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ANALYSIS OF ASSOCIATION LEVELS OF ACCIDENTS CAUSING MARINE POLLUTION

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ABSTRACT

Marine accidents have been one of the most significant phenomena in the maritime industry for many years. In addition to causing loss of life and property, these accidents also have a negative impact on the environment. This research aims to determine the relationships between the factors in marine accidents causing pollution. In this context, 208 marine accident reports in the IHS Sea-Web database, which occurred between 1999 and 2023 and resulted in marine pollution, were analyzed by Chi-square and Cramer's V methods. According to the results of the analyses, significant relationships were found, especially between vessel flag, vessel type, and gross tonnage. High-tonnage vessels and bulk carriers, container ships and general cargo vessels were mainly flew the flag of convenience. Vessel status was the only variable that had a significant relationship with the pollution quantity. Vessels in maneuvering and on voyage are more likely to have a high amount of pollution, while the amount of pollution in accidents occurring during bunkering is low. The research findings can help stakeholders to take preventive measures and raise awareness to prevent pollution resulting from accidents.

Keywords: *Marine Accidents, Marine Pollution, Cramer's V, Chi-square.*

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DENİZ KİRLİLİĞİNE NEDEN OLAN KAZALARIN İLİŞKİ DÜZEYLERİNİN ANALİZİ

ÖZ

Deniz kazaları, uzun yıllardır denizcilik sektörünün en önemli olaylarından biri olmuştur. Bu kazalar can ve mal kaybına yol açmanın yanı sıra çevre üzerinde de olumsuz etkilere sahiptir. Bu araştırma, kirliliğe neden olan deniz kazalarındaki faktörler arasındaki ilişkileri belirlemeyi amaçlamaktadır. Bu kapsamda, IHS Sea-Web veritabanında 1999-2023 yılları arasında meydana gelen ve deniz kirliliği ile sonuçlanan 208 deniz kazası raporu Ki-kare ve Cramer's V yöntemleri ile analiz edilmiştir. Analiz sonuçlarına göre, özellikle gemi bayrağı, gemi tipi ve gros tonaj arasında anlamlı ilişkiler bulunmuştur. Yüksek tonajlı gemiler ile dökme yük, konteyner ve genel kargo gemileri ağırlıklı olarak kolay bayrak taşımaktadır. Kirlilik miktarı ile anlamlı ilişkisi olan tek değişken gemi statüsü olmuştur. Manevra yapan ve seyirde bulunan gemilerin karıştığı kazalarda kirlilik miktarının yüksek olması daha muhtemel iken yakıt ikmali sırasında meydana gelen kazalarda kirlilik miktarı düşüktür. Araştırma bulgularının kazalardan kaynaklanan kirliliğin önlenmesi için paydaşların önleyici tedbirler almasına ve farkındalığı artırmasına yardımcı olacağı düşünülmektedir.

Anahtar Kelimeler: *Deniz Kazaları, Deniz Kirliliği, Cramer's V, Ki-Kare.*

1. INTRODUCTION

Maritime transport is of vital importance in the increasing world trade as it carries a large part of global trade. In this regard, besides the complexity of marine traffic, the growing number of vessels also raises the possibility of accidents occurring at sea. Marine accidents pose a serious threat to loss of life and property. Moreover, these accidents cause environmental problems by causing large-scale marine pollution (Chen et al. 2024; Hu et al. 2024). According to the European Maritime Safety Agency (EMSA), 54 pollution-related accidents were reported in 2023. The total number of reported accidents between 2014 and 2023 is 602. Although a downward trend is observed between 2014 and 2023, the number of accidents in 2023 is 20% more than the previous year (EMSA, 2024). The International Tanker Owners Pollution Federation Limited (ITOPF) also states that 37 accidents causing 7 tons or more of pollution were reported in the 2020s (ITOPF, 2024). Chronologically, Torrey Canyon (1967), Amoco Cadiz (1978), Atlantic Empress (1979), Ixtoc 1, Exxon Valdez (1990), ABT Summer (1991), and Erika (1999) are some of the historical marine accidents that caused serious oil spills and environmental pollution. Some of these accidents have had such severe impacts on humanity and the ecosystem that they have led to the creation

of environmental regulations in the maritime industry, such as the International Convention for the Prevention of Pollution from Ships (MARPOL), Oil Pollution Act of 1990 (OPA 90) and Erika Packages (Cakir et al. 2021; Sevgili, 2024). Figure 1 shows the locations of the 20 major marine accidents causing pollution.



Figure 1: Location of the Top 20 Major Spills
Source: ITOPF, 2024.

The aforementioned effects of pollution caused by marine accidents have led researchers to work intensively in this field. When these studies are examined, it is observed that researchers focus on post-accident processes such as pollution monitoring, pollution detection, and pollution response. However, there is comparatively limited work addressing the underlying factors contributing to pollution-related accidents and their interrelationships. In particular, empirical research examining statistical associations between vessel characteristics—such as flag, tonnage, and operational status—and pollution outcomes remains scarce. For instance, most of the previous studies indicate that vessels registered under flags of convenience may face less stringent inspection regimes, lower enforcement of safety regulations, and reduced crew training requirements. These conditions can increase the likelihood of operational failures, collisions, and consequent pollution incidents. However, quantitative analyses linking the flag of convenience with other vessel-specific factors in pollution-related accidents are limited. Identifying and quantifying the relationships among accident-related factors is also essential for targeted prevention strategies. Hence, understanding the factors that influence the severity and likelihood of pollution is crucial for policymakers, insurers, and shipping companies. In this context, this research analyzed 208 marine accidents causing pollution reported by the IHS Sea-Web database using chi-square and Cramer's V methods with the Statistical Package for Social Sciences (SPSS) Statistics 26.0 program. Moreover, determining the level of association between the related variables is another aim of the research.

