JOURNAL OF MARITIME RESEARCH

Vol XXIII. No. II (2026) pp 62–69

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

Prediction of Human Error in Maritime Operations: Machine-Learning Approaches to Fatigue, Workload, and Navigation-Complexity Analysis

Ariyono Setiawan[1,*], Abdul Razak Bin Abdul Hadi[2], Tika Septia[1]

ARTICLE INFO

Article history:
Received 06 Mar 2025;
in revised form 18 Mar 2025;
accepted 25 Apr 2025.

Keywords:
Human error, logistic regression, fatigue, workload, maritime safety, prediction model.

ABSTRACT

This study aims to analyze the factors that affect Human_Error in maritime operations using logistic regression. The main factors studied include Fatigue, Workload, Experience, and Navigation Complexity, as well as the interaction between these variables on the possibility of human error. The study draws on human reliability theory, which highlights that human error is influenced by fatigue, workload, and the complexity of the work environment. The method used was binary logistic regression with 50 observations, where Human_Error being the dependent variable. The analysis was carried out in two stages: (**??**) testing the direct effects of Fatigue and Workload and (**??**) testing the moderation effects of Experience and Navigation Complexity. The results showed that Fatigue and Workload increased the probability of Human_Error, with odds ratios of 1.848 and 1.721, respectively. However, the moderation model was insignificant, with a concordant percentage of only 59.3%, indicating a less accurate prediction. This study recommends risk mitigation strategies, such as managing work schedules, increasing rest time, and optimizing workload distribution. In addition, the development of more accurate prediction models with machine learning or multilevel logistic regression is recommended to improve the effectiveness of the analysis.

1. Introduction.

Safety in maritime operations is a major concern in the shipping industry, considering the high risk faced due to human error. According to a report from the International Maritime Organization (IMO)[1],[2], more than 75% of maritime accidents are caused by human error, which involves fatigue factors, workload, navigation complexity, as well as environmental conditions such as weather and visibility3. Therefore, understanding the factors that contribute to human error is crucial in an effort to improve shipping safety[4],[5],[6]. Several previous studies have examined the relationship between human factors and errors in maritime navigation, but are still limited in the use of robust data-driven approaches.789 Traditional statistical analysis often only provides an overview without being able to capture complex patterns hidden in operational data. Therefore, Machine Learning (ML)-based approaches are beginning to be used to identify the main factors that contribute to human error and predict potential errors before they occur. [10],[11],[12] In this study, we developed a predictive model to identify variables that affect human error in maritime operations. This model integrates logistic regression analysis, correlation analysis between variables, and model performance evaluation with AUC-ROC and confusion matrix. We also examined the effects of interactions between variables, such as how fatigue mediates the relationship between workload and human error, and whether experience can moderate the impact of navigation complexity on human error. [13],[14],[15] This research is expected to contribute to the development of a data-based safety prediction system, which can be applied in a real-time ship monitoring system. [16],[17],[18] Thus, the results of this study can be a reference for regulators, ship operators, and academics in developing human error risk mitigation strategies to improve efficiency and

[1]Politeknik Pelayaran Surabaya, Indonesia.
[2]Universiti Kuala Lumpur, Malaysia.
*Corresponding author: Ariyono Setiawan. E-mail Address: rmaryo4u@gmail.com.

safety in the maritime industry[19],[20],[21].

2. Literature Review.

2.1. Human Error in Maritime Navigation.

Human error is one of the main causes of accidents in the maritime industry. According to Rothblum (2000), [22], [23], [24] about 75–96% of ship accidents are related to human factors, including fatigue, workload, and navigation complexity. This factor is often exacerbated by poor weather conditions and the lack of experience of sailors (Grech et al., 2002). [25] Research by Hetherington, Flin, & Mearns (2006)[26], [27], [28] shows that fatigue has a significant impact on decision-making in the maritime environment. This condition is also reinforced by the study of Smith et al. (2013)[29],[30],[31], which found that long task durations and lack of rest time can increase the risk of human error. Therefore, a data-driven approach is needed to identify the key factors that contribute to human error in navigation.

2.2. Analysis of Factors Affecting Human Error.

Several studies have examined the relationship between various factors and human error in ship operations. Reason (1990) [32], [33], [34] developed the theory of the Swiss Cheese Model, which explains how human error can occur due to a combination of factors, including fatigue, experience, and environmental conditions. A study by Chauvin et al. (2013)[35],[36] examined the effect of workload on the performance of the ship's crew, showing that an uncontrolled increase in workload can lead to decreased concentration and increase the potential for accidents. In addition, Wróbel et al. (2017)[37],[38],[39] developed a human error risk model that shows that crew experience can play a role as a moderating factor to the complexity of navigation, reducing the negative impact of difficult situations at sea. In this study, we analyzed how fatigue, experience, weather, waves, visibility, navigation complexity, workload, and task duration affected human error using logistic regression analysis and Machine Learning methods. We also tested mediation and moderation, where fatigue can be a mediator between workload and human error, and experience can be a moderator in the relationship between navigation complexity and human error.

