

Article

Temporal Validation of a Human-Error Likelihood Model for Dynamic Positioning Incidents Using IMCA-Reported Data

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Abstract

Dynamic positioning (DP) operations are safety-critical maritime activities in which technical system performance, environmental conditions and human decision-making interact continuously. Previous research presented a prediction model based on binary logistic regression that estimates the likelihood of human-error-related DP incidents, identifying the percentage of thrusters online as the significant predictor, using IMCA-reported data from 2007–2015. This study evaluates whether the previously developed prediction model remains valid when applied to a more recent IMCA dataset, with DP incidents from 2016 to 2025. A retrospective documentary analysis was conducted, and 77 incidents met the inclusion criteria for statistical analysis. Human-related factors were identified as a main or secondary cause in 35 cases, representing 45.5% of the analysed sample. The original thruster-based relationship was not reproduced in the updated drilling subset, where the percentage of thrusters online did not distinguish between human-related and non-human-related incidents. Applying the previous model resulted in poor discriminatory performance (AUC = 0.541), indicating that the original relationship between thruster availability and human-related incidents was no longer observed. Additional regression analyses found no statistically significant association between the selected operational, technical or environmental variables and human-related causation. These findings suggest that historical prediction models should be re-evaluated before being applied to contemporary DP operations. They also indicate that the variables available in IMCA reports alone are insufficient to explain human-related incident causation, highlighting the need for future studies to investigate additional human and organisational factors.

Keywords: dynamic positioning; DP incidents; human error; temporal validation; binary logistic regression; maritime safety; offshore operations; incident analysis



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1. Introduction

Dynamic positioning (DP) systems are widely used in offshore maritime operations in which a vessel must maintain its position and heading without the use of anchors or mooring lines. These systems integrate thrusters, power generation, position reference systems, motion sensors, wind sensors and control algorithms in order to counteract the effects of wind, waves and current and maintain the vessel within acceptable operational limits. The technical principles and control architecture of DP systems have been extensively described by Sørensen [1], while the safety relevance of DP operations in offshore drilling has been discussed by Chen, Moan and Verhoeven [2]. At regulatory and operational level, the IMO Guidelines for Vessels and Units with Dynamic Positioning Systems provide an

important technical framework for DP system design, equipment classes and operational expectations [3].

DP capability is essential in several offshore activities, including drilling, diving support, subsea construction, remotely operated vehicle operations, cable and pipe laying, shuttle tanker operations and other activities requiring precise station keeping. In these operations, even a relatively small loss of position may interrupt the operation or create a hazardous situation. Depending on the type of operation, the proximity of the vessel to fixed or floating structures, environmental conditions and the ability of the DP system and crew to detect, manage and recover from developing failures, a DP incident may result in drift-off, drive-off, damage to subsea infrastructure, collision with offshore units, environmental pollution or, in the worst scenario, loss of life and assets. Previous research on DP safety has emphasised the importance of learning from accidents and incidents, particularly because DP events often emerge from the interaction between technical failures, operational circumstances and human response [4].

Although DP operations are highly automated, the human element remains central to safe performance. Automation has changed the role of the DP operator, but it has not eliminated the need for human supervision, judgement and intervention. DP operators are required to monitor complex information flows, understand system restrictions, communicate with other operational teams and make decisions under time pressure. The Nautical Institute's Dynamic Positioning Operator Training and Certification Scheme Standard reflects the importance of structured training and competence development for DP operators [5]. Research on critical DP incidents has also shown that operators' situation awareness and judgement remain essential in complex operational scenarios [6]. Human reliability in DP operations depends not only on operator competence but also on how control functions are shared between people and automated systems. Consequently, human performance should be analysed within the context of the overall socio-technical system rather than as an isolated individual factor [7].

Human-related factors in DP incidents may include factors such as inadequate monitoring, incorrect interpretation of alarms, poor ergonomic design, non-compliance with procedures or inappropriate decision-making under pressure. Recent DP risk research has continued to emphasise the contribution of human factors, particularly in relation to monitoring, competence, operational control and risk assessment [8]. Similar concerns are also present in the wider maritime domain, where increasing digitalisation, remote operation and automation have introduced new forms of human–system interaction. For example, Zhou et al. [9] analysed human errors in remotely controlled ship operations during collision avoidance, showing that human performance continues to be an essential issue even in highly digitalised maritime environments.

Previous studies have analysed DP incidents using a range of statistical and data-driven approaches. Binary logistic regression has been applied to identify relationships between incident characteristics and operational outcomes [10], while more recent studies have continued to examine the role of human factors across different DP operations [11]. Association rule mining has also been used to identify patterns that are not readily apparent through descriptive analysis alone [12].

Prediction models developed from historical incident data should not be assumed to remain valid indefinitely. As technology, operational procedures, training standards and reporting practices evolve, the relationships between predictors and outcomes may also change. Consequently, variables that were informative when a model was originally developed may lose explanatory value over time. For this reason, temporal validation has become an essential step in determining whether an existing prediction model remains suitable for application to more recent data.

This issue is central to the validation of prediction models. Ramspek et al. [13] explain that external validation is necessary to determine whether a model performs adequately outside the data from which it was originally developed. More recent methodological guidance by Collins et al. [14] and Riley et al. [15] further clarifies the logic and practical requirements of external validation studies, while Binuya et al. [16] emphasise that models may require recalibration, revision or extension when applied to new populations, time periods or operational contexts. Although these methodological frameworks were originally developed for clinical prediction models, the underlying principles are equally relevant to maritime safety research. In both fields, prediction models are intended to support decision-making and therefore require periodic evaluation to ensure that their predictive performance remains acceptable when applied to new populations, operational environments or time periods.

Although temporal validation has become an established step in the evaluation of prediction models in other disciplines, it has received relatively little attention in maritime safety research. Most published studies focus on developing new models or identifying significant risk factors, while comparatively few examine whether previously developed models remain valid when applied to more recent operational data. Addressing this gap is important if prediction models are to be used reliably in evolving maritime environments.

This issue is particularly relevant for DP incident analysis based on reports published by the International Marine Contractors Association (IMCA). IMCA reports and DP station keeping event reports are important sources of industry safety information and provide valuable insight into DP incidents, undesired events and observations [17]. These reports provide valuable information on reported DP incidents, but they do not represent a complete census of DP incidents worldwide. IMCA's DP station keeping reporting guidance explains the structure and purpose of the reporting system, particularly after changes introduced from 2016 onwards [18]. Therefore, conclusions drawn from IMCA-reported cases should be understood as patterns within a reported and selected dataset rather than as precise estimates of the global frequency of DP incidents.

The changing structure of DP incident reporting also affects temporal comparability. Incidents from different periods may not be fully comparable in terms of reporting structure, level of detail, categorisation and available variables. Recent IMCA DP station keeping reviews and annual reporting material provide useful context for understanding current reporting practices and the type of information available in recent DP event data [19]. Consequently, differences observed between the two study periods may reflect not only changes in operational practice but also changes in the way incidents are documented and classified.

In this study, temporal validation refers to evaluating whether a prediction model developed using data from one time period maintains its performance when applied to data collected during a later period. The objective is not to redevelop the model, but to assess whether the relationship identified in the original analysis remains stable despite changes in operational practice, technology and reporting.

The aim of this study is to evaluate the temporal validity of a previously developed human-error likelihood model for DP incidents by applying it to an updated dataset of IMCA-reported DP incidents from 2016 to 2025. The specific objectives are to describe the occurrence of human-related factors in the updated dataset; compare the updated findings with the earlier 2007–2015 period; assess whether the predictor included in the original model retains its explanatory value; examine whether other technical, operational or environmental variables show significant associations with human causation; and determine whether the updated evidence supports the continued applicability of the original prediction model or indicates the need for its future revision.

By addressing these objectives, the study contributes to maritime safety research in two ways. First, it provides evidence on the temporal validity of a previously developed prediction model for DP incidents. Second, it highlights the importance of periodically validating prediction models before they are applied in evolving operational environments, thereby supporting the more reliable use of predictive methods in maritime risk research.

