatigue, automation, situation awareness, communication, decision making, teamwork, and health and stress. Human failures, intended as errors and violations, are also reported to arise because of organizational factors, technologies, work environment and safety climate on ship (Galieriková, 2019). All these factors are recognized to be potential contributory causes in accident causation.

The foundations of actual accident investigation manuals are represented by the SCM - Swiss Cheese Model - (Reason, 1997) and the SHEL - Software, Hardware, Environment, Liveware Model - (Hawkins, 1987), both are used in risk analysis and risk management for analyzing accident causation. The SCM model aims at explaining human errors as a sign of a wider problem by applying a systemic approach to accident investigation. It assumes that organizations establish hierarchical level barriers to prevent accidents. Failures in levels occur because of holes in barriers. SCM levels include organizational influence, unsafe supervision, precondition, and unsafe acts. The SHEL model instead aims to understand man-machine interaction and related performance. The IMO adopted the aforementioned models and introduced guidelines for accident investigators to help the identification of specific human factors, unsafe acts or violations on-board which may have contributed to marine casualties and incidents (IMO, 1999; 2008). An upgrade of the SCM is represented by the Human Factor and Classification System model - HFACS (Shappel and Wiegmann, 2000). The latter is a more complex accident investigation model, based on the SCM, which includes a classification of active failures and latent conditions. The same framework has been adapted for different sectors, including maritime accidents. Chen et al. (2013) built the HFACS-MA (Human Factor And Classification System for Maritime Accidents) by adding external factors such as legislation gaps, design flows and administration oversight, and by incorporating correspondent content of the IMO guidelines into levels. Celik et al. (2008) integrate an analysis of marine surveyor's judgements in order to quantify human contribution on shipping accidents while Chauvin et al. (2013) reshape the framework specifically for ship collision (HFACS-Coll).

Several quantitative methods have so far been applied to maritime accident analysis, such as Bayesian networks and regression models. The former are attractive modelling approaches to represent complex problems such as maritime accidents (Hänninen, 2014). Among the others, Akhtar et al. (2014) exploited a Bayesian Network modelling approach to investigate the extent to which fatigue may affect the probability of grounding. A multinomial logistic regression model was instead developed by Weng et al. (2019) to analyze the relationship between external factors (environmental, accident and ship characteristics) and the occurrence likelihood of a human error. Results reveal that external factors are statistically associated with an increased occurrence likelihood of human errors.

Research in maritime safety and accident domain deal with underreporting of maritime accidents (Hassel et al., 2011) and fractioned data collection (Luo and Shin, 2016) that may have prevented a larger application of quantitative methods for investigating the role of human factors in maritime accidents. To the best of the authors' knowledge, only a few studies have employed clustering methods to investigate sea accidents. Among the available studies, Lema et al. (2014) applied K-means clustering to a dataset of 355 marine accidents founding that grounding and collision are the type of casualty most related to the human element. They also found that the condition of the ship and the bad weather can further concur to the onset of human error. Chauvin et al. (2013) applied a Multiple Correspondence Analysis and a Hierarchical Clustering to a dataset of 27 casualties founding three main classes of accident causation: communication and coordination problems, noncompliance with Safety Management System, instruments and operational problems.

In this study, a Semi-Supervised Recursively Partitioned Mixture Models - RPMM - clustering method is applied to a dataset generated from GISIS[1], including 1,079 sea accidents that occurred worldwide between 2009 and 2019. The main objectives of the study can be summarized as follows:

[1] Maritime accidents are recorded in the IMO's database known as Global Integrated Shipping Information System (GISIS), https://gisis.imo.org/.

- identify and categorize contributing factors to sea accidents, and compare them for homogeneous groups;
- investigate the relative contribution of human factors to sea accidents.

The paper is organized as follows: following this introduction, Section 2 illustrates the methodology while Section 3 describes the application data and the variables selection process. The quantitative results of the application are set out and discussed in Section 4. The main conclusions drawn from the analysis are in Section 5.