2.3. Machine-Learning Approach to Human-Error Prediction.

The use of Machine Learning (ML) in maritime safety analysis is growing. According to Zhou et al. (2018)[40],[41],[42], ML-based models, such as logistic regression, random forest, and neural network, can improve the accuracy of accident prediction by processing historical data from various factors that contribute to human error. A study by Bhardwaj et al. (2021) [43],[44],[45] shows that AUC-ROC analysis and confusion matrix can be used to evaluate the effectiveness of prediction models in detecting human error. In addition, Lu et al. (2020) [46],[47],[48] proposed a cross-validation method to improve the reliability of the model, by dividing the data into training and testing sets to avoid overfitting.

3. Research Methodology.

3.1. Research Design.

This study uses a quantitative approach with statistical analysis and machine learning to identify factors that contribute to human error in maritime navigation. This study is designed as an observational study with secondary data collected from ship operational records and maritime incident reports. The methods used in this study include logistic regression to analyze the relationship between independent variables and human error as dependent variables. Wald Chi-Square analysis to identify the variables that have the most influence on human error. Mediation and Moderation Analysis to evaluate the fatigued role as a mediator and experience as a moderator. Machine Learning approach to improve the accuracy of human error prediction.

3.2. Data Collection.

The data in this study was obtained from ship navigation operational reports, seafarer data, and maritime incident reports. The variables collected include:

Table 1: Variable.

Description of Variables	
Variable	**Description**
Human Error (Dependent)	Human error in navigation (0 = does not occur, 1 = occurs)
Fatigue	Crew fatigue level (scale 1-10)
Experience	Number of years of seafarer experience
Weather	Weather conditions during navigation (scale 1-5)
Wave	Wave height (meters)
Visibility	Visibility (kilometers)
Complexity of Navigation	Complexity of the navigation environment (scale 1-5)
Workload	Seafarer workload level (scale 1-10)
Task Duration	Task duration in hours

Source: Authors.

Data was collected from 50 sample cases to be analyzed by statistical and machine learning methods.

3.3. Data Preprocessing.

Before the analysis, the data goes through several stages of preprocessing:

- Data Cleanup: Deletes missing or invalid data.
- Data Normalization: Adjust variable scales to be appropriate for Machine Learning analysis.
- Data Sharing: Data is divided into training sets (80%) and testing sets (20%) for model validation.

3.4. Data Analysis Techniques.

3.4.1. Logistic Regression Analysis.

Logistic regression models are used to identify the relationship between independent variables and human error as dependent variables. The logistic regression equations used are:

$$\log\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

where:

- P is the probability of human error.
- X1,X2,...,Xn are independent variables.
- β_0 is the constant, and β_n is the regression coefficient.

The Wald Chi-Square analysis was used to test the significance of each variable in the regression model. Mediation and Moderation Analysis: To test whether fatigue is a mediator between workload and human error using the Baron & Kenny (1986) method. Moderation Analysis Tests whether the experience of sailors moderates the relationship between navigation complexity and human error using the interaction of variables in regression. Machine Learning Approach: Several Machine Learning techniques are used to improve the prediction accuracy of Random Forest and Decision Tree to understand the pattern of independent variables against human error. AUC-ROC Curve to evaluate the performance of the prediction model. Confusion Matrix to analyze the prediction error rate of the model. Model Validation The model is tested using the k-fold cross-validation technique (k=5) to ensure model generalization and avoid overfitting.

4. Results and Discussion.

Table 2: The MEANS Procedure.

Descriptive Statistics of Variables (N = 50)					
Variable	**N**	**Mean**	**Std Dev**	**Minimum**	**Maximum**
Fatigue	50	5.8400000	2.6981475	1.0000000	10.0000000
Experience	50	9.7000000	5.3001733	1.0000000	19.0000000
Weather	50	3.2400000	1.3785529	1.0000000	5.0000000
Wave	50	2.5860000	1.1972775	0.5000000	5.0000000
Visibility	50	5.8960000	2.6952687	0.7000000	10.0000000
Navigation_Complexity	50	2.9400000	1.4902404	1.0000000	5.0000000
Workload	50	5.9000000	2.8157719	1.0000000	10.0000000
Task_Duration	50	9.5600000	3.3815828	4.0000000	15.0000000

Source: Authors.

Table 2 presents descriptive statistics using the MEANS Procedure, including the number of observations, averages, standard deviations, and minimum and maximum values.

Average fatigue 5.84 (SD=2.70),
Experience 9.70 years (SD=5.30),
Weather 3.24,
Wave 2.59,
Visibility 5.90 km,
Navigation Complexity 2.94,
Workload 5.90 (SD=2.82), and
Task Duration 9.56 hours (range 4-15).