2. Materials and Methods

This study adopted a retrospective observational design based on documentary analysis of dynamic positioning (DP) incident and event reports. The methodology was designed to evaluate whether a previously developed human-error likelihood model remains applicable when applied to a more recent period of IMCA-reported DP cases.

2.1. Database Description

Data were obtained from the dynamic positioning incident and event reports published by the International Marine Contractors Association (IMCA) [17]. The IMCA DP reporting system provides publicly available information on DP events, incidents, observations and drill scenarios, with the purpose of promoting safety learning and sharing lessons within the offshore and DP community. The period 2016–2025 was selected in order to continue previous research based on earlier IMCA-reported data and to assess whether the relationships identified in the first model remain valid over time.

Reporting DP incidents or events to IMCA is voluntary. As a result, the data represent only IMCA-reported and publicly available DP cases, not all DP incidents worldwide. If an event is missing from the IMCA database, it does not mean no incident happened. The published reports show the information provided through IMCA's reporting and safety-learning process, and the amount of detail can differ from case to case. Because of this, this study looks for patterns in the reported and published cases instead of trying to estimate the total number of DP incidents globally.

2.2. Analytical Strategy

The methodology was structured in three main phases.

First, the updated 2016–2025 dataset was compiled, cleaned and coded using variables comparable to those applied in the prior 2007–2015 study. Descriptive statistics were then used to characterise the updated dataset and compare it with the earlier study period.

Second, the previously developed prediction model was temporally validated by applying it to the updated dataset. Model performance was assessed by examining its discriminatory ability using the receiver operating characteristic (ROC) curve and the corresponding area under the curve (AUC). Model classification performance was further evaluated using a predefined probability threshold of 0.50 to calculate classification accuracy, sensitivity and specificity.

Finally, additional binary logistic regression analyses were performed to investigate whether any of the available operational, technical or environmental variables independently explained the occurrence of human-related incidents in the updated dataset. These analyses were intended to explore whether alternative predictors emerged after the temporal validation of the original model.

2.3. Dataset Construction and Case Selection

The updated dataset was constructed from IMCA-published DP incident and event reports covering the period 2016–2025. An initial set of 86 cases was identified and reviewed. For each case, the available information was examined and coded according to the technical, operational, environmental and causation-related variables required for comparison alongside the original 2007–2015 model.

Cases were included in the final analytical dataset when sufficient information was available to code the dependent variable and the selected independent variables. Cases with missing values in key technical, operational or environmental variables required for the statistical analysis were excluded. After this filtering process, 77 valid cases remained and were included in the analysis.

The presence of a human-related cause was coded as the dependent variable. An incident was classified as human-related when human factors were identified either as the main cause or as a secondary/contributing cause. The detailed distribution of main causes, secondary causes and human-related cases is presented in the Section 3.

To ensure comparability with the original prediction model, variables were coded using the same definitions and coding procedures adopted in the 2007–2015 study whenever equivalent information was available in the IMCA reports. Only variables that could be consistently defined across both study periods were included in the comparative analyses. Variables that could not be coded consistently because of changes in reporting practices or insufficient information were excluded from the comparative and regression analyses.

2.4. Variable Definition and Coding

The variables included in the study covered technical, operational, environmental and causation-related information available in the IMCA reports. Technical variables included the percentage of thrusters online over the total number of thrusters, the percentage of generators online over the total number of generators, the number and type of position reference systems used, and the availability of gyros, motion reference units and wind sensors. Environmental and operational variables included wind force, current speed, wave height, visibility, water depth and the operation in progress at the time of the incident.

Visibility was coded as a categorical variable using three levels: 1 = poor visibility, 2 = moderate visibility and 3 = good visibility. Operational context was coded according to the operation in progress at the time of the incident. Because several operation types occurred only rarely, individual operation labels were grouped into wider operational categories in order to reduce limited data and improve interpretability.

Causation was coded using the categories reported in the IMCA material. Each incident was assigned a main cause. When a secondary or contributing cause was identified in the report, this was also recorded using the same causation categories. The causation categories considered in the analysis were computer problems, electrical failures, environmental and weather-related issues, external factors, human-related factors, power outages, reference system problems, sensor malfunctions and thruster failures.

The dependent variable for the statistical analysis was the presence of a human-related cause. This variable was coded as binary, with 1 indicating that the incident had a human-related cause and 0 indicating that no human-related cause was identified. A case was classified as human-related when human-related factors were identified either as the main cause or as a secondary or contributing cause. Therefore, the classification did not consider only incidents where human factors were the primary cause, but also cases where human contribution was reported as part of the causal chain.

Figure 1 presents the variables included in the study and their relationship to the analytical system.

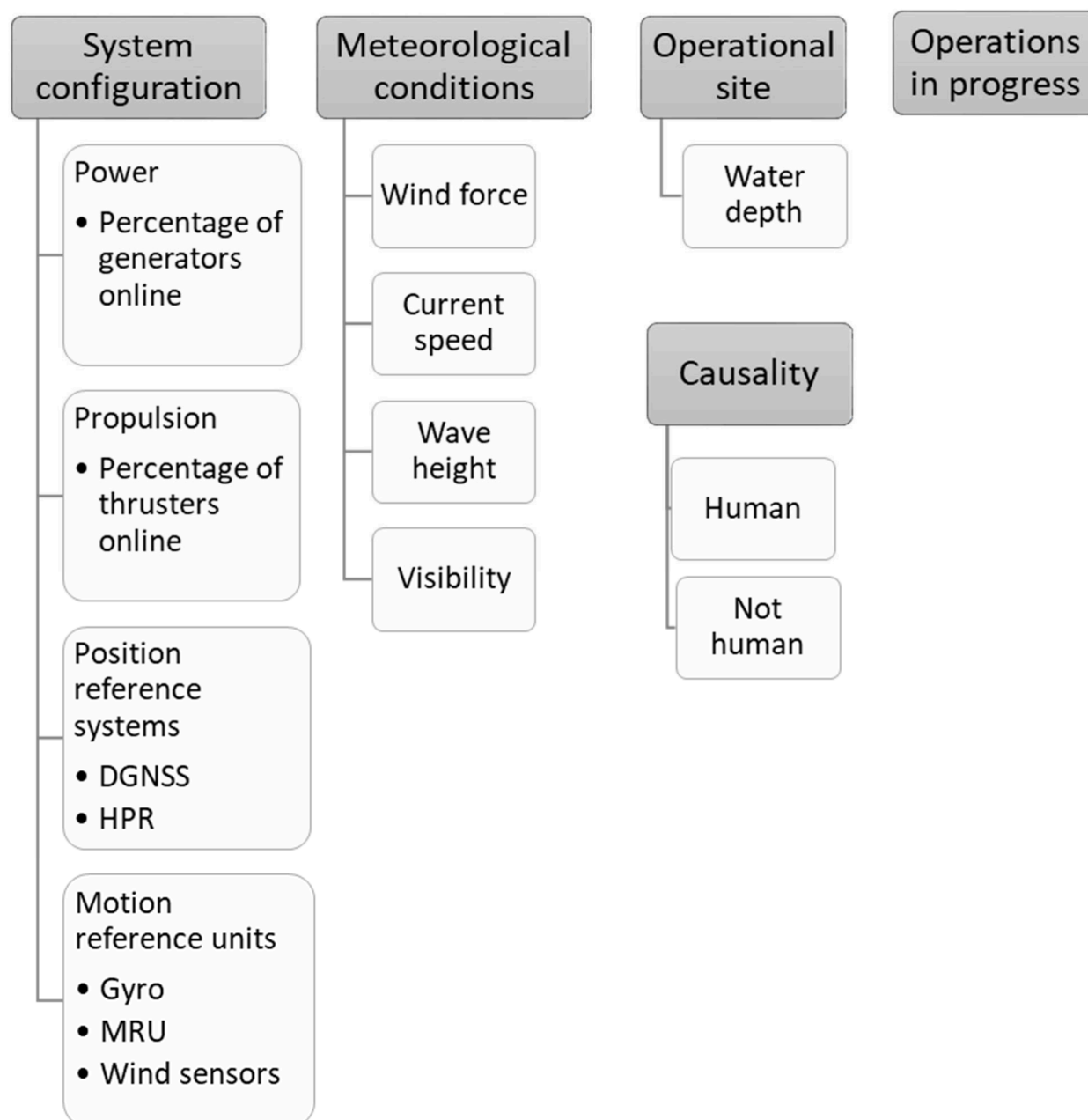


Figure 1. The diagram shows the different variables included in the study.

