Application of Machine Learning in the Characterization and Classification of Hazards in Underwater Operations in the Oil and Gas Industry

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Abstract: Underwater operations in the oil and gas industry involve hazardous activities for the extraction of the resources beneath ocean surfaces. These activities are inherently hazardous and can lead to significant health, safety and environmental consequences for both workers and the environment, impeding operations if proper risk management is not implemented. Reports available show fatality rate of 2.5 times higher in the oil and gas industry than obtainable in the construction industry. Classifying the risk of underwater hazards provides an effective risk profiling of the hazards and consequently application of fit for purpose control measures. This study leverages machine learning clustering algorithms, such as K-Means and Agglomerative Hierarchical Clustering (AHC), to categorize hazards from underwater activities and identify high-risk hazard groups. Questionnaire were used to collect data from 418 underwater workers across 5 Niger Delta oil and gas companies assessing likelihood, frequency, and severity perspectives across 20 potential hazards. AHC and K-Mean clustering with k=3 revealed Cluster 1 had 7 hazards associated with adverse weather, security threat, and structural failure. Cluster 2 had 9 underwater hazards associated with falling objects and loss of containment while cluster 3 had a total of 4 hazards which were hazards associated with fire, explosion, and blowout. Machine learning provides clustering of the underwater operation hazards resulting in data-driven taxonomies of the hazards based on risk attributes and enlightening areas demanding managerial focus. The clustering of similar hazards together implies that grouped hazards may benefit from common control measures rather than individual solutions hence achieve effectiveness, save cost and time. The study has shown that machine learning can be applied in risk assessment of hazards in underwater operations as in other reported areas of the oil and gas industry.

Keywords: Machine Learning, Clustering algorithms, K-Means, Characterization, Risk Assessment, Underwater

1. INTRODUCTION

The extraction of oil and gas resources from beneath the ocean surface presents a unique set of challenges. While offering vast reserves of energy, underwater operations (offshore operations) carry inherent risks that can lead to significant consequences for both workers and the environment. The risks associated with activities in underwater operation far exceed the risk in other industries like the construction industry that is considered to be highly risky. The fatality rate in the oil and gas industry was reported to be 2.5 times higher than what was obtainable in the construction industry [1],[2]. According to a report by the International Association of Oil and Gas Producers (IOGP), the offshore oil and gas industry had a fatal accident rate of 1.9 per 100 million hours worked in 2019, compared to 0.8 for the construction industry and 0.4 for the manufacturing industry [3]. Mitigating the threats/risks associated with underwater operation requires conducting risk assessment. Jia et al. in their study identified twenty hazards that are commonly associated with underwater operations in the Niger Delta region and performed risk assessment for these hazards. While this study evaluated the risk associated with each hazard, it did not categorize similar risks in term of risk level associated with underwater operations [4]. One critical aspect of successful risk management is effective categorization and profiling of underwater hazards. Grouping hazards based on their shared characteristics and risk levels can help to prioritize interventions and allocate resources efficiently. Proper risk management is crucial in mitigating the threats in underwater operations and ensuring the smooth running of operations. Machine learning has been shown to have a critical role in the grouping process. In their review of the application of machine learning in the upstream oil and gas sector, researchers have agreed that various types of machine learning and artificial intelligence techniques can be used for "data processing and interpretation in different sectors of upstream oil and gas industries [5]. They note that the achievements and developments promise the benefits of machine learning and artificial intelligence techniques towards large data storage capabilities and high efficiency of numerical calculations. Researchers have therefore, called for application of machine learning in diverse disciplines of the upstream oil and gas. The successful application of various machine learning techniques in reservoir engineering Well analytics [6] – [8], maintenance, data mining as well as other project administration methods as a supportive solution in conventional upstream oil and gas have shown potential for application in other areas of the industry.[9], [10].