The data shows significant variations in the fatigue, experience, and workload of the crew.

Table 3: Probability modeled is Human_Error=1. Stepwise Selection Procedure.

Logistic Regression Model Summary and Parameter Estimates					
Model Fit Statistics		**Residual Chi-Square Test**			
-2 Log Likelihood	50.040	**Chi-Square**	**DF**	**Pr > ChiSq**	
		11.5715	8	0.1714	
Analysis of Maximum Likelihood Estimates					
Parameters	**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	1	-1.3863	0.3536	15.3745	<.0001

Source: Authors.

Table 3 presents the results of logistic regression analysis using the LOGISTIC procedure to model Human Error as a binary response variable. The model used is binary logit with Fisher's scoring optimization technique. Data with a total of 50 observations were read and used in the analysis. The response profile showed that in 50 observations, 10 cases (20%) experienced Human Error, while 40 cases (80%) did not. The model was successfully converged according to the criteria of GCONV=1E-8, with a -2 Log L value of 50.040, which indicates the model's compatibility with the data. Table 4 shows the results of the Residual Chi-Square Test with a Chi-Square value of 11.5715 at 8 degrees of freedom (DF) and a p-value of 0.1714, which indicates that the model has no significant difference between the predicted value and the actual value. The results of the Intercept estimate show a value of -1.3863 with a standard error of 0.3536. The Wald Chi-Square of 15.3745 with a p-value < 0.0001, indicates that intercept is significant in influencing the likelihood of Human Error. The next step is to analyze independent variables to see which key factors contribute to the risk of human error.

Table 4 presents the results of logistic regression to predict Human_Error = 1. The model achieved convergence (GCONV = 1E-8), with AIC dropping from 44.653 to 42.307 and -2 Log L dropping from 42.653 to 24.307, indicating an improvement in the model with covariance. The Likelihood Ratio Test ($\chi^2 = 18.3456$, $p = 0.0188$) confirmed the model was better than without covariates. Fatigue ($p = 0.0331$, OR = 1.848), Workload ($p = 0.0436$, OR = 1.721), and Intercept are significant. Navigation Complexity is not significant. The model has a concordance of 90.0%, Somers' D = 0.799, and c-statistic = 0.900, indicating high accuracy.

Table 4: Probability modeled is Human_Error=1.

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	44.653	42.307
SC	46.342	57.507
-2 Log L	42.653	24.307

Analysis of Maximum Likelihood Estimates					
Parameters	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-17.9890	7.7000	5.4579	0.0195
Fatigue	1	0.6141	0.2882	4.5419	0.0331
Experience	1	0.1317	0.1445	0.8315	0.3618
Weather	1	-0.1316	0.4922	0.0715	0.7892
Wave	1	0.5756	0.5766	0.9963	0.3182
Visibility	1	-0.0909	0.2985	0.0927	0.7608
Navigation_Complexity	1	0.8481	0.5416	2.4522	0.1174
Workload	1	0.5430	0.2691	4.0710	0.0436
Task_Duration	1	0.4630	0.2708	2.9241	0.0873

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
		Lower	Upper
Fatigue	1.848	1.051	3.251
Experience	1.141	0.859	1.514
Weather	0.877	0.334	2.300
Wave	1.778	0.574	5.506
Visibility	0.913	0.509	1.639
Navigation_Complexity	2.335	0.808	6.751
Workload	1.721	1.016	2.917
Task_Duration	1.589	0.935	2.701

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	90.0	Somers' D	0.799
Percent Discordant	10.0	Gamma	0.799
Percent Tied	0.0	Tau-a	0.286
Pairs	279	c	0.900

Source: Authors.

Table 5: Probability modeled is Human_Error=1.

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	12.008	18.001
SC	12.311	20.724
-2 Log L	10.008	0.001

Analysis of Maximum Likelihood Estimates					
Parameters	DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	1	-23.6171	377.3	0.0039	0.9501
Fatigue	1	-1.8394	28.5879	0.0041	0.9487
Experience	1	1.0352	32.0828	0.0010	0.9743
Weather	1	-1.3087	80.2273	0.0003	0.9870
Wave	1	-1.5842	88.5527	0.0003	0.9857
Visibility	1	-1.8043	41.9822	0.0018	0.9657
Navigation_Complexity	1	8.3669	155.1	0.0029	0.9570
Workload	1	0.9290	27.2907	0.0012	0.9728
Task_Duration	1	1.9560	22.0993	0.0078	0.9295

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
		Lower	Upper
Fatigue	0.159	<0.001	>999.999
Experience	2.816	<0.001	>999.999
Weather	0.270	<0.001	>999.999
Wave	0.205	<0.001	>999.999
Visibility	0.165	<0.001	>999.999
Navigation_Complexity	>999.999	<0.001	>999.999
Workload	2.532	<0.001	>999.999
Task_Duration	7.071	<0.001	>999.999