2.5. Period Comparison

The 2007–2015 and 2016–2025 periods were compared to assess whether the structure of IMCA-reported DP incidents changed over time. The comparison focused on the proportion of human-related incidents, the distribution of main and secondary causes, operational situations and selected environmental and technical variables.

The purpose of the period comparison was not only to identify descriptive differences between the two periods, but also to assess whether the updated evidence supports the continued validity of the first human-error likelihood model or suggests the need for modification. Where variables were coded consistently across both periods, the two datasets were also considered together as an extended 2007–2025 dataset for exploratory interpretation.

2.6. Temporal Validation of the Prediction Model and Exploratory Logistic Regression Analysis

Binary logistic regression was selected because the outcome variable (human-related versus non-human-related incident) was binary. The approach allows the relationship

between a binary outcome and one or more independent variables to be quantified while estimating the probability that an incident is associated with human-related causation.

The dependent variable is the presence of the human element as a cause of the incident. This variable was coded as binary, with 0 indicating no human cause and 1 denoting a human cause. A case is classified as human-related when human-related factors were identified either as the main cause or as a secondary or contributing cause.

Exploratory data analysis was first performed to examine the structure of the dataset, assess the relationships among variables, and identify any possible issues or limitations. This stage involved the calculation of descriptive statistics and correlations, as well as the use of graphical techniques such as box-plots, histograms, or other visualisations to inspect variable distributions and potential patterns.

The regression analysis was then used to evaluate whether the independent variables included in the database contributed to explaining the occurrence of a human-related cause. In this context, the model assessed the extent to which selected operational, environmental and technical variables were associated with the likelihood that an incident was classified as human-related.

The general form of the binary logistic regression model is given by:

$$Z = B_1X_1 + \dots + B_kX_k + B_0, \quad (1)$$

where Z represents the linear predictor (logit) of the probability that a DP incident is classified as human-related; $X_1, \dots, X_k$ represent the independent variables included in the model; and $B_0, B_1, \dots, B_k$ are the estimated regression coefficients. Each regression coefficient B_i represents the expected change in the log-odds of a human-related incident associated with a one-unit increase in the corresponding independent variable, assuming all other variables remain constant. A positive coefficient indicates an increase in the estimated probability of human-related causation, whereas a negative coefficient indicates a decrease. The exponential transformation of each coefficient, $\exp(B)$, corresponds to the odds ratio (OR), which quantifies the magnitude of the association between the predictor and the outcome.

As determined in the previous model [11], the equation for estimating the likelihood of a DP incident having a human-related cause is given by:

$$Z = 1.489 - 0.031 \text{ percentage of thrusters online} \quad (2)$$

where Z represents the logit of the probability of a human-error-related incident. In the present study, this model is applied to the updated 2016–2025 dataset in order to assess whether the relationship identified in the original analysis remains valid over time. The purpose is to determine whether the percentage of thrusters online continues to provide explanatory or predictive value for human-related DP incidents in the more recent dataset.

Finally, the predicted probability P that an incident has a human-related cause in any given case is provided by the following expression:

$$P = 1/(1 + \exp(-Z)) \quad (3)$$

where P can take any value between 0 and 1. Values closer to 1 indicate a higher estimated probability that the incident involved a human cause.

The previously developed prediction model was applied unchanged to the updated dataset. Predicted probabilities were calculated for each observation using Equations (2) and (3). Model discrimination was evaluated using the receiver operating characteristic (ROC) curve and the corresponding area under the curve (AUC). Classification performance

was assessed using a probability threshold of 0.50, from which classification accuracy, sensitivity and specificity were calculated.

In addition to applying the previous model, individual binary logistic regressions were performed using the updated dataset. Each independent variable was analysed separately using the Enter method. Regression coefficients (B), Wald statistics, *p*-values, OR and their corresponding 95% confidence intervals were calculated for each predictor. The regression coefficients describe the direction and magnitude of the association between each independent variable and the log-odds of human-related incident causation, while the odds ratios provide a more intuitive measure of the corresponding change in the odds of the outcome. A *p*-value below 0.05 was considered statistically significant.

Because none of the individual predictors demonstrated statistically significant associations with the outcome, and given the limited sample size of the updated dataset, development of a combined multivariable model was considered likely to produce an unstable and potentially overfitted model. Consequently, additional multivariable modelling was not pursued.

3. Results

3.1. Dataset Overview

For the updated dataset, 86 cases were obtained and coded for the period 2016–2025.

Cases with missing values in the technical, operational or environmental variables required for the statistical analysis were excluded, leaving 77 incidents in the final analytical dataset.

According to IMCA classification, incidents were assigned to one of the nine main-cause categories. Where reported, a secondary or contributing cause was coded using the same classification. The categories were computer problems, electrical failures, environmental and weather-related issues, external factors, human-related factors, power outages, reference system problems, sensor malfunctions, and thruster failures.

The statistical distribution of the main causes is shown in Table 1.

Table 1. Distribution of main causes for DP incidents 2016–2025 (*n* = 77).

Main Cause	Frequency	Percentage
Human	19	24.7
Power	19	24.7
Reference	11	14.3
Thruster	10	13.0
Computer	6	7.8
Electrical	5	6.5
External	3	3.9
Environmental	2	2.6
Sensors	2	2.6
Total	77	100.0

A secondary cause was identified in 39 cases, representing 50.6% of the analytical sample. The distribution of secondary causes is presented in Table 2. Human-related factors were the most frequent secondary cause, occurring in 16 cases and representing 41.0% of the incidents for which a secondary cause was reported.

A case was classified as human-related when human-related factors were identified either as the main cause or as a secondary or contributing cause. According to this definition, 35 incidents, representing 45.5% of the updated analytical sample, were classified as human-related.

In the earlier 2007–2015 dataset, 19.9% of the incidents were classified as human-related. The updated dataset therefore contains a substantially higher proportion of reported

incidents involving human-related factors. However, this descriptive comparison should be interpreted in light of the changes in IMCA reporting structure and case composition between the two study periods.

Table 2. Distribution of secondary causes for DP incidents 2016–2025 (n = 39).

Secondary Cause	Frequency	Percentage
Human	16	41.0
Electrical	7	17.9
Computer	5	12.8
Power	5	12.8
Reference	2	5.1
Thruster	2	5.1
External	1	2.6
Sensors	1	2.6
Total	39	100.0

3.2. Operational Context of Human-Related Incidents

Figure 2 shows the distribution of human-related incidents according to type of operation being conducted at the time of the event. Cargo operations accounted for the largest proportion of human-related incidents, with 8 cases (22.9%), followed by Remotely Operated Vehicle (ROV) operations with 7 cases (20%), and Cable/pipe-laying operations with 6 cases (17.1%). Diving and drilling operations each accounted for 4 cases (11.4%), while the remaining operations—including Stand-by, Shuttle, Ploughing, Gangway, DP trials and Approaching—were each represented by a single human-related incident.