Machine learning techniques, specifically clustering algorithms like Agglomerative Hierarchical Clustering and K-mean, offer a promising solution in achieving this classification of underwater hazards [11]. Clustering enables the reliable categorization of complex data points [9] into homogeneous segments, sharing common characteristics [12]. Since clustering has many applications for solving real-world problems such as community identification, anomaly detection, pattern recognition, and image processing that can be used in the variety of situations [12], the algorithms therefore, presents a powerful tool for stratified hazard recognition. But it has to date been sparsely implemented in the domain of classifying underwater safety threats. This study is built on the previous works done [4] on the risk assessment and focus on the characterization and classification of the underwater hazards in the oil and gas industry in the Niger Delta region.

2. MATERIAL AND METHODS

2.1 Research Design

This study adopted a cross-sectional research design, which is suitable for making generalizable inferences about a population based on data collected at one point in time. A cross-sectional design is a kind of observational design where the investigator measures the cause and effect in a study population simultaneously [13]. The design was relevant as it involved presenting the data from respondents without manipulation. Therefore, quantitative method was used to evaluate and examine the hazard occurrence, frequency, severity, and consequences.

2.2 Study Area

The Niger Delta is located on the continental margin of the Gulf of Guinea in equatorial West Africa, within the latitudes of 4° and 6° N and the longitudes of 5° and 8° E [14]. The Niger Delta region comprises of nine states namely: Abia, Akwa Ibom, Bayelsa, Cross River, Delta, Edo, Imo, Ondo and Rivers as shown in Figure 1. It borders Ogun, Osun, Ekiti, Kogi, Anambra, Enugu and Ebonyi. The region is home to Nigeria's vast oil and gas resources. It is also a rich ecosystem with high biodiversity, diverse flora and fauna, fertile land that can grow various crops and economic trees, and more freshwater fish species than any other ecosystem in West Africa. The oil & gas reserves in the region account for 90% of the government revenue.

The Niger Delta is also known for its cultural diversity, with over forty ethnic groups and 250 languages spoken.

2.3 Participants

This study focused on underwater workers in the Niger Delta, who are exposed to hazards and risks that require risk assessment before performing their duties. The population of the study consisted of about 7500 employees from five selected oil and gas companies that operate offshore or underwater in the region. These companies were major oil multinationals, three of which were EU owned and two of which were America owned. This study assumed that the underwater hazards were similar across these companies. A purposive sampling technique was used to select a sample of 380 workers from the population, based on Taro-Yamane [15], sample size determination. To account for the attrition rate, 418 questionnaires were distributed, ensuring that the minimum sample size for a representative population was achieved. Only the valid questionnaires were used for the analysis.