A comprehensive flow diagram, including the research processes, is shown in Figure 2. Determining the associations and their levels between variables in accidents causing marine pollution and making comprehensive analyses has the potential to reduce accidents that may cause pollution. In addition, the fact that it has the potential to take preventive measures by stakeholders on marine pollution caused by vessel accidents, which is an essential problem of the maritime sector, increases the importance of the research.

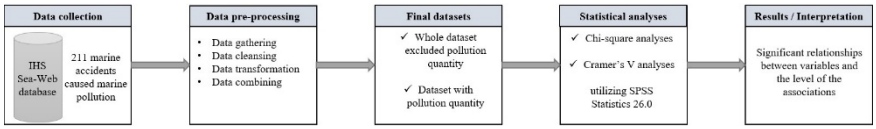


Figure 2: Flowchart of Research.

The remaining part of the research is designed as follows: Literature on marine pollution is given in Section 2. The methods of the research are described in Section 3. Chapter 4 presents the findings of the research. The findings of the research are compared and discussed with the findings of other studies, and the study is concluded in Section 5. In the conclusion section, the results, recommendations, and limitations of the study are explained.

2. LITERATURE REVIEW

When the literature on marine pollution is examined, it is observed that the studies conducted are on the processes after the pollution occurs. Response to pollution, trajectory of oil spill, and detection of contaminants are some of the areas where researchers are particularly focused.

One of the most critical processes to prevent the spread of pollution on water and the increase in the amount of pollution is the pollution response process. In this field, researchers have evaluated different aspects, such as the selection of response methods, governance strategies, and the location of the pollution prevention and response center. Davies and Hope (2015) developed a Bayesian Network model that can be effectively used as a decision support system to minimize environmental and socioeconomic damages by supporting optimal response strategies in environmental emergencies such as oil spills. Another research using the same method examined the preparedness and success of emergency intervention (Zhu et al. 2022). Xiong et al. (2015) analyzed the trends of ship-related marine oil spills in China during 1990–2010 and found that although significant progress has been made with the current five-level response system, the country faces challenges such as enhancing response

capacity, strengthening cooperation, and improving research and development (R&D) activities. Knol and Arbo (2014) evaluated the characteristics and development of Norwegian oil spill response systems for possible pollution in the Arctic, where maritime activities have intensified in recent years. Based on social big data analysis, Chun et al. (2020) revealed that negative public perception of oil spills in South Korea stems from economic, ecological, and health-based concerns and proposed multidisciplinary, transparent, and public-focused response strategies to improve this perception. Chen et al. (2024) developed an innovative Formal Concept Analysis (FCA) model based on 172 vessel accident reports in Chinese waters to identify the main accident causes and impact levels and propose strategies to reduce potential pollution. Wan et al. (2022) analyzed the pollution caused by accidents involving container ships in terms of risk characteristics, response methods, and regulatory developments, and determined the intensifying factors in the accidents. They also emphasized that factors such as the number of containers on ships and the variety of products in containers can cause different marine pollution. On the other hand, Chen et al. (2019) evaluated the development of global oil trade, pollution trends, and regulations by examining tanker-related oil spill data between 1970 and 2017 and presented strategies to prevent future oil spills. Similarly, Chen et al. (2020) examined the Sanchi tanker accident using fault tree analysis to reveal the interaction of human, management, environmental, and vessel factors and proposed governance strategies to guide future tanker management and emergency response decisions. Koseoglu et al. (2018) analyzed to determine the location of an oil spill response center in the Marmara Sea using AHP and TOPSIS methods, considering only technical and operational criteria, and determined that the most suitable location was the Izmit Gulf Entrance. Similarly, Buber and Toz (2018) determined risky areas for ship-related oil spills in Iskenderun Bay based on marine accident data and suggested the most appropriate response center location considering response time, equipment infrastructure, and geographical boundaries.

Since the trajectory of the oil spill after the accident is crucial for the risk of pollution to the shore and pollution response, it has been one of the areas where researchers have concentrated. Since sea and weather conditions are different in each region, researchers have made model recommendations for specific regions. To support emergency response and forecasting processes during oil spills in the Arctic regions, Nordam et al. (2019) improved the simulation of oil fate and transport in ice-covered waters by updating the Oil Spill Contingency and Response (OSCAR) model to use sea ice speed and coverage data from coupled ice-ocean models, supported by case studies. Qiao et al. (2019) analyzed the probabilities of pollution in the 180-day period after the sinking by means