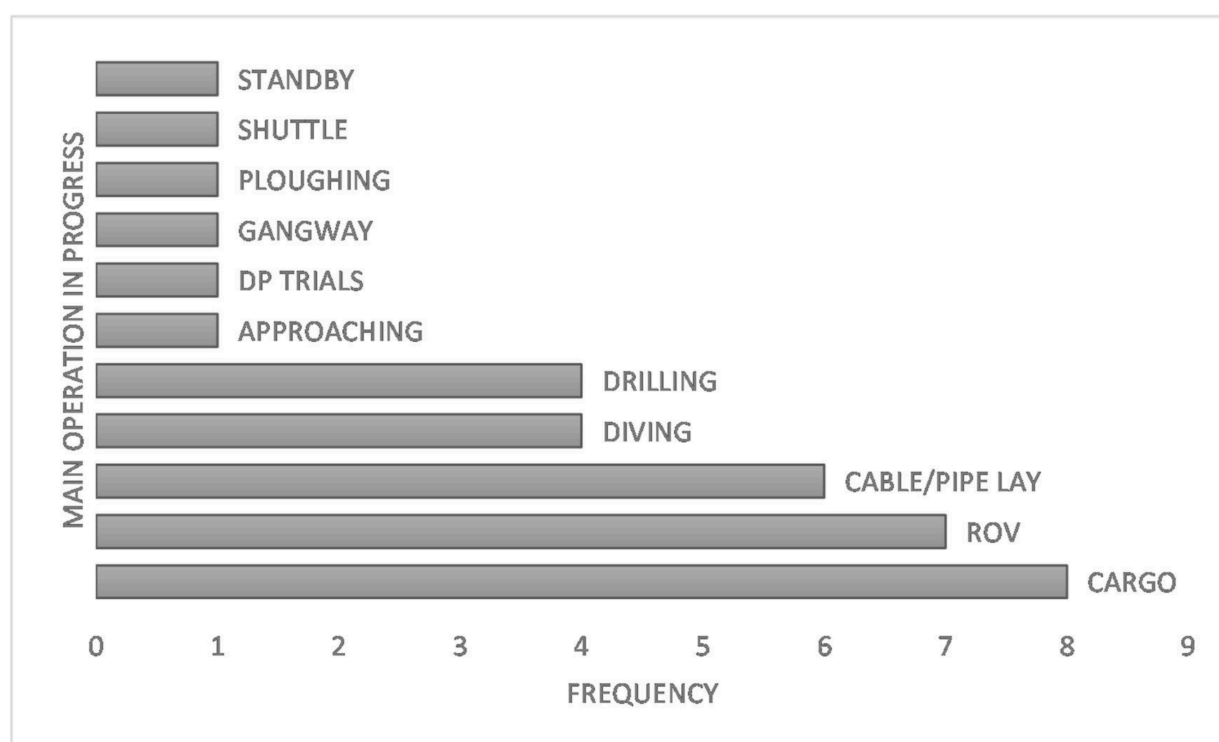


Figure 2. Distribution of the main operations in progress when a human-related incident occurred (n = 35).

3.3. Descriptive Statistics of Candidate Predictor Variables

Table 3 presents the descriptive statistics of the independent variables considered in the analysis. Among the position reference systems, DGNSS was the most frequently

represented, followed by HPR. Laser, microwave radar and Artemis appeared only rarely in the dataset and were therefore excluded from the regression analyses because of the limited number of observations.

Table 3. Descriptive statistics for the independent variables considered in the research (n = 77).

Variables ¹	Mean	Standard Error	Median	Standard Deviation	Minimum	Maximum
Water depth (m)	561.83	103.60	100.00	909.11	13.00	4800.00
Percentage of thrusters online	96.53	0.88	100.00	7.69	71.43	100.00
Percentage of generators online	70.52	2.32	66.67	20.39	33.33	100.00
No. of DGNSS	2.43	0.09	2.00	0.82	1.00	5.00
No. of HPR	0.71	0.09	1.00	0.76	0.00	2.00
No. of Tautwire	0.36	0.08	0.00	0.69	0.00	2.00
No. of Laser	0.32	0.05	0.00	0.47	0.00	1.00
No. of Microwave Radar	0.17	0.05	0.00	0.41	0.00	2.00
No. of Artemis	0.01	0.01	0.00	0.11	0.00	1.00
No. of Gyros	2.92	0.04	3.00	0.31	1.00	3.00
No. of MRU	2.55	0.06	3.00	0.55	1.00	3.00
No. of Wind sensors	2.56	0.07	3.00	0.64	1.00	4.00
Wind force (knots)	13.22	1.04	11.00	9.10	0.10	50.00
Current (knots)	1.33	0.15	1.00	1.31	0.00	9.50
Wave Height (m)	1.400	0.23	1.00	1.41	1.00	10.00
Visibility	2.83	0.05	3.00	0.41	1.00	3.00

¹ The following position reference systems had no data and therefore are not included in this table: FanBeam, RADIUS, Inertia system, and Gangway.

DP incidents occurred during a range of different offshore operations. Figure 3 shows the distribution of the DP incidents classified as human-related and non-human-related. The cases where there are only human-related incidents, or non-human-related incidents at all, should be taken with caution as they include only one case each.

Among the operation types represented by more than one incident, ROV operations (64%) and cable/pipe laying operations (60%) showed the highest observed proportions of human-related incidents, whereas drilling (31%) and diving (33%) showed the lowest. These values are descriptive and should be interpreted with caution because the number of incidents differed substantially between operation types.

The distribution of each independent variable was examined according to whether the incident was classified as human-related or non-human-related. As illustrated in Figure 4, substantial overlap was observed between the two groups for most variables, and no variable exhibited a visually distinct separation between the two classifications.

This pattern was particularly evident for the percentage of thrusters online, percentage of generators online, water depth, current speed and wave height, where the interquartile ranges and medians were broadly similar in both groups. The percentage of thrusters online, which constituted the sole predictor in the previously developed model, showed median values close to 100% in both human-related and non-human-related incidents, suggesting that its discriminatory ability may have diminished in the updated dataset.

Overall, the box plots indicate that no single technical, operational or environmental variable visibly distinguishes human-related from non-human-related incidents in the updated dataset.