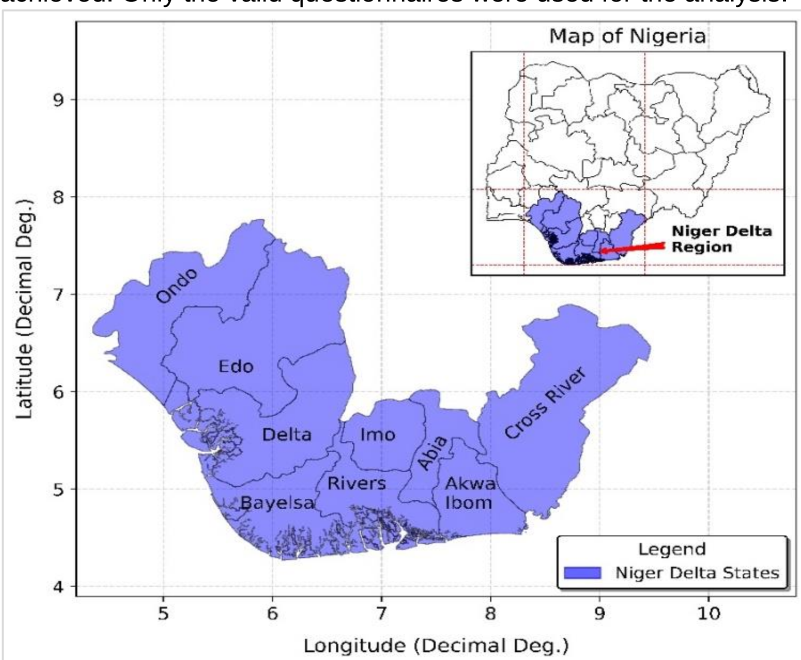

Figure 1: Map of the Niger Delta region in Nigeria

2.4 Data Collection and Quality Control

Data were collected via a questionnaire and checklist. The template and structure of the questionnaire and checklist were adopted from ISO 19900, ISO 19901-2, ISO 19904, ISO 19905-1 and industry Hazards Identification and Risk Assessment (HIRA) level 2. Before undertaking the data collection process, an official letter was addressed to respective management in the various studied facility seeking their consent. The management were assured of treating the information from respondents/participants confidentially. The questionnaire has three (3) sections namely, sections A, B, and C. Section A contained items on the likelihood of underwater hazards, in a 4-point likert scale of Very likely, Likely, Unlikely and Very Unlikely respectively. Section B contained items on frequency or occurrence of hazards; in a 4-point Likert scale of frequently, occasionally, rarely and never respectively. Section C contained information on severity of hazards; in a 4-point Likert scale of Highly Significant, Significant, Minor and Insignificant respectively. These sections were in a 4-point Likert scale with ratings as 4, 3, 2 and 1; respectively.

2.5 Data Analysis

Data from the questionnaire received from respondents were entered into SPSS version 26 sheet. SPSS was used in computing the mean and mode for likelihood, frequency, and severity ratings, providing an initial understanding of hazard perceptions from the respondents. Likelihood, frequency, and severity ratings were extracted as crucial features for subsequent machine learning algorithms, representing the nuanced perspectives of underwater workers. To categorize and profile underwater hazards, both Agglomerative Hierarchical Clustering (AHC) and K-Means clustering algorithms were employed. The utilization of AHC employing the ward method facilitated the creation of a hierarchical structure that delineated hazard relationships based on similarity. Simultaneously, K-Means clustering with a predefined value of k=3 was applied to classify the hazards into high, medium, and low-risk categories. This choice of k=3 was informed by observed hazard categorizations during the analysis. Python library called Sklearn enabled the execution of machine learning algorithms, ensuring precision in clustering analysis.

The questionnaires administered to 418 underwater workers. The workers were informed that the collected data was just for the purpose of conducting a scientific study and they could discontinue participation in the study whenever they wished. Out of the 418 questionnaires distributed, 401 were considered fit to be used for the study, representing a response rate of 95.93%.

3. RESULTS

3.1 Rating Of Likelihood, Frequency, And Consequence Of Hazards

The result of the rating of the likelihood, frequency, and consequence of the underwater operation hazards by the respondents is shown in Table 1. The result from Table 1 revealed that most of the respondents rated that Adverse weather and sea condition/heavy storms hazard was very likely to occur in underwater operations. Adverse weather and sea condition/heavy storms hazard was ranked 1st, making it the underwater hazard to be experienced the most. Both Strong current/wind and Piracy & bandit attack/kidnapping hazards were rated as likely to occur in underwater operation. Strong current/wind and Piracy/bandit attack/kidnapping hazards were ranked 2nd and 3rd respectively as the hazards to be experienced in underwater operations. The likelihood of Rotating capstan/winch hazard to occur in underwater operation was rated by respondents as unlikely with a ranking of 20th. Similarly, poor installation hazard was rated as unlikely to occur making it to be the 19th ranked hazard to be experienced in underwater operation. In term of frequency of occurrence of these hazards, Adverse weather and sea condition/heavy storms hazard was rated to be occasionally experienced by most of the respondents. Adverse weather and sea condition/heavy storms hazard was ranked as the most frequent underwater operation hazard to be experienced. Also, Strong current/wind and Shallow waterway/poor visibility was stated to occasionally occur and was ranked as the 2nd most frequent underwater operation hazard. In terms of frequency of the hazard occurring, Capsizing/overturning/toppling was stated rarely occur. Capsizing/overturning/toppling was ranked 20th as the least frequent hazard experienced in underwater operation. Loss of buoyancy or sinking/adrift was also stated to rarely occur by the respondents and was ranked 19th. For consequence of the underwater operation hazards, majority of the respondents were of the view that if Piracy & bandit attack/kidnapping occurred it will result to major injuries. Piracy & bandit attack/kidnapping was ranked 1st as the underwater operation hazard to have the most consequence if it occurs. Fire/explosion was also stated to result to major injuries if it occurred and was ranked to be the 2nd hazard to have the most consequence. Blowout/release of fluid or gas was shown to result to major injuries if it occurs and was ranked 3rd out of the 20 hazards with the highest consequences. Rotating capstan/winch was the hazard out of the twenty hazards evaluated to have the least severity if it occurred.