of a three-dimensional model developed to simulate the short- and long-term trajectories of oil spill from the Sanchi wreck, and their findings were consistent with SAR images and observation reports. Pradhan et al. (2021) predicted the movement of a possible oil spill that may occur in the Bay of Bengal off the coast of Odisha with scenarios simulated for various wind directions and speeds using the General National Oceanic and Atmospheric Administration Operational Oil Modeling Environment (GNOME) trajectory model. A risk assessment for ecologically sensitive regions was presented by revealing the effect of wind conditions on the spread of the spill. Another study conducted by GNOME analyzed the environmental vulnerability of coastal resources in Kota Tinggi, Malaysia, with 12 simulated 100 m^3 oil spill scenarios in different seasons. The results revealed that seasonal changes significantly affect the spread rate of oil spills and their impact on coastal resources (Balogun et al. 2021). Čović et al. (2024) developed simulations of oil spill trajectories in Kaštela Bay based on 18 different scenarios using the Potential Incident Simulation, Control, and Evaluation System (PISCES II) simulator. Wave height was found to be a significant variable affecting the oil-spreading rate, and important implications for risk assessments and adequacy of response equipment were provided. In another study using PISCES 2, the trajectory of a ship-sourced oil spill in the Gulf of Izmir was simulated to determine risky areas through two scenarios depending on the type and amount of pollutants. PISCES 2 gave reliable results in terms of evaporation and dispersion rates, which are consistent with the literature. (Toz and Buber, 2018) comparatively evaluated the performance of two advanced software systems, the Oil Spill Prediction Modeling System (OILMAP) and PISCES 2, on the early transport and fate of oil spills over four scenarios using algorithms widely accepted in the oil spill literature. The results showed that OILMAP predicted a wider spill area and provided more reliable results in evaporation calculations, closer to the literature, but both software provided high confidence level outputs in determining risky areas. Ciappa (2023) presented statistical data on the direction and source of spills reaching certain coastal areas by examining the 10-day oil trajectories monitored monthly in the Mediterranean Sea between 2015 and 2019 using Oil Trajectory Analysis (OTA) to establish prioritization criteria for satellite-based surveillance systems by applying marine protected areas (MPA). While the travel time increases and the probability of grounding decreases as the distance from the coast increases, within the framework of these dynamics shaped by winds and currents, high-monitoring priority offshore areas were defined in summer and winter months using a 5% attention threshold. Using oil entrainment and erosion models integrated into the hydrodynamic model established and validated by two-dimensional shallow water equations, Zhen et al. (2020) simulated

oil spill scenarios under different residual current conditions in Daya Bay and found that clockwise currents caused larger pollution areas.

Lee and Jung (2015) presented a model that assessed the risk of an oil spill in Garorim Bay, Korea, in environmentally sensitive sub-regions based on impact probability and initial impact duration factors and compared the differences in risk among sub-regions to identify the most vulnerable areas and improve the forecasts based on real-time sea conditions. Hu et al. (2024) developed an effective vessel pollution accident analysis method to support accident prevention and marine environment protection by constructing a knowledge graph with data from 411 vessel pollution accidents off the coast of China through entity and relationship extraction, cause analysis, and centrality algorithm. Cakir et al. (2021) investigated 1468 vessel accidents in the US Coast Guard database between 2002 and 2015 using Decision Tree and Tree Augmented Naive Bayes models to determine the main factors affecting the severity of the oil spill. Using 2080 non-US flagged vessel accident reports from the US Coast Guard (USCG) database, Sevgili et al. (2022) develop a data-driven Bayesian Network model that predicts the probability of oil spill in tanker accidents with 75.96% accuracy and identifies the most influential variables. Similarly, Anderson and Talley (1995), Talley and Anderson (1996), Eliopoulou and Papanikolaou (2007), Eliopoulou et al. (2012), Tromiadis and Stanca (2014), Uğurlu et al. (2015), Chen et al. (2018), Su et al. (2019), Chen et al. (2019), and Chen et al. (2020) also examined tanker accidents and analyzed the relationship between these accidents and oil pollution.

3. METHODOLOGY

In this research, the relationship between the variables in marine pollution accidents were analyzed by using chi-square test for statistical significance. After that, the strength of the association was analyzed with Cramer's V.

The data collection for this research was conducted utilizing marine pollution accident reports on the IHS Sea-Web database. The accidents are filtered according to the event type as "Marine Pollution", and 208 maritime accident reports between 1999 and 2023 were collected. After this step, data preprocessing and data transformation were conducted. The event details in the accident data were investigated, and it was found that there is pollution in all 208 accidents, but the pollution quantity is not declared in all reports. For this reason, the whole dataset and the dataset that includes the pollution quantity were prepared separately for the

analysis. During the preprocessing, the numerical variables were categorized, and then the data transformation step was completed by reducing the number of categories in the variables. The details of these datasets are explained below.

Season: classified as "summer", "autumn", "winter" and "spring", considering the hemisphere and date in which the accident occurred.
Total Loss: classified as "yes" and "no" according to the accident report.
Pollution: classified as "yes" and "no" according to the accident report.
Vessel Flag: classified as either "flag of convenience (FOC)" or "non-FOC" that is used in many studies and is categorized based on the assumption that FOCs are riskier in terms of meeting safety standards.
Vessel Status: classified as "moored/anchored", "alongside the shore facility", "maneuvering", "bunkering" and "on voyage" according to the classification of the IHS in the accident report.
Gross Tonnage: classified as "under 3000 GRT", "between 3000 and 10000 GRT", "between 10000 and 30000 GRT", and "above 30000 GRT" according to the quartiles of dataset. This categorization is also supported by the fact that ships differ significantly in terms of their operational profiles, port usage, maneuverability, fuel, and cargo capacity.
Vessel Type: classified as "tanker", "bulk carrier", "general cargo", "container", "supply vessel" and "other (fishing and passenger)" according to the accident reports.
Vessel Age: classified as "below or equal to 12 years (≤12)", "above 12 years (>12)", categorized by the Paris MoU's Ship Risk Profile, which considers vessel age as a critical risk factor influencing safety and pollution likelihood. The cutoff at 12 years reflects common operational practices and findings in the literature that vessels older than this threshold tend to have increased maintenance needs and higher accident risk (Sevgili, 2024).

In addition to these variables, pollution quantity is declared in 111 of the 208 accident reports. Quantity variable was added to the dataset for the additional analysis.

Pollution Quantity: classified as below 250 gallons and equal or above 250 gallons to divide the dataset almost half, and is based on the average amount of pollution found in marine accidents examined in a study conducted by Cakir et al. (2021).