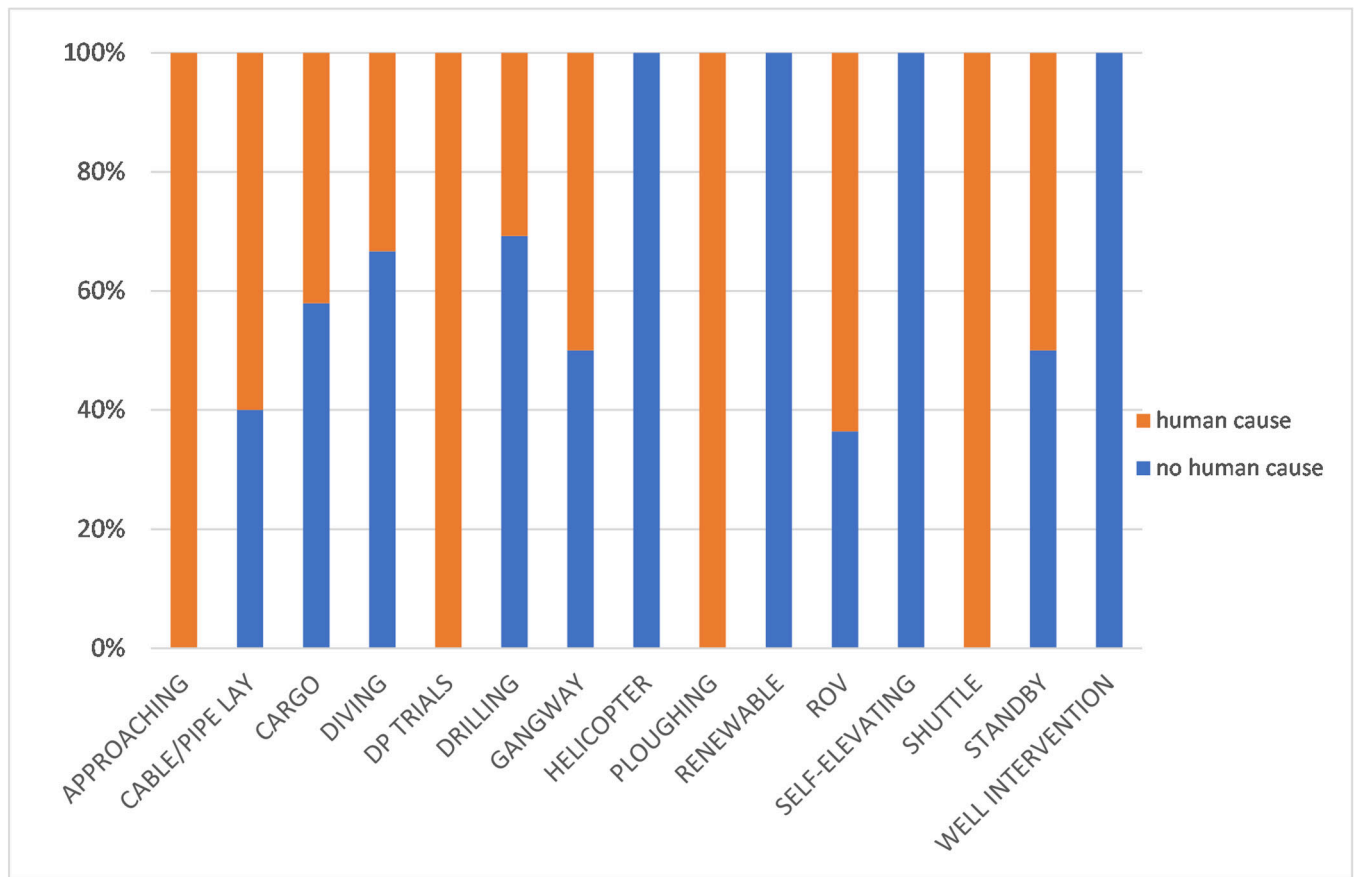


Figure 3. The percentage of incidents having a human cause for each operation in progress.

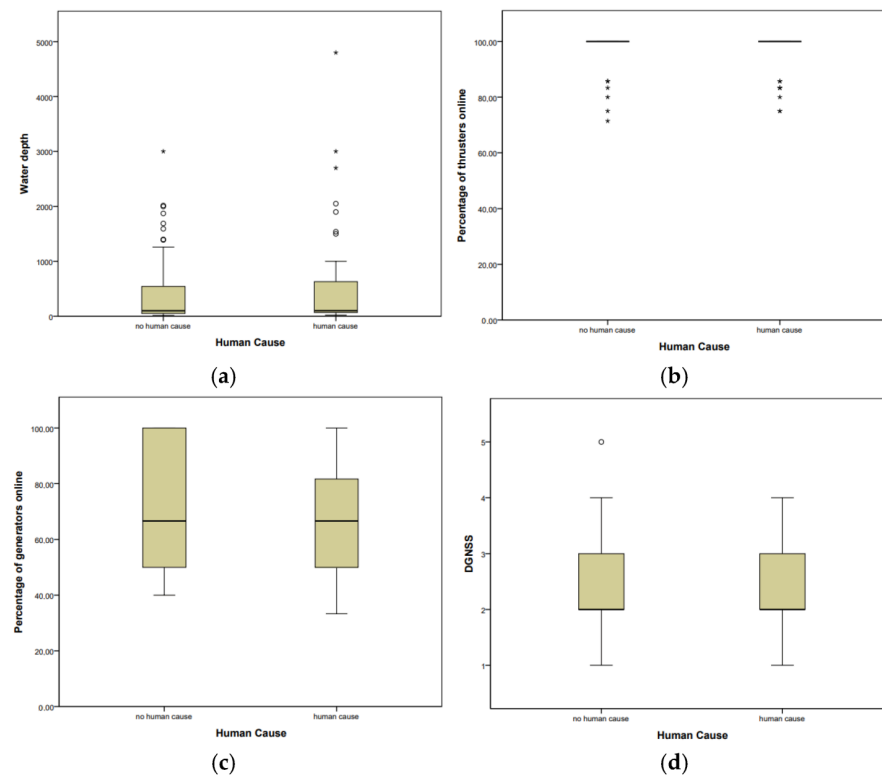


Figure 4. Cont.

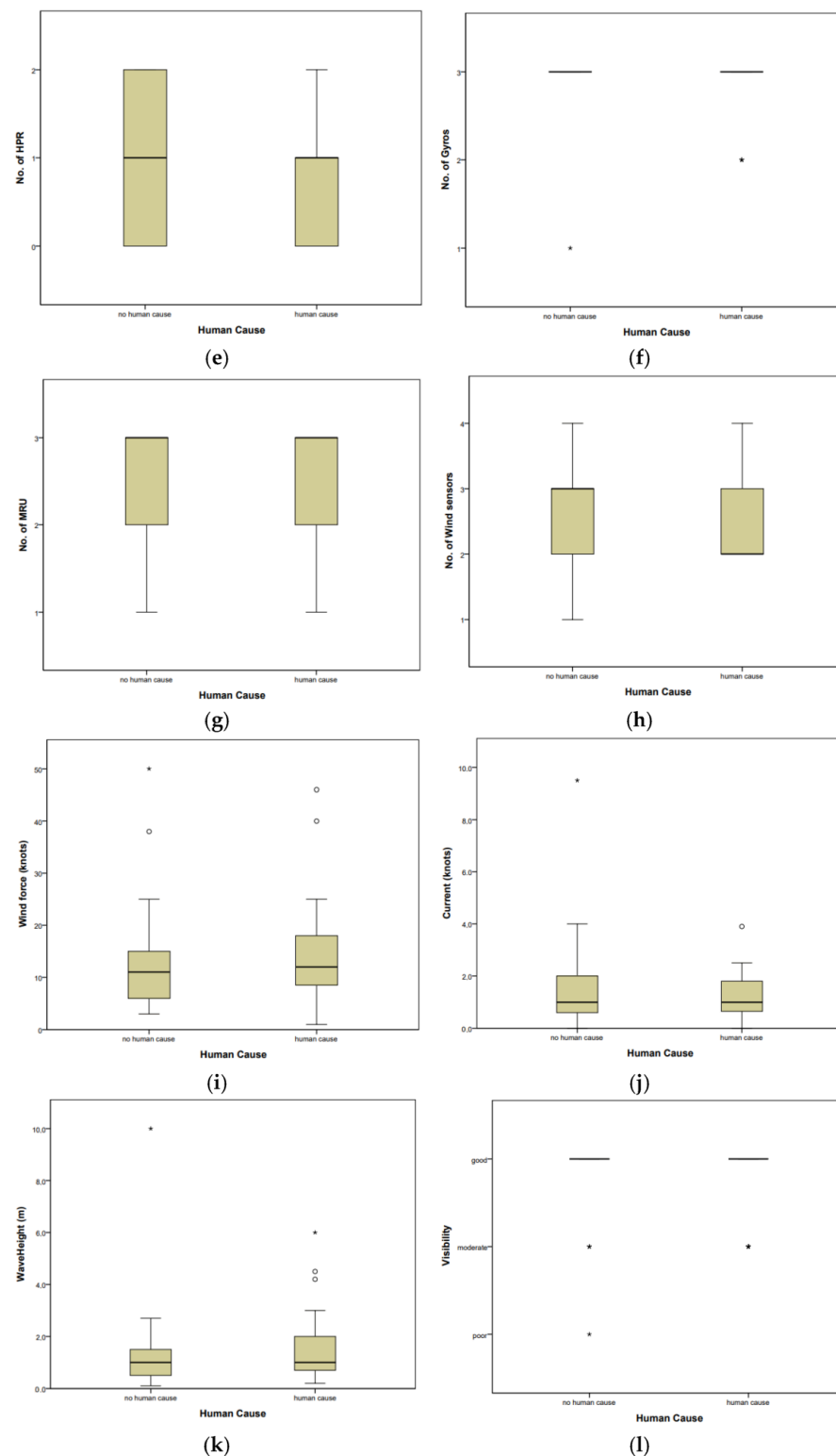


Figure 4. Distribution of the most relevant variables for the model, stratified by whether the incident had a human-related cause or not: (a) water depth, (b) percentage of thrusters online, (c) percentage of generators online, (d) DGNSS, (e) HPR, (f) gyros, (g) MRU, (h) wind sensors, (i) wind force, (j) current speed, (k) wave height, (l) visibility. In the boxplots, the horizontal line within each box represents the median. When the interquartile range is zero, the box collapses and is displayed as a single horizontal line. Hollow circles indicate outliers, and asterisks indicate extreme outliers.