Table 1: Mean Response and Ranking of Likelihood, Frequency and Consequence of Underwater Hazards (Jia et al. 2022)

Hazard ID	Hazards	Likelihood		Frequency		Consequence	
		Mean	Rank	Mean	Rank	Mean	Rank
H01	Piracy & bandit attack/kidnapping	3.3	3	2.82	5	3.40	1
H02	Shallow waterway/poor visibility	3.27	4	3.08	3	2.93	18
H03	Adverse weather and sea condition/heavy storms	3.48	1	3.15	1	3.21	6
H04	Strong current/wind	3.43	2	3.13	2	3.13	7
H05	Hyperbaric operations/falling overboard	3	9	2.48	13	2.95	16
H06	Rotating capstan/winch	2.73	20	2.41	15	2.71	20
H07	Entrapment/entanglement of personnel	2.88	14	2.46	14	2.98	15
H08	Other main vessels/heavy object dropping or falling load/collision	2.93	11	2.58	11	3.07	8
H09	Embarking and disembarking from SPM	3.03	8	2.74	6	2.76	19
H10	Fire/explosion	3.06	6	2.42	16	3.39	2
H11	Blowout/release of fluid or gas	2.87	16	2.43	18	3.34	3
H12	Capsizing/overturning/toppling	2.82	15	2.23	20	3.22	4
H13	Breakage or fatigue	3.13	6	2.83	8	2.96	10
H14	Uncontrolled inclination/ leakage into hull	2.79	17	2.38	17	2.88	17
H15	Loss of buoyancy or sinking/adrift	2.78	18	2.25	19	3.15	5
H16	Valve system/pump/pipeline failure	2.97	12	2.66	9	2.95	11
H17	Remote operation/power/cooling/gauging system failure	2.9	13	2.66	10	2.93	14
H18	Corrosion/debris accumulation	3.16	5	2.93	4	3.02	9
H19	Malfunction of instrumentation or mechanical system	3.08	10	2.83	6	3.01	12
H20	Poor installation	2.78	19	2.54	12	2.99	13

Likelihood: 4—Very likely (having a high probability of occurring more than once per year or more often), 3—Likely (expected to occur once (approx. once in 10 years), 2—Unlikely (not expected for at least 100 years), 1—Very Unlikely (Not expected to happen for at least 1000 years Severity: (Health Effects), 4—Fatality (Potential for one or fatalities), 3—Major injuries (Potential for one or more serious injuries; irreversible), 2—Minor injuries (Potential for one or more lost time injuries), 1—Negligible injuries (Potential for minor injuries or irritation).