After all these steps, the two datasets were ready for the chi-square and Cramer's V analysis. Firstly, chi-square analysis was performed among the variables with formula 1. The main principle of the chi-square test is analyzing the nominal variables by comparing the expected and the observed frequencies. This difference is important to define the statistical significance between the variables.

$$x^2 = \sum \frac{(O-E)^2}{E} \sim x^2 \quad (1)$$

O is the observed frequency, and *E* is the expected frequency. After this step, to analyze the strength of the association, Cramer's V is used to calculate the values in which the dataset has the number of rows and columns larger than 2. Cramer's V value shows the strength of association.

Rea and Parker (2014) determined Cramer's Phi or Cramer's V values as 0.00 and under 0.10 for "negligible association "; 0.10 and under 0.20 "weak association"; 0.20 and under 0.40 "moderate association"; 0.40 and under 0.60 "relatively strong association". They classified 0.60 and under 0.80 as "strong association" and 0.80 and under 1.0 as "very strong association".

4. FINDINGS

In this section, the findings of the analysis were evaluated in three subsections. Firstly, descriptive statistics about the datasets were given. After that the chi square analysis was performed and then the Cramer's V analysis performed.

4.1. Descriptive Statistics

This section includes two different descriptive statistics: the whole dataset and the dataset containing accidents where the quantity of pollution was reported.

Table 1 shows the descriptive statistics of the whole dataset. The total number of accident reports was 208. The distribution of the accidents among the seasons was not significantly different. The most accidents occurred in the winter season (26.4%), and the least accidents occurred in spring (23.6%). The state of total loss was "no", and the state of pollution occurrence was "yes" for the whole dataset. For this reason, total loss and pollution occurrence variables could not be used in the analyses. Distribution of the vessel flag is (63%) for the flag of convenience (FOC) and (37%) for the non-flag of convenience. The distribution of vessel status was diverse, and the vessels alongside the facility and moored/anchored situations had the highest rates, with 55.8% and 21.6%, respectively. The maneuvering (3.4%) situation had the lowest rates. Vessel size (GRT) was analyzed according to the equal frequency binning method and categorized under four categories (under 3000 GRT, between 3000 and 10000 GRT, between 10000 and 30000 GRT, above 30000 GRT). The most common

vessel size based on gross tonnage was between 3000 and 10000 GRT with a rate of 29.3%, while the lowest rate is for vessels above 30000 GRT (21.6%). When vessel types were examined, tankers (34.6%) and general cargo vessels (19.2%) were the vessel types with the highest rates. The least vessel type was supply vessels accounted for 9.1%. Vessel ages were categorized according to the Paris MoU Ship Risk Profile. While 36.1 % of the vessels in the dataset were below or equal to 12 years, 63.9% were above 12 years old.

Table 2 shows the descriptive statistics of the dataset, including pollution quantity in accident reports. The total number of accident reports was 111. The distribution of the accidents among the seasons was slightly different. The most accidents occurred in the summer season (29.7%), and the least accidents occurred in winter and spring (22.5%). Pollution quantity was below 250 gallons in 51.4% and equal or above 250 gallons in 48.6% of the cases. When the flag distribution of the vessels was analyzed, 62.2% of the vessels had FOC, while 37.8% of the vessels had non-FOC. In vessel status, vessels alongside the facility and moored/anchored situations had the highest rates with 50.5% and 21.6%, respectively, while the maneuvering (3.6%) situation had the lowest rates. For vessel size, vessels under 3000 GRT had the highest rate (27.0%), while vessels between 10000 and 30000 GRT had the lowest rate (20.7%). Tanker (35.1%) and bulk cargo (18.9%) vessels were the vessels with the highest rates. The least vessel type was supply vessels with 9.0%. Finally, 44.1% of vessels were below or equal to 12 years, and 55.9% of vessels were above 12 years old.

Table 1: Descriptive Analysis of the Variables of Marine Pollution Accidents

Variable	Item	Frequency	Percentage (%)
Season	Summer	50	24.0
	Autumn	54	26.0
	Winter	55	26.4
	Spring	49	23.6
Total Loss	Yes	0	0.0
	No	208	100.0
Pollution Occurrence	Yes	208	100.0
	No	0	0.0
Vessel Flag	Flag of convenience (FOC)	131	63.0
	non-Flag of convenience (FOC)	77	37.0
Vessel Status	Moored/Anchored	45	21.6
	Alongside Shore Facility	116	55.8
	Maneuvering	7	3.4
	Bunkering	22	10.6
	On Voyage	18	8.7
Vessel Size (Gross Tonnage)	Under 3000 GRT	55	26.4
	Between 3000 and 10000 GRT	61	29.3
	Between 10000 and 30000 GRT	47	22.6
	Above 30000 GRT	45	21.6
Vessel Type	Tanker	72	34.6
	Bulk Carrier	31	14.9
	General Cargo	40	19.2
	Container	26	12.5
	Supply Vessel	19	9.1
	Others (Fishing, Passenger)	20	9.6
Vessel Age	Below or equal to 12 years	75	36.1
	Above 12 years	133	63.9