2. Methodology

In this study, cluster analysis techniques are applied to partition the IMO database into homogeneous groups of accidents. Cluster analysis is known to be an unsupervised method which seeks to discover proximities among observations in unlabelled data (Hastie et al., 2009). When preliminary information about the clusters or outcome variables exist, those can also be used to enhance the analysis. Sometimes clusters are in fact associated with given outcome variables that act as "noisy surrogates" (Bair et al., 2004). In case conventional clustering methods fail in identifying suitable clusters, these variables can be considered good proxies of the unknown clustering structure when used in combination with the other features. The clustering methods that fit with labelled data or outcome variables are known as semi-supervised clustering methods. Although these semi-supervised methods are usually evolved algorithms of k-means clustering, there also exist semi-supervised hierarchical methods, which belong to an emerging research area. The semi-supervised hierarchical methods are quite recent, and only a few studies assessing their advantages and disadvantages are available so far (Bair, 2013).

In this research, Semi-supervised Recursively Partitioned Mixture Models - RPMM (Koestler et al., 2010) are performed pointing the human element as the outcome variable. Semi-supervised RPMM algorithm begins sorting the features according to their association to the outcome variable, and then selects the best partition obtained by RPMM model trying different subsets of features taking into account the informative power of the features. The algorithm proceeds as follows:

1) for each feature in the data set, it calculates a test statistic T_{ij} for testing the null hypothesis of no association between the j_{th} feature and the i_{th} outcome variable;
2) then it chooses a threshold M, and applies Hierarchical Clustering to the features for which $|T_{ij}| > M$. Features with $|T_{ij}| \leq M$ are discarded and do not affect the cluster assignment.

Originally, the algorithm has been developed for genetic data, consequently the adopted methods (for instance the Cox regression in step 1) were related to the specificity of that kind of data. Consequently, we followed the general strategy of the Semi-supervised RPMM, bringing some changes according to the characteristics of our kind of data. Specifically, since our outcome variables are dummies, the connection between the i_{th} outcome variable and the j_{th} feature is calculated by performing a logistic regression and testing the null hypothesis of no association between i and j, in other words if the coefficient of the model is statistically equal to zero. The intensity of that connection is measured by $|Z_{ij}|$: the absolute value of the Z statistic test performed on the coefficient of the logistic model that explains i by j. Once all the $|Z_{ij}|$ are calculated, the vector of the marginal sum $Z_{.j} = \sum_i |Z_{ij}|$ is sorted in a decreasing way. Successively, RPMM is iteratively carried out using, at the first iteration, solely the most informative feature, and then adding at each iteration the next feature for importance, until all features are used. Finally, the best partition obtained among all RPMM models carried out, is selected by maximizing the median differences between clusters in relation to the outcome variables. The difference between clusters is measured through the Kruskal-Wallis Rank Sum Test (Myles and Douglas, 1973). In this study, no quantitative validation is performed in the clustering procedure since the different parameters of the analysis are compared mainly based on the interpretability of the clusters.

3. Data and variables selection

Information on worldwide sea accidents used in this research has been obtained from the IMO Marine Casualties and Incidents Database, which can be found at https://gisis.imo.org/ and contains information collected on ship casualties from investigation reports received at IMO. Specifically, the analysis performed in this research covers the 11-year period 2009-2019. The considered accident database includes 4,347 records and 70 variables, of which

17 relating to the vessel (a.o., IMO number, flag, length, tonnage, type of ship, type of service, and classification society) and 53 to the accident (a.o., date and time, position, crew on board, initial event, consequences). The total number of casualties included in the database is 3,710, while 4,347 referred to the total number of ships involved in a casualty during the period under consideration. Due to underreporting, our statistical analysis is not performed on the total number of accidents in the database, but only on the casualties that report complete information. A final sample consisting of 1,151 records (number of ships involved) referred to a total number of 1,079 accidents was obtained as a result of several data cleaning operations (scrubbing for duplicates, imputing missing values by using other observations, fixing typos, categorizing strings objects, etc.) aimed at improving the completeness, consistency and accuracy of the data. Collisions and work accidents are the most frequent casualties in our sample, the port is where accidents take place with higher probability. 32% of the accidents reports a loss of life. An unsafe act (human error, human violation, or both) is pointed out as a contributing factor in 72% of fatal accidents.

In selecting the variables to include in the analysis, we refer to the five levels of human failure proposed by Chen et al. (2013) in their HFACS-MA model:

- external factors;
- organizational influences;
- unsafe supervision;
- preconditions;
- unsafe acts.