3.4. Temporal Validation of the Previously Developed Prediction Model

The previously developed binary logistic regression model, based on the percentage of thrusters online as the sole predictor, was applied unchanged to the updated 2016–2025 dataset. Predicted probabilities were calculated using Equations (2) and (3), and the model's ability to discriminate between human-related and non-human-related incidents was evaluated using ROC analysis and AUC, consistent with recommended approaches for external validation of prediction models [14,15].

Figure 5 presents the ROC curve obtained by applying the original model to the updated dataset. The AUC was 0.541, indicating discrimination only marginally better than random classification. This result suggests that the predictive relationship identified in the 2007–2015 dataset was not reproduced when applied to the more recent incidents.

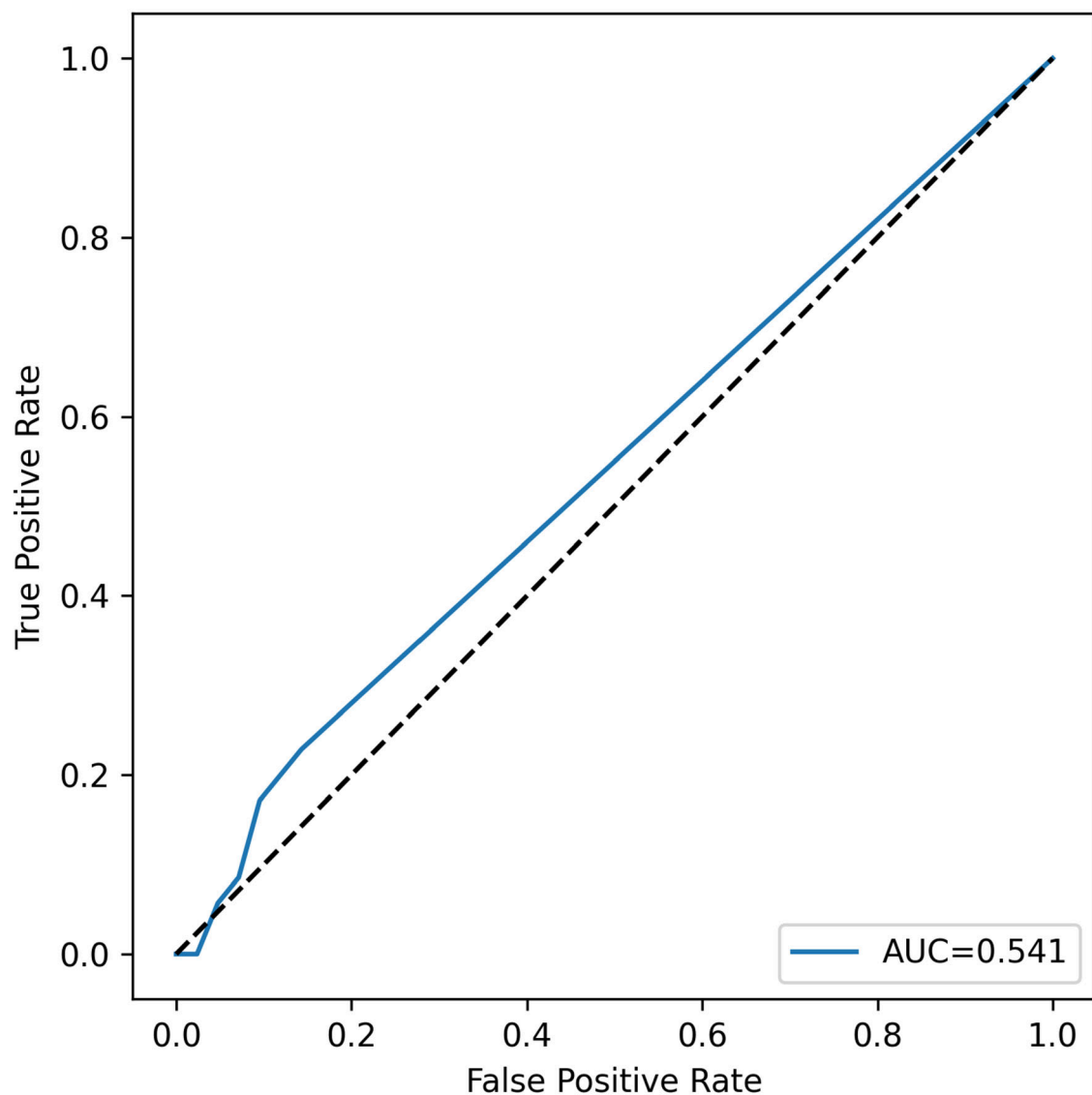


Figure 5. Receiver operating characteristic (ROC) curve for the previously developed prediction model applied to the 2016–2025 dataset.

The classification performance of the model is summarised in Table 4. Using the predefined probability threshold of 0.50 adopted in the original study, the model correctly classified 54.5% of the incidents. However, all predicted probabilities remained below the classification threshold, resulting in all incidents being classified as non-human-related.

Consequently, the model achieved a specificity of 100%, but a sensitivity of 0%, indicating that it failed to identify any of the human-related incidents in the updated dataset.

Table 4. Performance of the previously developed prediction model when applied to the 2016–2025 dataset.

Performance Metric	Value
Area under the ROC curve (AUC)	0.541
Classification threshold	0.50
Accuracy	54.5%
Sensitivity	0.0%
Specificity	100.0%

This behaviour is consistent with the descriptive analysis presented in the previous subsection. In particular, the percentage of thrusters online showed very limited variation across the updated dataset, with median values close to 100% for both human-related and non-human-related incidents. As a result, the predictor no longer provided sufficient discriminatory power to distinguish between the two outcome categories.

Overall, the temporal validation indicates that the previously developed prediction model does not retain its predictive performance when applied to the updated IMCA dataset, supporting the need for periodic reassessment of prediction models developed from historical DP incident data.

3.5. Performance of the Original Predictor in the Updated Drilling Subset

To better understand the reasons for the deterioration in model performance, the behaviour of the original predictor was examined separately within the drilling subset from which the original model was derived. The original drilling-specific prediction model identified the percentage of thrusters online as a significant predictor of the likelihood of a human-related DP incident (Equation (2)). Following the overall temporal validation presented in the previous subsection, the updated drilling subset was examined to determine whether this predictor retained its explanatory value in the 2016–2025 data.

In the updated drilling subset, the median percentage of thrusters online was 100% for both human-related and non-human-related incidents. The Mann–Whitney U test did not identify a statistically significant difference between the two groups. Moreover, all human-related drilling incidents occurred with 100% of thrusters online, whereas reduced thruster availability was observed only among non-human-related cases.

These findings contrast with those obtained from the original 2007–2015 dataset, in which lower thruster availability was associated with an increased likelihood of human-related incidents. In the updated dataset, the percentage of thrusters online no longer distinguished between the two outcome groups, indicating that the predictor had lost its explanatory value within the drilling subset.

This drilling-specific analysis is consistent with the overall temporal validation results presented in the previous subsection, which demonstrated poor discriminatory performance of the original prediction model when applied to the updated dataset. Together, these findings indicate that the relationship between thruster availability and human-related incident causation identified in the original study was not reproduced in the more recent IMCA-reported drilling incidents.

3.6. Binary Logistic Regression Modelling

Following the temporal validation of the previously developed prediction model, individual binary logistic regression analyses were performed to examine whether any of the available operational, technical or environmental variables were independently

associated with human-related incident causation in the updated dataset. These analyses were exploratory and intended to identify whether any alternative predictors emerged in the more recent data. The results thus obtained are shown in Table 5.

Table 5. Results of individual binary logistic regression analyses for the candidate predictor variables (n = 77).