3.2 Agglomerative Hierarchical Clustering (AHC).

The dendrogram showing the clustering of the twenty underwater operation hazards is shown in Figure 2. Three distinct clusters were identified after AHC clustering algorithm was ran on the data. Cluster 1 identified as the red leg in the dendrogram tree comprised of seven (H01, H02, H03, H04, H13, H18, and H19) underwater hazards with similar characteristics. The underwater hazards in cluster 1 were predominately related to weather, security threat, and structural failure hazardous events. For cluster 2 which is represented by the blue leg in the dendrogram tree, nine underwater hazards (H05, H07, H08, H20, H09, H16, H17, H06, and H14) were in this cluster. The hazards in cluster 2 were related to falling/dropped objects, loss of containment, and structural failure hazardous event. For cluster 3 which is represented by the green leg in the dendrogram, four underwater operation hazards belong to that cluster. It was noticed that the hazards in that cluster were predominately fire/explosion and blowout hazardous events.

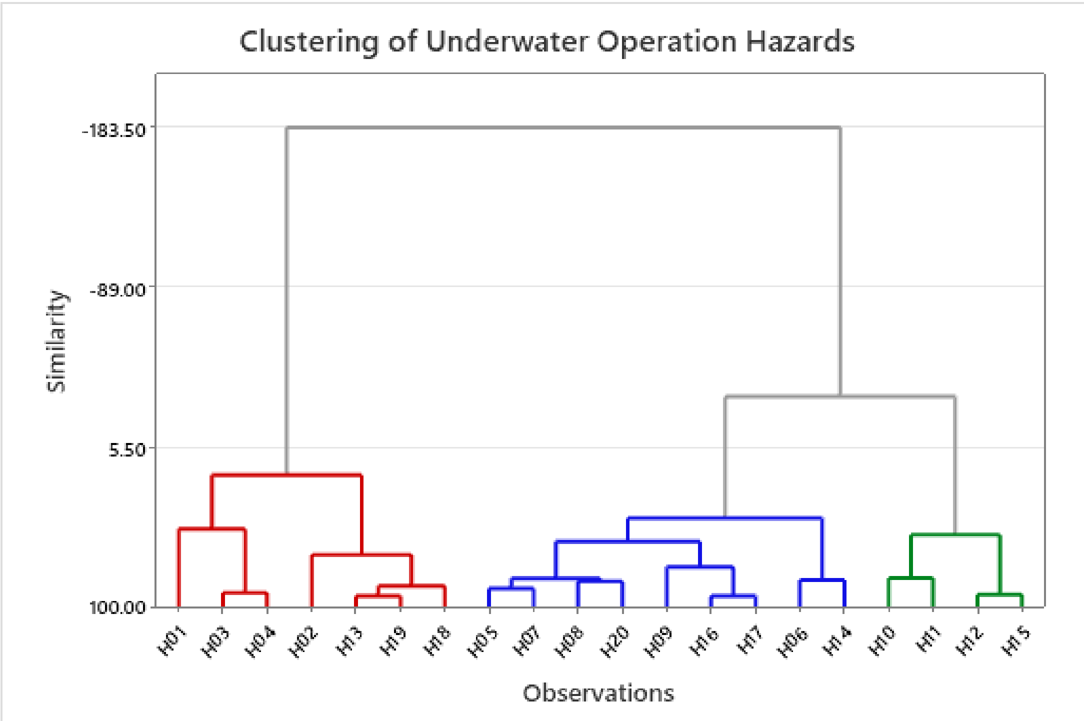

Figure 2: Dendrogram of clustering of hazards using AHC.

The level of likelihood, frequency, and consequence in each cluster was represented by a parallel coordinate plot shown in Figure 3. The parallel coordinate plot showed that cluster 1 (red line) which was made up of predominately weather, security threat, and structural failure hazardous events had a much higher likelihood of occurrence than the other two clusters. In terms of frequency, it was also revealed that cluster 1 is likely to occur more on a yearly basis than the other two clusters. In the case of the consequence, cluster 1 showed a greater consequence if the hazard occurred than cluster 2 (blue line) but a lesser consequence than cluster 3 (green line). For cluster 2, the consequence associated with that cluster was the lowest but the frequency of occurrence of the hazards was relatively higher than cluster 3 hazards. For the likelihood, cluster 2 had similar likelihood with cluster 3 implying that hazards in cluster 2 and 3 are likely to occur at almost similar rate. The result from the parallel coordinate plot showed that cluster 3 had the least likelihood and frequency of occurrence than the remaining two clusters. For the consequence, cluster 3 had the greatest consequence than the remaining two clusters.