Specifically, this application focuses on *Unsafe acts,* which occupy the bottom level of the proposed framework and consist of two categories: errors and violations committed by humans. They are defined as active failures directly leading to the accident, but they also are the consequence of a series of underlying factors and latent conditions included in the higher levels of the model. This specific relationship between unsafe acts and the other latent factors led us to determine the unknown clustering structure by considering two variables, human errors and human violations, as labelled patterns in semi-supervised analysis. Furthermore, 14 unlabeled patterns were also included. According to their features, the latter can be grouped in the following four groups:

- ship
  - ship type: cargo ship, fishing vessel, passenger ship, tanker, special and pleasure craft;
- accident
  - type of casualty: capsizing/listing, collision/contact, damage to ship or equipment, fire/explosion, flooding/foundering, grounding/stranding, machinery failure, work accident;
  - location: port, coastal waters, open sea, inland waters;
  - loss of life;
  - consequences to the ship: fit to proceed, unfit to proceed, total loss of the ship;
  - pilot on board: yes or no;
- preconditions
  - software factors (including company policy, standing orders, procedures, management and supervision);
  - hardware factors (including lack of equipment, ergonomics, design failures, maintenance, repair faults);
  - communication and condition of operators divided into fatigue or excessive workload and standards of personal competence or lack of training;
- other causes
  - structural failure;
  - technical failure;
  - problems with cargo;
  - adverse weather conditions;
  - navigational tools problem.

The analysis also tries to understand if and how some specific errors (incorrect operation of controls, failure to report information, inappropriate choice of route, error in judgement, failure to respond appropriately, etc.) and violations (routine violations, necessary violations, etc.) spread out into the groups.

4. Results

The described semi-supervised methodology has been applied to the data sample using the “R” free software environment for statistical computing and graphics.
The results of clustering suggested dividing the sample into 11 homogeneous classes whose main features are reported in Table 1. The first row details the global composition of the sample according to each variable. The remaining rows refer to the individual clusters and illustrate the modalities that most characterize each group. For each modality, the *cla/mod* and *mod/cla* percentage values are shown in brackets. The former relates the number of cases presenting the modality in the group to the total of cases presenting the same modality in the whole sample. The latter measures the presence of the characteristic modality with respect to the number of observations in the group.
A general description of the types of maritime accidents that characterize the 11 clusters is provided below.

- Cluster 1: is the most numerous cluster. It mainly includes collision and grounding casualties involving cargo ships. While bad weather conditions are recognized as a common cause of these accidents, the human factor does not seem to play an important role in this group.
- Cluster 2: groups collision or grounding casualties in coastal waters. The lack of supervision and errors in management procedures (software factors) are reported among the main causes of these accidents.
- Cluster 3: the accidents in this group concern fire or machinery failures caused by technical problems. The human element does not seem to play an important role in this group of accidents.
- Cluster 4: groups work accidents associated with no specific causes.
- Cluster 5: groups work accidents caused by incorrect operations due to inadequate supervisory policy (software factors).
- Cluster 6: it mainly groups accidents caused by a cargo-related problem. This type of accident frequently occurs in open sea and causes the total loss of the ship. No specific causes linked to human factors emerge.
- Cluster 7: groups work accidents for which human errors (error in judgement and failure to respond appropriately) and/or human violations (routine violation) are reported as the main cause. In this type of accident, inadequate standard of personal competence combined with hardware and software deficiencies induce the occurrence of human errors and violations.
- Cluster 8: groups work accidents during cargo operations. Main causes of these accidents are technical problems connected with human failures (error in judgement, incorrect operation of controls, failure to respond appropriately, routine and necessary violations). Even in this group, hardware and software deficiencies combined with communication problems and inadequate standards of personal competence have a key role in inducing human errors and violations.
- Cluster 9: includes work accidents and grounding casualties caused by a human failure induced by software deficiencies, lack of communication or coordination, inadequate standards of competence or fatigue.
- Cluster 10: the accidents in this group are mainly grounding or collision casualties caused by navigational tool problems and consequent inappropriate route choice. Communication problems related to fatigue and software deficiencies are recognized as contributing factors.
- Cluster 11: the accidents in this group concern machine failures combined with technical problems. The latter are often caused by incorrect operation of control and hardware deficiencies.