Table 2: Descriptive Analysis of the Variables of With Pollution Quantity

Variable	Item	Frequency	Percentage (%)
Season	Summer	33	29.7
	Autumn	28	25.2
	Winter	25	22.5
	Spring	25	22.5
Total Loss	Yes	0	0.0
	No	111	100.0
Pollution	Yes	111	100.0
	No	0	0.0
Pollution Quantity	Below 250 gallons	57	51.4
	Equal or above 250 gallons	54	48.6
Vessel Flag	Flag of convenience (FOC)	69	62.2
	non-Flag of convenience (FOC)	42	37.8
Vessel Status	Moored/Anchored	24	21.6
	Alongside Shore Facility	56	50.5
	Maneuvering	4	3.6
	Bunkering	16	14.4
	On Voyage	11	9.9
Vessel Size (Gross Tonnage)	Under 3000 GRT	30	27.0
	Between 3000 and 10000 GRT	29	26.1
	Between 10000 and 30000 GRT	23	20.7
	Above 30000 GRT	29	26.1
Vessel Type	Tanker	39	35.1
	Bulk Carrier	21	18.9
	General Cargo	17	15.3
	Container	11	9.9
	Supply Vessel	10	9.0
	Others (Fishing, Passenger)	13	11.7
Vessel Age	Below or equal to 12 years	49	44.1
	Above 12 years	62	55.9

4.2. Chi-square analysis

Firstly, chi-square analysis with the whole dataset was performed. The results of this analysis can be seen in Figure 3.

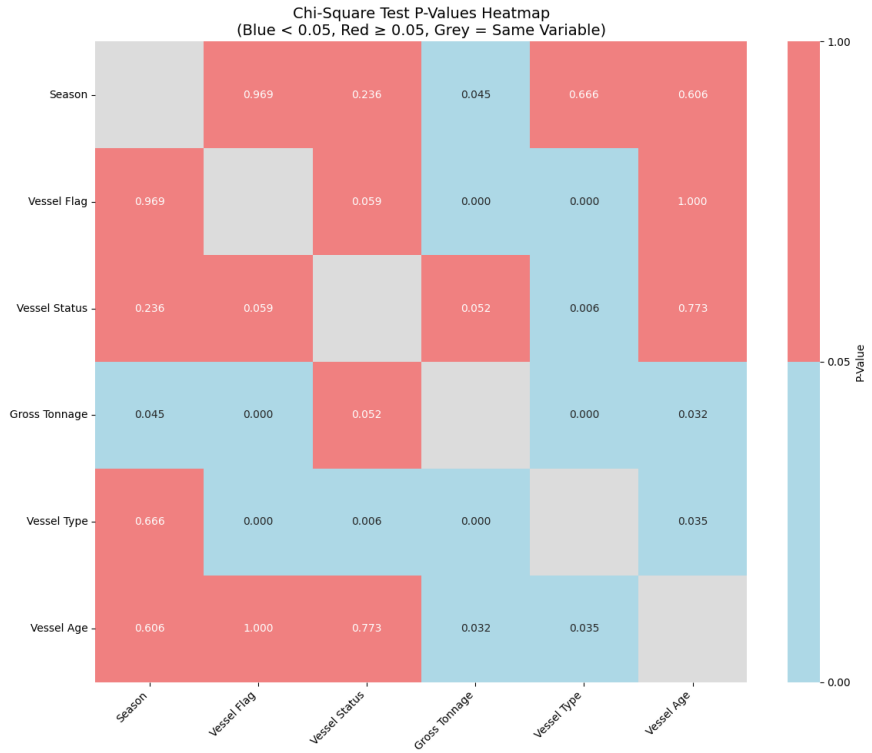


Figure 3: Chi-square Analysis of the Whole Dataset

Figure 3 shows the statistical significance ($p<0.05$) between the variables with blue color. There are significant relationships between "season and gross tonnage" ($p=0.045$), "vessel flag and gross tonnage" ($p=0.000$), "vessel flag and vessel type" ($p=0.000$), "vessel status and vessel type" ($p=0.006$), "gross tonnage and vessel type" ($p=0.000$), "gross tonnage and vessel age" ($p=0.032$), "vessel type and vessel age" ($p=0.035$).

Secondly, chi-square analysis was performed on datasets that declared the pollution quantity. There are also accident reports in the dataset that do not report the pollution quantity. Therefore, this analysis was conducted after removing these accident reports from the dataset. The results of this analysis can be seen in Figure 4.