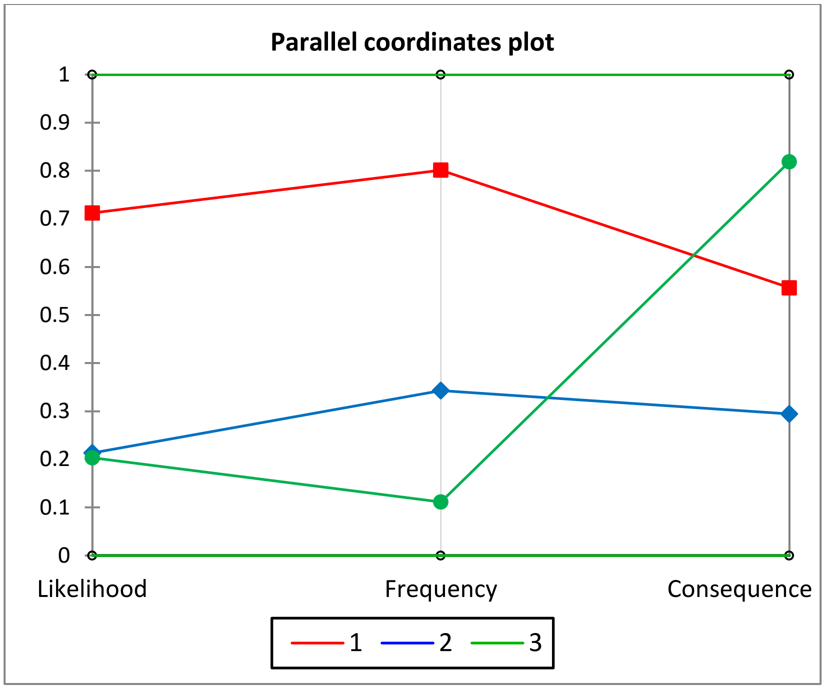

Figure 3: Parallel coordinate plot.

3.3 K-Mean Clustering

The result of clustering with the K-Mean algorithm showed similar pattern as obtained with AHC. The centroid of the three clusters is presented in Table 2 and the cluster of the hazards based on the likelihood, frequency, and consequence is shown in the 3D plot as presented in Figure 4. The result showed that cluster 1 had seven hazards in the cluster similar to what was obtained using the AHC algorithm. Cluster 2 had nine hazards in the cluster and cluster 3 had four hazards in the cluster. The result from the K-Mean algorithm produced identical result as the AHC.

The result from the 3D plot showed that cluster 1 had relatively high frequency and likelihood as the value of the standardized score were positive. The consequence of cluster 1 was also relatively high as shown in the 3D plot. For cluster 2, it was observed that likelihood was low but the frequency of the hazards was slightly positive but it had a generally low consequence. For cluster 3, the likelihood and frequency were relatively low but the consequence were relatively high.

Table 2: Centroid of the clusters after final clustering

Variable	Cluster1	Cluster2	Cluster3	Grand centroid
Likelihood	2.8543	2.9712	3.3280	3.0195
Frequency	2.3871	2.6487	3.0220	2.6505
Consequence	3.1357	2.9175	3.1380	3.0490