The 5th, 7th and 8th clusters describe three scenarios where human failure plays a crucial role in causing the accidents that take place during working procedures and turn out to be fatal. The human element is also critical in the 9th and 10th clusters where grounding, collisions and work accident are caused by an unsafe act induced by the presence of preconditions like fatigue, inadequate competence of the operators or software deficiencies.

Table 1: Clustering results.

	Size	Type of casualty	Ship type	Location	Loss of life	Consequences to the ship	Hardware factors	Software factors	Personnel factors	Human error	Human violations	Other causes
Whole sample	1151	Capsizing (5%), Collision (34%), Damage to the ship (5%), Fire (15%), Flooding (1%), Grounding (14%), Machinery Failure (6%), Work Accident (20%)	Cargo (57%), Fishing (12%), Passenger (10%), Special Craft (8%), Tanker (13%)	Coastal waters (25%), Inland waters (8%), Open sea (27%), Port (40%)	Yes (32%) No (68%)	Ship remains fit to proceed (49%) Ship rendered unfit to proceed (28%) Total loss of the ship (23%)	Yes (19%) No (81%)	Yes (40%) No (60%)	Communication (11%), Standards of personal competence (18%), Fatigue (8%), Other (11%), No (66%)	Failure to report information (7%), Error in judgement (29%), Failure to respond appropriately (12%), Incorrect operations of control (11%), Inappropriate choice of route (5%), Other Errors (24%), No (46%)	Necessary (6%), Routine (12%), Other (9%), No (75%)	Problem with cargo (10%), Technical failure (33%), Structural failure (8%), Adverse weather (29%), Navigational tool problems (6%), No (40%)
Cluster 1	226	Collision (33%, 58%) Grounding (29%, 20%)	Cargo (22%, 64%)	Inland waters (32%, 14%)	No (29%, 100%)		No (23%, 95%)	No (33%, 100%)	No (29%, 97%)		No (22%, 85%)	Adverse weather (25%, 38%)
Cluster 2	83	Collision (11%, 51%) Grounding (12%, 23%)	Fishing (19%, 31%)	Coastal waters (13%, 46%)	No (11%, 100%)	Ship rendered unfit to proceed (11%, 41%)	No (8%, 90%)	Yes (18%, 100%)	No (9%, 86%)	No (10%, 65%)		No (14%, 80%)
Cluster 3	157	Fire (30%, 34%), Machinery failure (44%, 18%), Damage to the ship (30%, 12%)	Passenger (30%, 21%)		No (20%, 100%)	Ship rendered unfit to proceed (19%, 38%)		No (18%, 79%)	No (20%, 95%)	No (24%, 82%)	No (17%, 95%)	Technical failure (41%, 100%)
Cluster 4	134	Work accident (29%, 49%)	Cargo (14%, 66%)	Open sea (18%, 43%)	Yes (36%, 100%)	Ship remains fit to proceed (15%, 64%)	No (13%, 89%)	No (20%, 100%)	No (16%, 88%)		No (13%, 84%)	No (19%, 64%)
Cluster 5	72	Work accident (15%, 46%)			Yes (19%, 100%)	Ship remains fit to proceed (8%, 63%)		Yes (16%, 100%)	No (8%, 86%)	Incorrect operations of control (11%, 19%)		No (9%, 56%)
Cluster 6	72	Fire (17%, 40%) Capsizing (29%, 24%)		Open sea (11%, 46%)		Total loss of the ship (11%, 40%)						Problem with cargo (63%, 100%)
Cluster 7	112	Flooding (43%, 5%) Work accident (14%, 29%)			Yes (13%, 42%)		Yes (14%, 27%)	Yes (15%, 61%)	Standards of personal competence (54%, 100%)	Error in judgement (17%, 52%), Failure to respond appropriately (17%, 21%)	Routine (25%, 31%)	
Cluster 8	25	Work accident (6%, 56%)			Yes (5%, 76%)	Ship remains fit to proceed (4%, 80%)	Yes (7%, 64%)	Yes (4%, 80%)	Communication (15%,76%) Standards of personal competence (6%, 52%)	Failure to report information (12%, 36%), Error in judgement (4%, 56%), Failure to respond appropriately (9%, 48%), Incorrect operations of control (8%, 40%)	Necessary (16%, 44%) Routine (6%, 32%)	Problem with cargo (22%, 100%) Technical failure (5%, 72%)
Cluster 9	128	Work accident (17%, 30%) Grounding (17%, 21%)	Tanker (21%, 25%)					Yes (20%, 71%)	Fatigue (70%, 48%) Communication (63%, 65%) Standards of personal competence (22%, 35%)	Failure to report information (36%, 22%), Error in judgement (19%, 50%), Failure to respond appropriately (26%, 28%), Incorrect operations of control (19%, 20%)	Necessary (20%, 11%) Routine (20%, 23%)	No (16%, 55%)
Cluster 10	51	Grounding (12%, 37%) Collision (6%, 49%)			No (6%, 92%)	Total loss of the ship (7%, 35%)		Yes (8%, 69%)	Fatigue (13%, 22%) Communication (10%, 26%)	Inappropriate choice of route (18%, 22%)		Navigational tool problems (81%, 100%)
Cluster 11	91	Machinery failure (31%, 22%)			No (9%, 78%)	Total loss of the ship (13%, 40%)	Yes (18%, 44%)			Incorrect operations of control (14%, 20%)	Necessary (19%, 14%)	Structural failure (100%, 100%), Technical failure (18%, 75%)