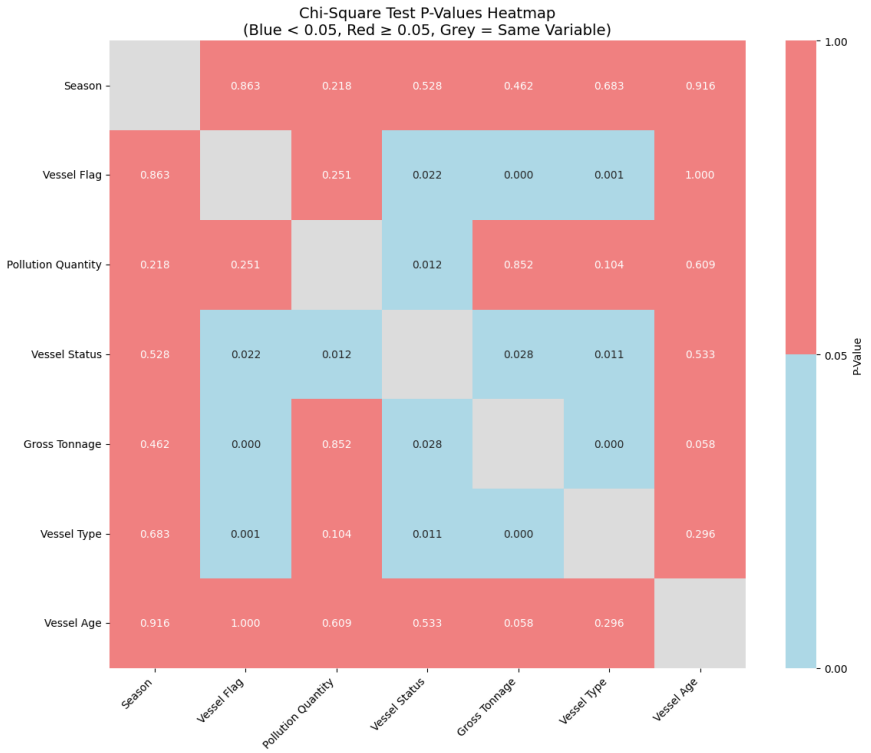


Figure 4: Chi-square analysis of the dataset with pollution quantity

Figure 4 shows the statistical significance ($p<0.05$) between the variables with blue color. These variables are "vessel flag and vessel status" ($p=0.022$), "vessel flag and gross tonnage" ($p=0.000$), "vessel flag and vessel type" ($p=0.001$), "pollution quantity and vessel status" ($p=0.012$), "vessel status and gross tonnage" ($p=0.028$), "vessel status and vessel type" ($p=0.011$), "gross tonnage and vessel type" ($p=0.000$).

After this step, Cramer's V analysis was performed to analyze the strength of the association between these variables.

4.3. Cramer's V analysis

In this step, Cramer's V analyses were performed on the whole dataset and on datasets that declared the pollution quantity. The results of the whole dataset can be seen in Figure 5. Among the variables with significant differences, those with the highest Cramer's V value were "gross tonnage and vessel flag" and "gross tonnage and vessel type" with 0.38. According to the scale of Rea and Parker (2014), this value indicates moderate association between these variables. Another moderate

association was found between “vessel type and vessel flag” with a Cramer's value (V=0.37) very close to these associations. It can be said that the values of these associations are close to the “relatively strong association”, which is the upper association level in the scale. Other variables with moderate correlations were "Vessel age and vessel type" (V=0.24), "vessel status and vessel type" (V=0.22), and "gross tonnage and vessel age" (V=0.21). Finally, a weak association was determined between season and gross tonnage (V=0.17).

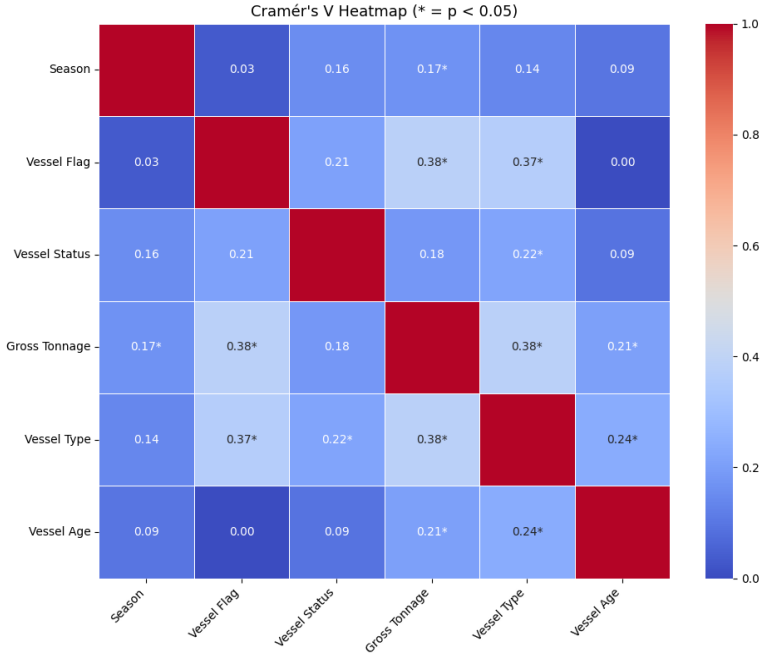


Figure 5: Cramer’s V Analysis of the Whole Dataset

In the second step of Cramer's V analysis, the data reporting the pollution quantity were analyzed. The results of the whole dataset can be seen in Figure 6. As in the analysis covering all data, the highest level of association was between “gross tonnage and vessel type”, with 0.46. This value indicates a relatively strong association between these two variables. “Vessel flag and gross tonnage” and ‘vessel flag and vessel type’ were the other correlations with relatively strong associations (V=0.44). The pollution quantity was found to be associated only with vessel status. The moderate association between these two variables was identified (V=0.34). Other associations identified in this analysis, namely "vessel flag and vessel status", "vessel status and vessel type", and "vessel status and gross tonnage", had a moderate level of associations with values of 0.32, 0.29, and 0.26, respectively.