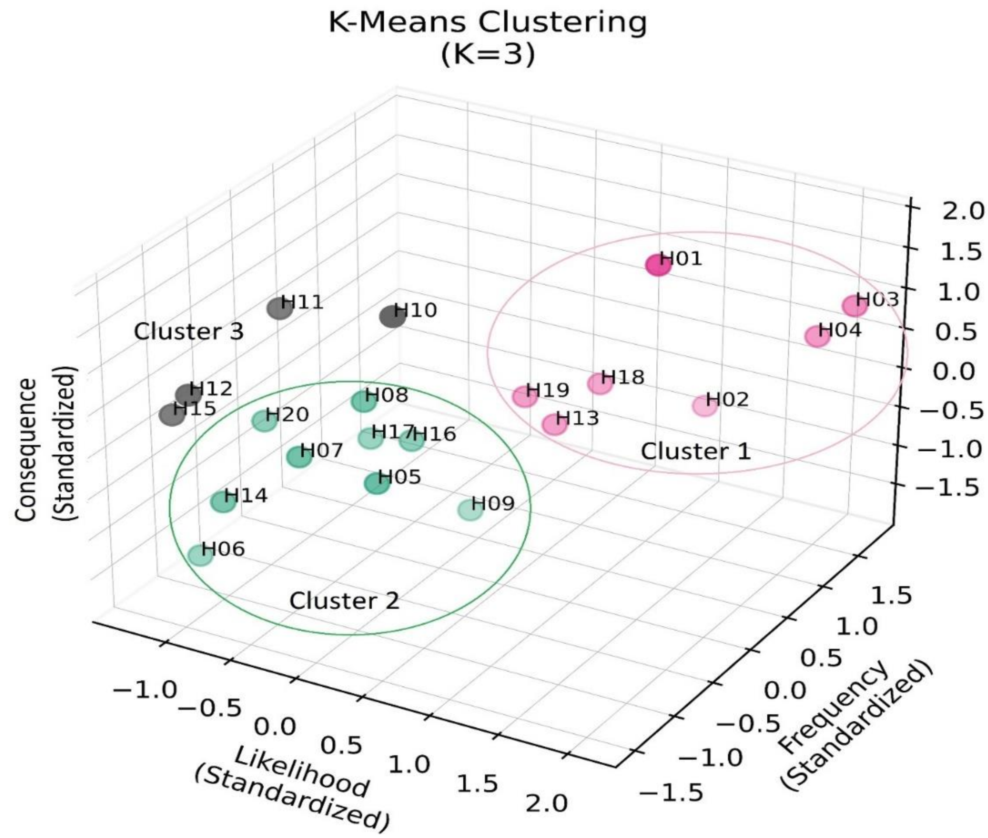

Figure 4: K-Mean plot of clustering of the hazards

4. DISCUSSION

The results of this study showed that the underwater workers in the Niger Delta faced various hazards and risks that could affect their health and safety. The most likely and frequent hazards experienced in underwater operations in the Niger Delta were adverse weather and sea condition/heavy storms. Storms and hurricane are regular occurrence experienced around the coastal communities and on offshore platforms thereby posing a threat to both the communities and the platforms [16]. Annually, approximately 100 tropical disturbances form in the Atlantic Ocean from May to November [16]. The risk associated with adverse weather and sea condition can cause operational delays, disruptions, damage, or injuries to the workers and the equipment [16],[17]. When severe weather conditions develop, Operators shutdown production and evacuate personnel ahead of the storm, and after the storm makes landfall, crews return to work, damage assessments are performed, and facilities are repaired, if required, prior to the resumption of production [17]. Adverse weather and sea condition also affect other support operations such as crane works and helicopter activities [18]. Therefore, it is important to monitor and forecast the weather and sea condition accurately and timely, and to plan and execute the operations accordingly. The second and third most likely hazards to occur in underwater operations in the Niger Delta were strong current/wind and piracy/bandit attack/kidnapping respectively. These hazards could pose serious threats to the security and stability of the workers and the vessels. Strong current/wind could affect the maneuverability and positioning of the vessels, as well as the performance and reliability of the underwater equipment. In challenging environments, subsea systems, including the riser, mooring system, and umbilical, are vulnerable to the impacts of currents, and their responses can be destructive [19]. Piracy/bandit attack/kidnapping could endanger the lives and property of the workers and the companies, and could disrupt the operations. Maritime Domain Awareness for Trade Gulf of Guinea in 2020 notes that twenty-five successful piracy attacks have resulted in 142 kidnapped seafarers in 2020. Despite the initiatives undertaken by coastal nations, including Nigeria, and external entities, the Gulf of Guinea (GoG) continues to be recognized as one of the world's most hazardous maritime regions. Records show that incidents of piracy have expanded from Ivory Coast to Congo-Brazzaville [20]. Therefore, it is essential to implement effective measures to prevent and mitigate these hazards, such as enhancing the surveillance and protection systems, improving the communication and coordination among the stakeholders, and strengthening the legal and regulatory frameworks. The least likely and frequent hazards were rotating capstan/winch and poor installation, respectively. These hazards could cause mechanical failures or accidents that could result in injuries or fatalities to the workers or damage to the equipment.