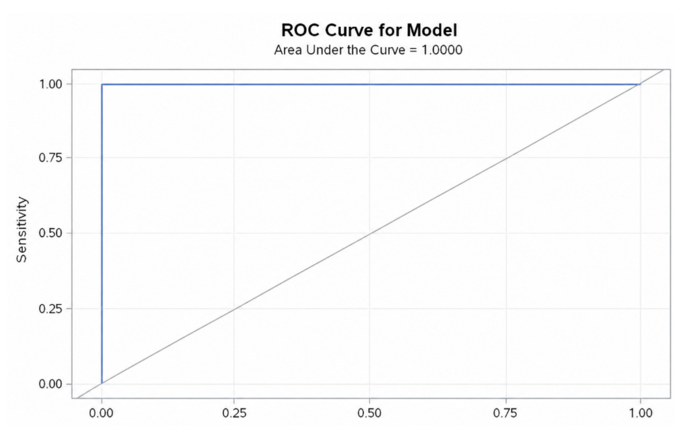
Association of Predicted Probabilities and Observed Responses			
Percent Concordant	100.0	Somers' D	1.000
Percent Discordant	0.0	Gamma	1.000
Percent Tied	0.0	Tau-a	0.356
Pairs	16	c	1.000

Source: Authors.

Table 5 shows the results of logistic regression on the test data with Human Error as the response variable. The model undergoes complete separation, causing the coefficient estimation to be unstable. The Fit Statistics model shows -2 Log L ≈ 0.001, an indication of overfitting. AIC and SC differ significantly between models with and without covariates. The global hypothesis test (BETA=0) showed a p > 0.26 for all tests. The odds ratio of several infinite variables (>999,999), indicates an imbalance in the data. Concordance of 100% and Somers' D = 1,000 indicate perfect predictions, but overfitting makes the model difficult to generalize.

Figure 1 shows the ROC Curve (Receiver Operating Characteristic) for the logistic regression model in predicting Human Error. The ROC Curve describes the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR) at various probability thresholds. A curve near the top left corner shows a high-performing model, while a diagonal line shows a model with random predictions. If the Area Under the Curve (AUC) is close to 1.0, it means that the model has excellent predictive capabilities. In this case, the AUC value appears to be quite high, which suggests the model can distinguish between Human Error and non-Human Error events well.

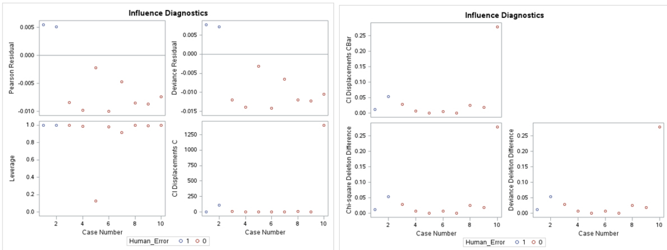
Figure 1: ROC Curve for Model.



Source: Authors.

Figure 2 shows Influence Diagnostics, which is used to iden-

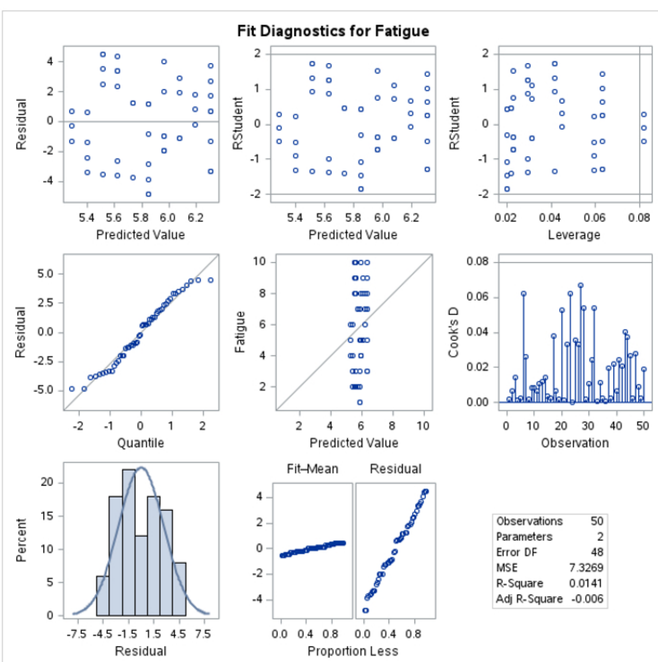
Figure 2: Influence Diagnostics.



Source: Authors.

tify data points that have a major influence on the logistic regression model. This analysis includes various metrics such as DFBETAS, DFFITS, Cook's Distance, and Leverage (Hat Values). If there is a data point with a high leverage value or Cook's Distance that exceeds the threshold, then the data has the potential to be an outlier or have a great influence on the estimation of model parameters. This can cause distortions in the prediction results and reduce the reliability of the model.