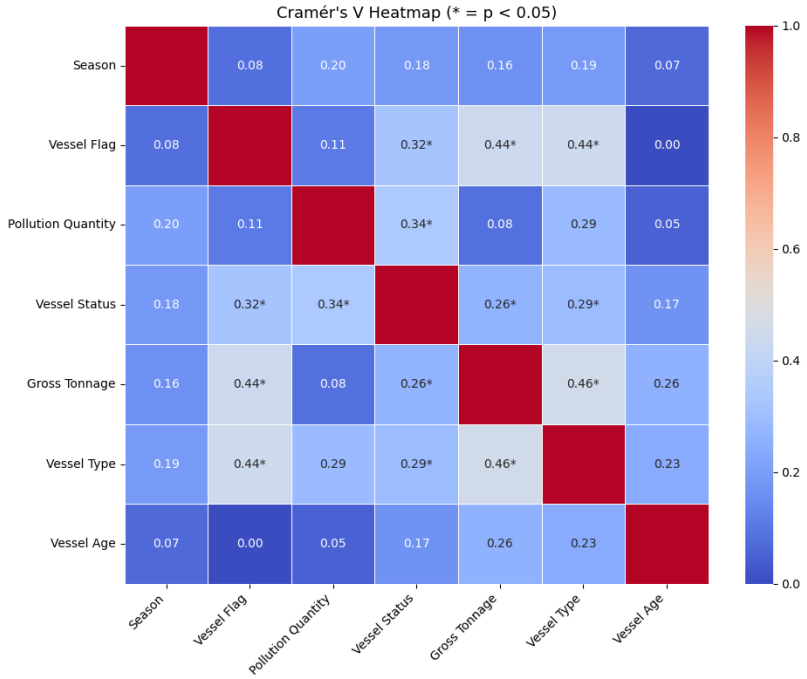


Figure 6: Cramer's V Analysis of the Dataset with Pollution Quantity

Chi-square tables were examined to further evaluate the relationships with the highest correlation levels in Cramer's V analyses. Table 3 shows the chi-square table between vessel size and gross tonnage. Upon examination, it was found that the large-tonnage ships (above 2999 GRT) causing pollution were flying the flags of FOC countries. However, it was observed that the low-tonnage vessels involved in the accident causing pollution were predominantly non-FOC.

Table 3: Chi-square Table of Vessel Flag and Gross Tonnage

			GRT			
			Above 30000	Between 10000 and 30000	Between 3000 and 10000	Under 3000
Flag	FOC	Count	21	26	26	4
		Expected Count	16.7	17.4	22.6	20.4
	Non-FOC	Count	24	21	35	51
		Expected Count	28.3	29.6	38.4	34.6
Total		Count	45	47	61	55
		Expected Count	45	47	61	55

The chi-square table demonstrating the relationship between gross tonnage and vessel type is given in Table 4. In bulk carriers and container ships, it was found that larger tonnage ships were more prone to pollution-

causing accidents. On the other hand, relatively small tonnage vessels were more likely to be involved in accidents in general cargo, supply vessels and other vessel types. There was no significant difference between expected and observed values for tanker ships.

Table 4: Chi-square Table of Gross Tonnage and Vessel Type

			Vessel Type						Total
			Bulk Carrier	Container	General Cargo	Others	Supply Vessel	Tanker	
GRT	above 30000	Count	18	8	3	1	1	14	45
		Expect. Count	6.7	5.6	8.7	4.3	4.1	15.6	45
	btw. 10000 and 30000	Count	11	10	6	3	1	16	47
		Expect. Count	7.0	5.9	9.0	4.5	4.3	16.3	47
	btw. 3000 and 10000	Count	2	8	19	3	4	25	61
		Expect. Count	9.1	7.6	11.7	5.9	5.6	21.1	61
	under 3000	Count	0	0	12	13	13	17	55
		Expect. Count	8.2	6.9	10.6	5.3	5.0	19.0	55
Total		Count	31	26	40	20	19	72	208
		Expect. Count	31	26	40	20	19	72	208

Table 5 provides the chi-square table representing the relationship between vessel flag and type. The observed value of FOC-flagged bulk carriers, container vessels, and general cargo vessels was higher than the expected value. In other words, it can be said that these vessels involved in the accident causing pollution are more likely to have FOC flags. This situation was the opposite for tankers. Like tankers, supply vessels and other types of vessels were also found to have a higher rate of non-FOC flags.

Table 5: Chi-square Table of Vessel Flag and Type

			Vessel Type						Total
			Bulk Carrier	Container	General Cargo	Others	Supply Vessel	Tanker	
Flag	FOC	Count	19	15	18	3	1	21	77
		Expected Count	11.5	9.6	14.8	7.4	7.0	26.7	77
	non-FOC	Count	12	11	22	17	18	51	131
		Expected Count	19.5	16.4	25.2	12.6	12.0	45.3	131
Total		Count	31	26	40	20	19	72	208
		Expected Count	31	26	40	20	19	72	208

Finally, the relationship between the pollution quantity and vessel status, which had a statistically significant relationship, was analyzed (Table 6). The frequency of pollution quantity being <250 gallons was higher when the vessel status was bunkering. However, the expected value of pollution >=250 gallons in maneuvering or on voyage status was higher than the observed value. From this finding, it can be inferred that the pollution quantity in the event of an accident is higher for ships in this status.

Table 6: Chi-square Table of Vessel Status and Pollution Quantity

			Quantity		Total
			<250 gallons	>=250 gallons	
Vessel Status	Alongside shore facility	Count	30	26	56
		Expected Count	28.8	27.2	56
	Bunkering	Count	12	4	16
		Expected Count	8.2	7.8	16
	Maneuvering	Count	0	4	4
		Expected Count	2.1	1.9	4
	Moored/anchored	Count	13	11	24
		Expected Count	12.3	11.7	24
	On voyage	Count	2	9	11
		Expected Count	5.6	5.4	11
Total		Count	57	54	111
		Expected Count	57	54	111

These findings suggest operational and regulatory implications. Larger tonnage ships, particularly bulk carriers and container vessels, exhibited higher involvement in pollution-related accidents, especially when flagged under flags of convenience (FOC). FOC-flagged vessels are often assumed to be linked to differences in safety culture and regulatory oversight, which may contribute to their disproportionate representation in

serious incidents. FOC-flagged bulk carriers and general cargo ships exceeded expected accident frequencies, indicating a potential gap in compliance or operational risk management for these ship categories. Conversely, tankers, supply vessels, and passenger vessels were more commonly registered under non-FOC flags, aligning with the stricter safety and environmental requirements imposed on these segments by international conventions and oil majors' vetting practices.