Independent Variable	B	Wald	p-Value	OR	95% CI for OR	
					Lower	Upper
Water depth	0.000	0.425	0.515	1.000	1.000	1.001
Percentage of thrusters online	−0.024	0.647	0.421	0.976	0.920	1.035
Percentage of generators online	−0.002	0.033	0.856	0.998	0.976	1.020
DGNSS	−0.326	1.245	0.264	0.722	0.407	1.280
HPR	−0.186	0.368	0.544	0.830	0.456	1.513
Gyros	−0.712	0.797	0.372	0.491	0.103	2.343
MRU	−0.366	0.758	0.384	0.694	0.304	1.581
Wind sensors	−0.071	0.039	0.844	0.931	0.459	1.891
Wind force	0.027	1.052	0.305	1.027	0.976	1.081
Current speed	−0.160	0.647	0.421	0.852	0.577	1.259
Wave height	0.152	1.231	0.267	1.164	0.890	1.524
Visibility	−0.67	1.318	0.251	0.512	0.163	1.607

The results of the individual binary logistic regressions indicate that none of the examined independent variables was statistically significant as an individual predictor of whether a DP incident was attributed to a human cause for the analysed dataset. All *p*-values were far above the conventional significance threshold of 0.05, suggesting that, when considered separately, the operational and technical variables included in the analysis do not show any significant association with the classification of the incident as human-caused.

Among the analysed variables, the percentage of thrusters online, percentage of generators online, DGNSS, HPR, gyros, MRU, wind sensors, visibility, current speed and water depth showed odds ratios below or close to unity, indicating either a reduction or virtually no change in the estimated odds of a human-related incident with increasing values of these variables. However, none of these associations reached statistical significance, and all corresponding confidence intervals included the null value (OR = 1).

Wind force and wave height were the only variables with positive regression coefficients, suggesting a tendency towards higher estimated odds of human-related incidents under more demanding environmental conditions. For example, the estimated odds increased approximately 16% for each additional metre of wave height and by approximately 3% for each additional knot of wind speed. Nevertheless, these associations were also not statistically significant, and the corresponding confidence intervals included unity.

Water depth showed an odds ratio close to 1.000, indicating practically no change in the odds of a human-caused incident with increasing water depth. This suggests that, in

the present dataset, water depth alone does not appear to contribute meaningfully to the prediction of human causation.

To summarise, the individual logistic regression results suggest that none of the analysed variables independently explain the occurrence of human-caused DP incidents in a statistically significant manner. Given the absence of statistically significant individual predictors, the limited sample size and the risk of overfitting, the development of a combined multivariable logistic regression model was not considered methodologically justified. Overall, the exploratory analysis did not identify any operational, technical or environmental variable that independently explained human-related incident causation in the updated dataset. Together with the temporal validation results presented in the previous subsections, these findings indicate that the variables available in the IMCA reports do not provide sufficient explanatory power for reliable prediction of human-related DP incidents using the present dataset.

4. Discussion

4.1. Interpretation and Implications of the Findings

The principal finding of this study is that the previously developed prediction model for human-related DP incidents did not retain its predictive performance when applied to the updated 2016–2025 IMCA dataset. Temporal validation demonstrated poor discriminatory ability ($AUC = 0.541$), while the original predictor, the percentage of thrusters online, no longer distinguished between human-related and non-human-related incidents. Furthermore, the exploratory logistic regression analyses did not identify any alternative operational, technical or environmental variable that independently explained human-related incident causation. Together, these findings indicate that the relationships identified in the original dataset were not reproduced in the contemporary IMCA reports.

Several factors may explain the deterioration in model performance over time. DP systems, redundancy philosophies, operator training, alarm management practices and operational procedures have evolved considerably since the period covered by the original model. At the same time, the IMCA reporting framework has undergone substantial changes. The original prediction model was developed using DP incident reports published prior to 2016, when detailed event trees and comprehensive operational descriptions were routinely available for individual incidents. This reporting format enabled the extraction of a broad and relatively consistent set of operational, technical and environmental variables from nearly all published incidents. In contrast, the current reporting framework places greater emphasis on annual statistical summaries and safety-learning event bulletins, while the published reports provide detailed operational descriptions for only a subset of the reported DP station-keeping events. Consequently, the validation dataset was derived from a different reporting process than that used for model development and may therefore not represent an equivalent statistical sample. If the selection criteria for publishing detailed case reports have also evolved over time, the statistical relationships between the available predictors and human-related incident causation may likewise have changed. Although the influence of these reporting changes cannot be quantified within the present study, they represent a plausible explanation for the reduced temporal transferability of the original model. Rather than representing a limitation of the original modelling approach, the present findings illustrate an inherent characteristic of prediction models developed from historical operational data: their performance depends on the stability of both the operational environment and the underlying reporting process. Consequently, prediction models should not be assumed to remain valid indefinitely but should be periodically reassessed before being applied to contemporary operational environments.

More fundamentally, the present findings suggest that the deterioration in predictive performance reflects a change in the relationship between the available predictors and the underlying mechanisms of human-related incident causation. The original model assumed that the percentage of thrusters online acted as an informative proxy for conditions associated with human error. However, as DP systems, operational practices and human-machine interaction have evolved, this technical variable may no longer represent the same causal pathway. Although the percentage of thrusters online remains an important descriptor of vessel redundancy, it provides only indirect information about the cognitive and organisational processes that ultimately influence operator performance. Consequently, the observed decline in predictive performance should not be interpreted as a failure of the original modelling approach, but rather as evidence that the predictive relevance of individual technical variables may change as operational systems evolve.

The proportion of incidents classified as human-related was substantially higher in the updated dataset than in the earlier study period (45.5% compared with 19.9%). This difference should not automatically be interpreted as evidence of a deterioration in human performance. Rather, it is likely to reflect, at least in part, changes in the IMCA reporting framework after 2016. Compared with the earlier reports, the newer reporting system provides greater emphasis on identifying contributing causes and documenting human involvement within the causal chain, thereby increasing the visibility of human-related factors in the published case reports. At the same time, increasing automation may have shifted the operator's role towards system supervision, alarm interpretation and intervention during abnormal situations, making human-system interaction more prominent in incident analysis. Because these factors cannot be separated using the available data, the observed increase should be interpreted as a characteristic of the reported dataset rather than as evidence that the true frequency of human-related DP incidents has increased.

The exploratory regression analyses likewise failed to identify statistically significant predictors of human-related incident causation. This should not be interpreted as evidence that technical, operational or environmental conditions are irrelevant to DP safety. Rather, the findings suggest that the variables available in the IMCA reports, when considered individually, do not adequately capture the complexity of the mechanisms leading to human-related incidents. The absence of statistically significant predictors therefore reflects the limited explanatory power of the available variables rather than the absence of meaningful human-factor influences.

Some variables showed directional trends that may be operationally meaningful, although they were not statistically significant. Wind force and wave height were associated with increased estimated odds of human-related incidents, whereas visibility showed the opposite tendency. Although these associations cannot be interpreted as confirmed effects, they suggest that environmental conditions may still influence indirectly by increasing workload, cognitive demands and decision complexity. Confirmation of these relationships would require larger datasets with greater statistical power.

The lack of statistically significant associations for the technical variables is also noteworthy. The percentage of thrusters and generators online, together with the availability of DGNSS, HPR, gyros, MRUs and wind sensors, describes the technical configuration of the vessel at the time of the incident. However, these variables provide little information about how the DP system was monitored, how alarms were interpreted, whether redundancy was correctly understood, or whether operators responded appropriately to developing conditions. In practice, human performance depends not only on the availability of technical resources but also on the way those resources are managed during complex operational situations.

These findings support the view that human causation in DP incidents is inherently multifactorial. Human-related incidents are unlikely to arise from a single technical or environmental condition alone, but rather from the interaction between operational demands, technical system behaviour, and human decision-making. Factors such as situational awareness, workload, communication, procedural compliance, organisational support and safety culture are not represented in the available IMCA variables, yet they are likely to play an important role in determining how operators perceive, interpret and respond to abnormal situations. Consequently, operational and technical variables may describe the context in which an incident occurs, but they do not necessarily capture the mechanisms through which human errors develop.