4.1 Discussion

The 11 clusters provide patterns of accidents. Results clearly show that grounding, collision and work accidents are mainly related to human factors. Furthermore, as a confirmation of the hierarchy described in the HFACS-MA model, human error and violations seem to mainly arise as a consequence of other preconditions (hardware, software and personnel deficiencies). Specifically, software factors seem to characterize clusters more than hardware factors, meaning that most of the accidents seem to result from procedural and process failures rather than from equipment or ergonomics deficiencies. This aspect is especially relevant for clusters where the type of accident is closely related to work accidents. In this regard, the maritime sector may benefit from more stringent and standardized protocols for operations in which human errors and violations have a major likelihood to occur. As an example, work operations related to the highest rate of life losses may benefit from protocols designed for respecting the timing of cargo operations and specific training for improving safety procedures.

Collision and grounding during navigation are the accidents that mostly characterize the identified patterns. Inadequate operating procedures and instructions and lack of supervision increase the occurrence likelihood of a collision or grounding accident. Similarly, limited visibility due to bad weather conditions and large-scale of ships could affect maneuvers of ships in narrow sea.

Problems with the navigational infrastructure are reported to lead to unclear communication (on-ship, ship-to-ship and ship-to-land). The latter, combined with excessive workload and frequently interlocutor changes, can negatively affect route choice decisions thus favoring the occurrence of accidents.

Work accidents are often a consequence of human errors and violations and play a crucial role in addressing the composition of the accident patterns. When work accidents occur, they are often caused by an error in judgement or an unsuccessful attempt to react appropriately because of insufficient training of seafarers, inadequate operating procedures and hardware imperfections. On the other hand, the occurrence likelihood of work accidents during cargo operations may be affected by human failures strictly related to a lack of communication or the constant pressure on seafarers for the rapid development of operations. Unfortunately, fatalities at work are not uncommon and seem often related to insufficient supervision and low-quality management.

According to the analysis, the patterns less related to human factors are those involving fires and machinery failures caused by technical problems, for which only in a few cases a failure in human monitoring is reported.

5. Conclusion and implications

Despite important technological advances and progress in terms of safety, merchant shipping is still marked by a high rate of accidents. Fatigue, stress, work pressure and communication are recognized as important contributors to accidents in the complex 24-hour working environment of shipping where both vessels and crews are often pushed to the limits to meet schedules.

This study has applied semi-supervised clustering techniques to a sample of 1.079 sea accidents in an attempt to elucidate causal links between human factors and accidents from real data.

Findings point to poor education and training of seafarers combined with lack of monitoring as common issues in maritime accidents. Hardware, software and personnel deficiencies are confirmed as the underlying factors behind human errors and violations. Furthermore, the human factor turns out to have a prevalent role in collision, grounding and work accidents.