The agglomerative hierarchical and K-Mean clustering revealed three distinct groups of underwater hazards based on their likelihood, frequency, and consequence ratings. Cluster 1 contained weather, security, and structural failure hazards like storms and capsizing. The high likelihood and frequency ratings match literature identifying adverse weather as a predominant contributor in offshore incidents. The clustering of these hazardous events might indicate that there is a relationship between these hazardous events. The reliability of offshore platform is adversely affected by adverse weather and sea condition [21], [22]. Good understanding of the most prevalent underwater operation hazard (adverse weather) can help in mitigating the risk associated with structural failure hazardous event. This highlights the importance of good and reliable meteorological modeling and forecasting which can be utilized in the design stage of offshore platform. Cluster 2 grouped hazardous event such as falling objects, loss of containment, and additional structural failures into the same cluster. These set of hazards in this cluster were deemed to have the least consequences. Dropped object accidents are recognized risks in offshore operations. Monitoring crane lifts and preventative maintenance are key mitigations strategies to help reduce the risk. Building Information Modeling (BIM) can aid in the real time monitoring of equipment and worker on platform to help mitigate the risk of falling object. Hydrocarbon leaks also carry major consequences, necessitating design, procedures, and barriers to limit escalation. Cluster 3 represented fire, explosion, and blowout hazardous events. The low probability of occurrence but high consequence hazards align with major incidents like Piper Alpha and Macondo [23],[25]. Robust well control and emergency response preparedness are crucial to limit the safety and environmental impacts associated with these hazards. Overall, these groupings based on hazard characteristics can inform risk management strategies tailored to each cluster. Cluster 1 may benefit from monitoring, planning, and maintenance. Cluster 2 could prioritize dropped object and asset integrity controls. Cluster 3 points to the critical need for well control and emergency response given the potential severe consequences. In each of the clusters, the application of machine learning provides opportunity for decision-makers to assess the risk level for handling activities in during underwater operations as in the case of logistics business [26].

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5. CONCLUSION

In conclusion, the study characterized and classified underwater hazards in Oil and Gas Operations in the Niger Delta region using Cluster algorithms such as K-Means and Agglomerative Hierarchical Clustering. Analyzing data from 418 respondents in the Niger Delta, distinct hazard clusters emerged, revealing potential shared control measures within each cluster. This data-driven taxonomy enhances risk profiling, allowing targeted risk management. The findings also underscore the importance of a nuanced approach to risk mitigation and provide practical insights for safeguarding underwater operations in the oil and gas sector thus saving money, time and achieving efficiency in controls.

Consent

As per international standards or university standards, respondents' written consent has been collected and preserved by the author(s).

Disclaimer (Artificial intelligence)

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

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AUTHORS' CONTRIBUTIONS

Author 1 designed the study, performed the statistical analysis, wrote the protocol, and wrote the first draft of the manuscript. 'Author 2'. Managed the literature searches and participated in curating statistical analysis. All authors read and approved the final manuscript.

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