From an educational and training perspective, the findings support the need to address human factors in DP training beyond the technical understanding of equipment status and environmental limits. Since human-related causation was not adequately explained by isolated technical or environmental variables, simulator-based training should continue to emphasise situational awareness, alarm interpretation, communication, workload management, procedural compliance and decision-making under changing operational conditions. This interpretation is consistent with previous research showing that simulator training can support the development of human-factor competence in complex offshore operations [20], and with studies highlighting the need to adapt maritime education and training to increasingly digitalised and technology-supported operational environments [21]. More specifically, Bogachenko and Pipchenko [22] showed that monitoring behavioural traits and common errors during DP simulator training provides useful insight into how operators respond to abnormal and emergency scenarios. Similarly, recent studies on DP emergency response training also support the use of simulators to expose operators to degraded redundancy, alarm sequences, environmental changes and time-critical decision-making in a controlled learning environment [23]. Broader simulation-based approaches to maritime education and training have been proposed as a way to develop emergency competence and prepare operators for increasingly complex operational environments [24], while Baldauf et al. emphasised the relevance of simulation for addressing growing complexity in maritime traffic and operational decision-making [25]. Therefore, the results of the present study reinforce the importance of training approaches that integrate technical system knowledge with behavioural, procedural and decision-making competencies.

If future data provide sufficient support for updating the model, several approaches could be considered. Recalibration of the intercept may be appropriate when the overall frequency of human-related incidents changes but the predictor effects remain stable. Revision of the regression coefficients would be required if the strength or direction of the existing predictor–outcome relationships has changed. Model extension would involve adding new predictors, particularly organisational, behavioural and cognitive variables that more directly reflect human performance. Given the poor discrimination observed in the present validation and the loss of explanatory value of the original predictor, simple recalibration alone is unlikely to be sufficient; future work would more likely require model revision or extension followed by validation in an independent dataset.

Overall, the findings demonstrate that historical prediction models should not be assumed to remain valid as technology, operational practices and reporting systems evolve. Temporal validation should therefore become an integral stage in the lifecycle of prediction models developed for maritime safety applications. At the same time, future models are likely to benefit from incorporating organisational, behavioural and cognitive variables that more directly represent the mechanisms underlying human performance during DP operations. Such an approach may provide more robust and transferable prediction models capable of supporting future maritime safety analysis and decision-making. More broadly,

the present findings illustrate that prediction models developed for historical operational data should be regarded as dynamic tools requiring continuous validation and adaptation as technology, operational practices, and human–machine interaction evolve.

4.2. Limitations of the Study

The principal limitation of this study relates to the source, completeness and consistency of the incident database. The analysis was based on IMCA DP station keeping reports, which represent an important source of industry safety information but should not be interpreted as a complete record of all DP incidents occurring during the study period. IMCA's reporting scheme relies on voluntarily submitted and published events, meaning that the available material represents a collection of reported cases rather than the full population of DP incidents. Reporting practices may vary according to company safety culture, incident severity, commercial sensitivity, geographical region, operational context and willingness to share lessons learned. Therefore, the findings should be interpreted as patterns within IMCA-reported cases rather than as precise estimates of the global frequency of human-related DP incidents.

This limitation is particularly relevant in the context of temporal validation because IMCA reporting practices evolved during the study period. Since 2016, the reporting system has gradually shifted from the incident-focused reports towards a broader DP station-keeping event-reporting framework. IMCA Information Note IN 1328 [18] describes the introduction of a new electronic reporting form, periodic DP event bulletins, and complementary reporting tools intended to improve industry learning. These developments influenced both the level of detail available for individual reports and the variables that could be consistently extracted for analysis.

Although the variables included in the present study were harmonised with those used in the original 2007–2015 dataset whenever possible, differences in reporting structure, the availability of detailed event descriptions and the selection of published case reports inevitably affect the comparability of the two study periods. Consequently, the temporal validation presented in this study should be interpreted as an assessment of model performance under evolving operational and reporting conditions rather than as a comparison of two perfectly equivalent datasets. At the same time, this characteristic reflects the reality of operational prediction models, which are expected to perform under changing technological and organisational conditions rather than under static experimental settings.

The evolving nature of the reporting system also limits the generalisability of the statistical results. Certain categories of incidents may be more likely to be reported, selected, anonymised or published than others, while some operational contexts may be underrepresented. Consequently, the absence of statistically significant predictors should not be interpreted as evidence that technical, operational or environmental factors are unrelated to human performance. Rather, it indicates that the variables available within the present IMCA dataset were insufficient to explain human-related incident causation with the level of statistical confidence required for predictive modelling.

Finally, the analytical dataset comprised 77 incidents after applying the inclusion criteria. The available sample allowed the temporal validation of the previously developed prediction model and exploratory analyses of the individual predictors; however, it limited the statistical power to detect weaker associations and did not justify the development of a new multivariable prediction model. Future studies would benefit from larger datasets, longer observation periods and the inclusion of variables describing organisational conditions, operator behaviour, workload and decision-making processes, allowing more comprehensive prediction models to be developed and externally validated.

5. Conclusions

This study evaluated the temporal validity of a previously developed prediction model for human-related DP incidents by applying it to an updated dataset of IMCA-reported incidents covering the period 2016–2025. The original model, developed using the 2007–2015 dataset, identified the percentage of thrusters online as a significant predictor of human-related incident causation. The objective of the present study was therefore not to develop a new prediction model, but to determine whether the previously identified relationship remained valid when applied to more recent operational data.

The temporal validation did not support the continued predictive performance of the original model. When applied to the updated dataset, the model demonstrated poor discriminatory ability ($AUC = 0.541$), indicating performance only marginally better than random classification. Furthermore, within the updated drilling subset, the percentage of thrusters online no longer differentiated between human-related and non-human-related incidents, confirming that the relationship identified in the original study was not reproduced in the more recent IMCA reports.

The exploratory logistic regression analyses likewise failed to identify statistically significant operational, technical or environmental predictors of human-related incident causation. Although some variables, particularly wind force, wave height and visibility, showed trends that may be operationally relevant, none reached statistical significance. Consequently, the available variables did not provide sufficient statistical evidence to justify the development of a new multivariable prediction model using the present dataset.

The findings also confirm that human-related factors remain an important component of DP incident causation. In the updated dataset, 35 of the 77 analysed incidents (45.5%) involved a main or secondary human-related cause. However, the results indicate that this contribution cannot be adequately explained using isolated technical, operational or environmental variables alone. Instead, the findings suggest that human-related DP incidents arise from the interaction between technical systems, operational context, organisational conditions and human decision-making, highlighting the socio-technical nature of DP operations.

Beyond the specific findings for DP operations, this study demonstrates that the predictive performance of models developed from historical operational data cannot be assumed to remain stable as technology, operational practices and reporting systems evolve. Changes in the relationships between predictors and outcomes may reduce model performance over time, making temporal validation an essential component of prediction model development and maintenance in maritime safety research.

Future studies should combine incident-reporting data with richer information on organisational conditions, operator behaviour, workload, decision-making processes and simulator-based observations. Such an approach is likely to improve the understanding of human-related DP incidents and support the development of more robust, transferable prediction models for maritime safety applications.

Ultimately, the present findings reinforce that temporal validation should become a routine component of the lifecycle of operational prediction models, ensuring that they remain scientifically valid and operationally relevant as maritime systems continue to evolve.

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Abbreviations

The following abbreviations are used in this manuscript:

AUC	Area Under the Receiver Operating Characteristic Curve
CI	Confidence Interval
DGNSS	Differential Global Navigation Satellite System
DP	Dynamic Positioning
DPO	Dynamic Positioning Operator
HPR	Hydroacoustic Position Reference
IMCA	International Marine Contractors Association
IMO	International Maritime Organization
MRU	Motion Reference Unit
OR	Odds Ratio
ROC	Receiver Operating Characteristic
ROV	Remotely Operated Vehicle

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