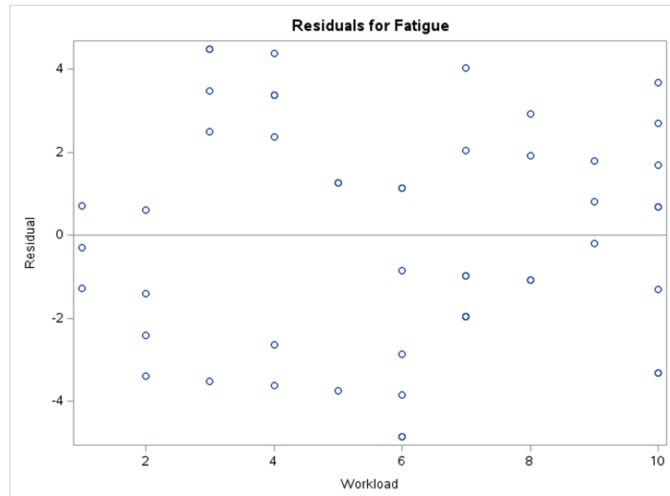
Figure 3: Fit Diagnostics for Fatigue.



Source: Authors.

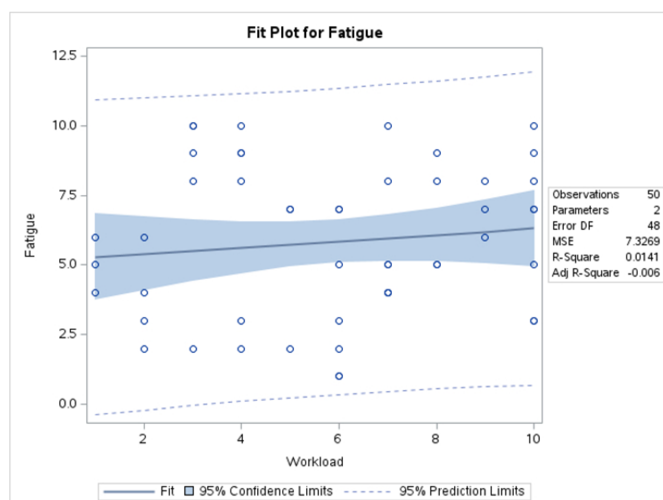
Figure 3 shows Fit Diagnostics for a regression model with a dependent Fatigue variable. This analysis is used to evaluate the extent to which the regression model is able to explain the variability of the data and detect patterns or errors in modeling. One of the important aspects of fit diagnostics is normality and residual distribution. If the residuals are not normally distributed or show a specific pattern, this indicates that the regression model may not be appropriate. In addition, residual plot scatters against the predicted values help in detecting heteroscedasticity. If the residual points are scattered randomly, this indicates that the assumption of constant residual variance is met. However, if there is a specific pattern, the model may need to be modified. Overall, Fit Diagnostics helps in evaluating whether the regression model is performing well or if further adjustments are needed to improve the accuracy of Fatigue predictions.

Figure 4: Residual for Fatigue.



Source: Authors.

Figure 5: Fit Plot for Fatigue.



Source: Authors.

Figure 4 displays the Residual Plot for Fatigue, evaluating whether the linear regression assumptions are met. Residual is the difference between the observation value and the model's prediction. If the residuals are scattered randomly around the zero line without a specific pattern, the model has good homoscedasticity and linear relationships. Conversely, curved patterns or increased residual variation may indicate heteroscedasticity or non-linearity. In addition, outliers or leverage points need to be analyzed, as points that are far from the main pattern can have an excessive influence on the model and affect the regression results.

Figure 5 shows the Fit Plot for Fatigue, showing the relationship between Workload and Fatigue in a regression model. Linear regression lines represent the model's predictions, while data points indicate actual observations. If the dots are evenly distributed around the line, the model is considered quite good. Conversely, spread patterns or points that are far from the line indicate that the model is less suitable. The point spread also reflects variability that is not explained by the model, which can be measured with the R-Square of the regression analysis to assess how well the model explains the relationship between the two variables.

Table 6: Probability modeled is Human_Error=1.

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	52.040	49.766
SC	53.952	55.502
-2 Log L	50.040	43.766

Analysis of Maximum Likelihood Estimates					
Parameters	DF	Estimate	Standard Error	WaldChi-Square	Pr > ChiSq
Intercept	1	-4.5904	1.5975	8.2570	0.0041
Workload	1	0.2351	0.1457	2.6056	0.1065
Fatigue	1	0.2629	0.1617	2.6428	0.1040

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
		Lower	Upper
Workload	1.265	0.951	1.683
Fatigue	1.301	0.947	1.786

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	74.0	Somers' D	0.485
Percent Discordant	25.5	Gamma	0.487
Percent Tied	0.5	Tau-a	0.158
Pairs	400	c	0.743

Source: Authors.