The relationship between vessel status and pollution quantity further highlights operational risk factors. Bunkering-related pollution events, though frequent, tend to involve lower spill volumes, likely due to controlled port environments and established response capacity. In contrast, maneuvering or en-route incidents, which often occur in more dynamic or offshore conditions, were associated with higher spill volumes, indicating the need for enhanced navigational safety protocols and spill-prevention measures during these critical operation phases.

Overall, these findings not only provide a quantitative understanding of the statistical relationships between vessel attributes and pollution risk but also highlight operational patterns and regulatory considerations. Policies targeting FOC-registered large tonnage vessels, especially in bulk and container shipping, could play a significant role in mitigating pollution risk. Furthermore, operational best practices and monitoring during high-risk ship statuses such as maneuvering and en route operation could reduce the scale of accidental discharges.

5. DISCUSSION AND CONCLUSION

This research aimed to determine the associations between variables by analyzing marine accidents causing marine pollution. In this context, 208 vessel accidents between 1999 and 2023 obtained from the IHS Sea-Web database were analyzed using Chi-Square and Cramer's V methods. Chi-square analysis revealed many statistically significant relationships resulting from pollution accidents. Significant relationships were found especially between the vessel's flag and vessel type, tonnage, and status. In addition, vessel status had a significant relationship with pollution quantity, vessel type, and tonnage. In the second stage, Cramer's V analysis was performed to determine the strength of the detected associations. In particular, the level of association between the vessel flag and the vessel type and tonnage was found to be higher than other associations. Moreover, in the analysis made on accidents with a certain quantity of pollution, these association levels were found to be relatively strong associations. The

pollution quantity was only associated with vessel status. A moderate association was observed between these two variables.

The analysis results of Cakir et al. (2021) show that tanker vessels and general dry cargo vessels can cause more severe oil spills than other types of vessels. Also, fishing and recreational vessels are less likely to cause a severe oil spill. This may be the result of these types of vessels being relatively smaller in size than other types of vessels. Our results show that bulk carriers and container ships involved in pollution accidents were large-tonnage vessels, while general cargo, support vessels, and other types of vessels were small-tonnage. It was also found that the tankers were medium-tonnage vessels. It is an established fact that oil tankers are more prone to causing significant oil spills due to the nature of the cargo they carry (Cao et al. 2023), and tanker vessels have the highest percentage in our dataset. Wang et al. (2021) mentioned that accidents involving fishing vessels, yachts and sailing vessels are more likely to result in serious consequences. The dataset in this research, vessels involved in pollution-causing accidents, shows that the fishing vessels, passenger vessels, and supply vessels have the lowest percentage in the whole dataset.

Vessels on maneuvering and voyage were found to be more likely to have high pollution levels. However, the pollution quantity in accidents occurring during bunkering was lower. This finding is consistent with the study conducted by Cakir et al. (2021), which found that the quantity of pollution in accidents occurring in the open sea and straits was higher. Sevgili et al. (2022) similarly found that the risk of pollution after an accident is highest in the open sea. The establishment of vessel-specific risk protocols is also important. Such protocols should include dynamic risk assessments for larger ships, such as oil tankers and bulk carriers, considering their unique potential for pollution and the challenges they face in terms of maneuverability (Zhang et al. 2025).

The bulk carriers, container ships, and general cargo vessels involved in the pollution-causing accident carried the flags of FOC countries. In contrast, tankers, supply, and other types of vessels were registered in the registry of non-FOC countries. While Zhang et al. (2022) mentioned that FOC ships may cause more fatalities and injuries than non-FOC ships, the results of this study show that flag and vessel type are important together, and both FOC and non-FOC vessels with different types are involved in pollution-causing accidents. On the other hand, the percentage of the vessels involved in pollution-causing accidents have FOC with 63%. Bye and Aalberg (2018) mentioned that a higher incidence of flag-of-convenience-related accidents is observed in the context of

navigation-related incidents when compared with vessels not bearing such a flag.

The findings may help relevant authorities take preventive measures to prevent the occurrence of accidents that may result in pollution in the future. The findings may help relevant authorities design and implement effective preventive measures aimed at reducing the risk of marine accidents and minimizing potential pollution. Such measures could include stricter safety protocols, targeted inspections, and vessel-specific risk assessments. In addition, it can also enable them to predict the occurrence of pollution in case of accidents. Early actions could substantially reduce the likelihood and severity of pollution-causing accidents.

An important limitation of this research is that it relies solely on the IHS Sea-Web database, primarily due to restricted access to alternative database and the challenges of obtaining standardized accident records from multiple sources. Consequently, some potentially relevant main and root variables could not be incorporated into the analysis. These include human factor indicators (e.g., crew fatigue levels, certification and training background, working hours), environmental conditions at the time of the accident (e.g., wave height, wind speed, visibility, current velocity), and operational safety management factors (e.g., vessel maintenance history, inspection frequency, safety management system performance). The exclusion of these variables was mainly due to the absence or inaccessibility of detailed accident investigation reports. In future research, access to more comprehensive and harmonized datasets from multiple sources would allow the integration of these missing variables. Such data would enable the development of more robust analytical models, including predictive approaches using advanced machine learning algorithms, to better identify high-risk conditions and inform targeted preventive strategies for the maritime industry.

AUTHOR CONTRIBUTION

CONTRIBUTION RATE	EXPLANATION	CONTRIBUTORS
Idea	Pointing out the research idea or forming hypotheses	Author 1 and 2
Review of Literature	Conducting the literature review for the study	Author 1 and 2
Research Design	Forming the research design, including research methodology, deciding on scales and samples	Author 1 and 2
Data Collection and Editing	Data collection, editing, and analyzing	Author 1 and 2
Findings and Discussion	Reporting and discussing the findings	Author 1 and 2

Conflict of Interest

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