The results of this study confirm the importance of human factor-oriented measures that are being applied in maritime transport and can further contribute to giving shipping practitioners a focus for maritime safety interventions (such as tailored training programs for crews or improved communication tools and protocols based on human factor research) which can potentially enhance maritime safety.

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References

Akhtar, M.J., Utne, 1.B., 2014. Human fatigue's effect on the risk of maritime groundings – a Bayesian Network modelling approach. Daf. Sci. 62, 427-440.

Allianz Global Corporate and Speciality, 2019. Safety and shipping review 2019. An annual review of trends and developments in shipping losses and safety. Available at: https://www.agcs.allianz.com/news-and-insights/reports/shipping-safety.html

Bair E., 2013. Semi-supervised clustering methods. WIREs Computer Stat, 5:349.

Bair E., Tibshirani R., 2004. Semi-supervised methods to predict patient survival from gene expression data. PLoS Biol 2:e108.

Celik, M., Cebi, S., 2008. Analytical HFACS for investigating human errors in shipping accidents. Accident Analysis and Prevention 41 (1), 66–75.

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

Chen, S., Wall, A., Davies, P., Yang, Z., Wang, J., Chou, Y., 2013. A Human and organizational factors (HOFs) analysis method for marine casualities using HFACS-Maritime accidents (HFACS-MA). Saf. Sci. 60, 105-114.

Galieriková, A., 2019. The human factor and maritime safety. Transportation research procedia, 40, 1319-1326.

Koestler D.C., Marsit C.J., Cristensen B., Karagas M.R., Bueno R., Sugarbaker D.J., Kelsey K.T., Houseman E.A., 2010. Semi-supervised recursively partitioned mixture models for identifying cancer subtypes. Bioinformatics 26: 2578-2585.

Hänninen, M. 2014. Bayesian networks for maritime traffic accident prevention: benefits and challenges. Accident Analysis & Prevention, 73, 305-312.

Hansen, H. L., Nielsen, D., & Frydenberg, M., 2002. Occupational accidents aboard merchant ships. Occupational & Environmental Medicine, 59(2), 85−91.

Hassel, M., Asbjørnslett, B. E., & Hole, L. P., 2011. Underreporting of maritime accidents to vessel accident databases. Accident Analysis & Prevention, 43(6), 2053-2063.IBM Corp. Released 2012. IBM SPSS Statistics for Windows, Version 21.0. Armonk, NY: IBM Corp.

Hastie T., Tibshirani R., Friedman J.H., 2009. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer Series in Statistics. 2nd ed. New York: Springer.

Hawkins, F.H., 1987. Human Factors in Flight. Gower Technical Press. Aldershot, UK.

Hetherington, C., Flin, R. and Mearns, K., 2006. Safety in shipping: The human element. Journal of safety research, 37(4), pp.401-411.

IMO, 1999. Resolution A.884(21): Amendments to the Code for the Investigation of Marine Casualties and Incidents (resolution A.849(20)). International Maritime Organisation (IMO), London, UK.

IMO, 2008. Casualty Investigation Code. IMO Publishing, London, UK, ISBN: 978-92-801-1498-0.

Lema, E., Vlachos, G. P., & Zikos, D., 2016. Linking causal factors and the human element in maritime accidents using K-means clustering. International Journal of Risk Assessment and Management, 19(3), 214-227.

Luo, M., & Shin, S. H., 2019. Half-century research developments in maritime accidents: Future directions. Accident Analysis & Prevention, 123, 448-460.

Myles Hollander and Douglas A. Wolfe (1973), Nonparametric Statistical Methods. New York: John Wiley & Sons. Pages 115–120.

Pourzanjani, M., 2001. Analysis of human error in coordinating ship's collision avoidance action. In: Proceedings of ICCGS 2001: 2nd International Conference on collision and Grounding of Ships, pp. 85–91

Reason, J., 1997. Managing the risks of organizational accidents. Ashgate, Burlington.

Shappell, S.A., Wiegmann, D.A., 2000. The Human Factors Analysis and Classification System – HFACS. Federal Aviation Administration Technical Report No. DOT/FAA/AM-00/7. National Technical Information Service, N Springfield.

Weng, J., Yang, D., Chai, T., & Fu, S., 2019. Investigation of occurrence likelihood of human errors in shipping operations. Ocean Engineering, 182, 28-37.