Table 6 shows the results of logistic regression to predict Human_Error, with Workload and Fatigue predictor variables. The model has achieved convergence according to the criteria (GCONV=1E-8), indicating that the parameter estimation has been stable. The results of the model match statistics show that by including independent variables, the AIC drops from 52,040 to 49,766, and the -2 Log L value decreases from 50,040 to 43,766. This decrease indicates that the model with Workload and Fatigue is better compared to intercept alone. The global hypothesis test showed that the Likelihood Ratio Test (Chi-Square = 6.2743, p = 0.0434) was significant at a rate of 5%, indicating that at least one independent variable contributed to the model. However, the Wald test for each parameter was insignificant (p > 0.05), so the individual contribution of Workload and Fatigue to Human Error still needs to be further investigated. From the estimated odds ratio, increasing Workload by one unit increases the possibility of human error by 1,265 times, while Fatigue increases risk by 1,301 times. The accuracy level of the model (percent concordant = 74%) is quite good, but it can still be improved with other variables.

Table 7: Probability modeled is Human_Error=1.

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	52.040	57.523
SC	53.952	65.171
-2 Log L	50.040	49.523

Analysis of Maximum Likelihood Estimates					
Parameters	DF	Estimate	Standard Error	WaldChi-Square	Pr > ChiSq
Intercept	1	-1.7145	1.7111	1.0040	0.3163
Experience	1	-0.00155	0.1702	0.0001	0.9927
Navigation_Complexit	1	0.2344	0.5418	0.1872	0.6652
Interaction_Term	1	-0.0121	0.0510	0.0566	0.8119

Odds Ratio Estimates			
Effect	Point Estimate	95% Wald Confidence Limits	
		Lower	Upper
Experience	0.998	0.715	1.394
Navigation_Complexit	1.264	0.437	3.656
Interaction_Term	0.988	0.894	1.092

Association of Predicted Probabilities and Observed Responses			
Percent Concordant	59.3	Somers' D	0.192
Percent Discordant	40.0	Gamma	0.194
Percent Tied	0.8	Tau-a	0.063
Pairs	400	c	0.596

Source: Authors.

Table 7 presents the results of logistic regression with moderation effects for Human_Error, testing Experience, Navigation_Complexity, and Interaction_Term. The Fit Statistics model showed a slight improvement (AIC = 57.523, -2 Log L = 49.523), but the Likelihood Ratio Test (p = 0.9152) showed the model was not significant. Maximum Likelihood Estimates showed that all variables had a Pr > ChiSq > 0.05, so it did not have a significant effect on Human_Error. Odds Ratio Estimates have a wide confidence interval, signaling high uncertainty. The percent concordant is 59.3%, indicating that the model has low predictive ability.

5. Conclusion and Recommendations.

Based on the results of logistic regression analysis, it was found that Fatigue and Workload have the potential to be factors that affect Human_Error. These results show that the higher the level of fatigue and workload, the more likely it is that human error occurs. However, the level of significance of this variable is still relatively low, so more research is needed to confirm a stronger relationship. The odds ratio shows that an increase in Fatigue and Workload can increase the probability of Human_Error with values of 1,848 and 1,721, respectively. However, when the analysis was carried out with a moderation effect, the results obtained did not show significance. The Experience, Navigation_Complexity, and Interaction_Term variables had no significant effect on Human_Error, with a p-value well above 0.05. In addition, moderation models have a low level of prediction accuracy, with a concordant percentage of only 59.3%, suggesting that the model is not yet robust enough to predict Human_Error effectively. Based on these findings, several steps are recommended to improve the accuracy of predictions and reduce Human_Error. First, there is a need for a mitigation strategy for fatigue and workload, such as setting more optimal working hours, a work rotation system, and increasing rest time. Second, the prediction model must be improved by considering machine learning methods or multilevel logistic regression to be more accurate. In addition, the amount of data used in this study is still limited, so it is necessary to collect data on a larger scale to get more representative results. Finally, other factors such as training type, operational policies, and navigation technologies also need to be considered in future analyses to improve the model's effectiveness in understanding the factors that cause Human_Error.

References.

[1]. Purwangka, F., Wisudo, S. H., Iskandar, B. H., Haluan, J. (2013). *Identification of potential hazards and occupational safety technology in payang fishery operations in Palabuhanratu, West Java*. 8, 60.

[2]. Pracicilia, D. A., Sianturi, I. N., Asdiana, F., Rahmawati, M. (2024). *The effect of the implementation of verified gross mass (VGM) on the risk of ship accidents in the waters of Tanjung Perak Port. Malahayati Maritime Journal*.

[3]. Sibagariang, E., Sihotang, W. Y., Hartono, H., Soleh, A., Zulfahmi, Z. (2021). *Determinants of work fatigue in the furniture manufacturing industry in Medan City. Jurnal Prima Medika Sains*.

[4]. Emir, O., Yuamita, F. (2023). *Analysis of human error to reduce work accidents at PG milling stations Madukismo using the SHERPA and HEART methods. Scientific Horizon Journal*.

[5]. Salsabil, A. Z., Fakhrudin, A. (2024). *The influence of safety culture factors, safety management system and flight traffic guides on aviation safety at Perum LPPNPI MATSC. VISA: Journal of Vision and Ideas*.

[6]. Santoso, K. T., Agung, C., Prebawa, A., Adenanthera, E. (2024). *Analysis of the role of Syahbandar, communication skills and the ISM Code on shipping safety. Manuhara Journal: Research Center for Management and Business Sciences*.

[7]. Rosita, R., Apriyani, R. (2023). *Factors causing duplication of medical record numbers of J-REMI patients. Journal of Medical Records and Health Information*.

[8]. Zulkarnain, J., Hidayat, T. (2024). *Classification of maturity levels of fresh oil palm fruit bunches using the JST deep learning approach. Journal of Science and Technology*.

[9]. Santoso, R., Parwati, C. I., Yusuf, M. (2016). *Analysis of occupational safety and health management systems (SMK3) with a human error factor approach in PT. Khalifah Niaga Lantabura*. 4.

[10]. Supangat, S. A., Tama, I. P., Efranto, R. Y. (2014). *Identification of human error in the yarn spinning process in ring spinning using the SHERPA method (case study at PT. Nusantara Clothing Industry, Patal Lawang Unit)*. 2, 846–858.

[11]. Rismayadi, A. A., Febrianto, R. W., Raharja, A. R., Hariyanti, I. (2024). *Comparison of the performance of machine learning support vector machine (SVM), random forest, and K-nearest neighbors (KNN) methods in apple stock price prediction. Media Informatics*.

[12]. Rosyid, M. R., Mawaddah, L., Akrom, M. (2024). *Investigation of regression machine learning models in drug compounds as corrosion inhibitors. Journal of Algorithm*.

[13]. Nurussakinah, A., Puspitasari, N. B., Rumita, R. (2014). *The effect of mental workload and work fatigue on the errors of train controller operators at DAOP IV Semarang. Industrial Engineering Online Journal*, 3.

[14]. Sadewo, R. (2016). *Analysis of the effect of workload on work fatigue using the NASA-TLX method at PT. Sasmito*.

[15]. Harnadini, S., Wicaksono, P. A. (2012). *The effect of workload, work fatigue and awareness level on error level in an effort to minimize human error (case study at R.S. Semarang). Industrial Engineering Online Journal*, 1, 1–14.

[16]. Kartini, A. Y., Ishlahuddin, M. (2022). *Multivariate adaptive generalized Poisson regression splines for the development of rice production prediction models in Bojonegoro Regency. Journal of Mathematics Education and Science*.

[17]. Wayan, I., Suranata, A. (2023). *Development of a rainfall prediction model in Denpasar City using the LSTM and GRU methods. Journal of Systems and Informatics (JSI)*.

[18]. Agung, P., Hadi, M. P., Mukti, S. H. (2016). *Contribution of remote sensing to the development of a space utilization monitoring system in regional spatial planning*. 23, 77–89.

[19]. Syaputra, P. E., Putri, A. E., Setiadi, M. Y. (2024). *Analysis of level of service (LOS) using fuzzy clustering on the Ketapang–Gilimanuk ferry crossing. Journal of Economic, Business and Accounting (COSTING)*.

[20]. Putra, I. E., Atmadipoera, A. S., Manik, H., Harsono, G., Purwandana, A., Keulana, M., Handoko, D., Setiyadi, J., Pranowo, W. S. (2022). *Oil and gas industry teleconnection and*

underwater defense strategy for improving Indonesia's marine defense. *Journal Chart Datum*.

[21]. Khoiroh, S. (2016). *Formulation of a policy strategy roadmap for strengthening the regional innovation system (SIDa) in the maritime shipbuilding industry of Lamongan*.

[22]. Sihaloho, R. M., Mende, J., Rondonuwu, I. R. (2023). *Evaluation of human reliability using the Human Error Assessment and Reduction Technique (HEART) method in the wood processing industry in Manado City*. *Journal of Machine Technology*.

[23]. Santoso, R., Parwati, C. I., Yusuf, M. (2016). *Analysis of occupational safety and health management systems (SMK3) with a human error factor approach in PT. Khalifah Niaga Lantabura*. 4.

[24]. Kurniawan, A., Setiawan, D., Tambunan, R. P. (2024). *Development of an accident data analysis system for the mining industry using the Human Factors Analysis and Classification System (HFACS) method*. *Indonesian Mining Professionals Journal*.

[25]. Tjahyono, E. B., Umasangaji, F., Prakarsa, L. (2020). *Efforts to deal with bad weather (typhoons) to prevent shipping accidents on MV Pan Kristine*. 2, 56–63.

[26]. Roger, I., Flin, R., Mearns, K., Hetherington, C. (2009). *Safety leadership: A view of the senior managers' role offshore*. Europe.

[27]. Roger, I., Flin, R., Mearns, K., Hetherington, C. (2010). *Leading safely: Development of a safety leadership tool for senior managers*.

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

[29]. Alawdin, D. A., Kamila, R. R., Khasanu, M. W. N., Kusumasari, I. (2024). *Analysis of risk-based decision-making theory in project management*. *Journal of Accounting, Management, and Policy Planning*.

[30]. Bangkit, M., Kususma, A., Febrian, H., Yudha, A., Noer, M., Amin, F. A. (2024). *Fishbone analysis of river normalization policy decision making in the city of Surabaya*. *ARIMA: Journal of Social and Humanities*.

[31]. Safitri, R. (2023). *Local community empowerment in environmental decision-making: A study on community participation in natural resource management*. *Journal of Mandalika Social Science*.

[32]. Pagau, J., Anugrah, P. P. (2021). *Analysis of the influence of human error on work accidents at PT. Indonesian Ship Industry using a cross-sectional approach*. *Journal of Marine Science and Technology Innovation*.

[33]. Abrori, M. Z. L., Demeianto, B., Siahaan, J. P., Priharanto, Y. E., Yaqin, R. I., Tumpu, M., Faqih, M., Pujianto, A., Nurfauzi, A. (2023). *Analysis of human error in the operation of fishing boat propulsion engines in Bitung, North Sulawesi*. *Coastal and Ocean Journal (COJ)*.

[34]. Yaqin, R. I., Septianda, D., Priharanto, Y. E., Abrori, M. Z. L. (2024). *Application of SHERPA for identification of performance and human error in the operation of fishing vessel propulsion systems*. *Journal of Industrial System Engineering*.

[35]. Ratriwardhani, R. (2020). *Analysis of work accidents using the HFACS method at PT. X*. 4, 79–90.

[36]. Afi, Y. (2014). *Human negligence in flight accidents: A case study using the Swiss Cheese Model*.

[37]. Lamentowicz, W. (2015). *Europeizacja prawa administracyjnego*. Tom 3, *System prawa administracyjnego*, ed. Roman Hauser, Zygmunt Niewiadomski, Andrzej Wróbel. Warsaw, 2014, 209–212.

[38]. Wrobel, M. (2020). *Global Toxicology 2020: If atrazine has a potential to impair a function of bovine cervix during the periovulation period of the oestrous cycle, in vitro?* 9, 1–10.

[39]. Wróbel, M. (2020). *Wróbel, Monika*. *Encyclopedia of Personality and Individual Differences*.

[40]. Hidayah, H. K., Ekojono, E., Sintiya, E. S. (2024). *Implementation of machine learning in the power transformer maintenance information system*. *Polylinema Informatics Journal*.

[41]. Wahyuni, S., Passarella, R. (2024). *Analysis of a prediction model for Jakarta school bus services using a machine learning approach*. *Indonesian Journal of Computer Science*.

[42]. Ramadhan, A. F., Harsono, G., Wadjdi, A. F. (2024). *Machine learning in the development of maritime defense technology: Model design, object analysis, and predictive performance*. *Journal on Education*.

[43]. Hikmah, I. R., Yasa, R. N. (2022). *Comparison of diagnosis prediction results in the Indian Liver Patient Dataset (ILPD) using supervised learning techniques with Orange software*. *Telematics Journal*.

[44]. Santoso, C. (2023). *Implementation of Orange Data Mining for insurance cost prediction*. *Aisyah Journal of Informatics and Electrical Engineering (A.J.I.E.E.)*.

[45]. Lukmana, H., Al-Husaini, M., Puspareni, L. D., Hoeronis, I. (2024). *Design and development of an information system for early detection of stunting using the artificial neural network method*. *Journal of Information Systems and Technology (JustIN)*.

[46]. Natzir, S. M. (2023). *Comparison of the performance of machine learning models in flood prediction using KNN, Naive Bayes, and Random Forest*. *HOAQ (High Education of Organization Archive Quality): Journal of Information Technology*.

[47]. Abdi, K., Warjaya, A., Muthmainnah, I., Pahutar, P. H. (2024). *Application of the Random Forest algorithm in predicting the feasibility of drinking water*. *Journal of Computer Science and Informatics*.

[48]. Saputra, D. B., Atina, V., Nastiti, F. E. (2024). *Application of the CRISP-DM model to credit customer prediction using the Idealistic Random Forest algorithm*. *Indonesia Journal Information System*.