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Human Factors Analysis by Classifying Chemical Accidents into Operations

Esra Yalcin [1,*], Gokcen Alev Ciftcioglu [2] and Burcin Hulya Guzel [3]

[1] Department of Occupational Safety, Institute of Pure and Applied Sciences, Marmara University, Istanbul 34722, Türkiye
[2] Department of Chemical Engineering, Marmara University, Istanbul 34722, Türkiye; gciftcioglu@marmara.edu.tr
[3] Ministry of Labour and Social Security, Ankara 06520, Türkiye; burcingzl@gmail.com
* Correspondence: esradilek.yalcin@gmail.com; Tel.: +90-532-483-4107

Abstract: In the chemical industry, organizational and operational human factors significantly contribute to accidents. Chemical accidents occur in various operations of the industry due to a range of factors. Understanding the relationship between these factors and the accidents that happen is crucial in preventing similar accidents from happening repeatedly and promoting sustainability. Therefore, this study was divided into five operations: maintenance repair, process, loading unloading, storage, and shutdown startup of the chemical industry, to provide a more concrete, intuitive explanation of the interplay between causes and illustrate the routes to failure. The data were collected from 251 accident reports from various online data. The study was analyzed using the Human Factors Analysis and Classification System (HFACS) method as a conceptual framework. Each level's frequency variables were obtained to define nominal and ordinal data. The chi-square test and Fisher's exact test were used in the difference analysis of data in the model. The results show that the high-frequency accidents caused under the HFACS framework were organizational processes in the process (63.73%), in the storage (70.58%), and in the shutdown startup (91.66%), and skill-based errors in the maintenance repair (81.81%) and in the loading unloading (66.03%). Furthermore, resource management, technological environment, and personal readiness were significantly correlated with the operations. Human factors have differences in different operations in the chemical industry.

Keywords: human factor; human error; chemical accident; HFACS; accident analysis

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1. Introduction

Human error is one of the most critical contributory factors in various accidents in different industries, including aviation, healthcare, transportation, and manufacturing. Many studies have pointed out the fundamental role of human errors in accident occurrence, with them being involved in 70–80% of aviation accidents [1], 60% of petrochemical accidents, 90% of road traffic accidents, 90% of steel and iron metallurgy accidents [2], over 90% of nuclear accidents, over 75–96% of marine accidents, and over 80% of chemical process accidents [3,4]. For this reason, deaths and injuries or health problems, financial losses, non-financial losses, and environmental damages happen due to human errors [5].

The Bhopal gas tragedy occurred in 1984 in India. The tragedy was caused by a gas leak from a pesticide plant, which released a toxic cloud of methyl isocyanate (MIC) gas into the surrounding area. The gas spill resulted in thousands of deaths. In addition, it affected about 300,000 people's genetic factors and caused many other long-term health problems [6]. A combination of operator errors, poor maintenance, inadequate use of an early warning system, poor risk perception, and poor safety management led to this accident [7]. The Piper Alpha disaster was a catastrophic oil rig explosion. It happened in 1988 in the North Sea off the coast of Scotland. Being one of the deadliest industrial accidents in history, the incident caused 167 deaths. Poor communication between operators, insufficient training, lack of safety procedures, improper installation of pressure safety valves, work permit system in work shifts, and inadequate maintenance procedures all contributed to the incident [7,8]. The Chernobyl nuclear power plant catastrophe in 1986 in Ukraine, the Texaco Refinery explosion in 1994 in Wales, and the BP Deepwater Horizon Oil Spill disaster in 2010 in the Gulf of Mexico were all significant industrial accidents that were directly or indirectly linked to human error [8–10].

Human-caused accidents in the chemical industry have caused significant harm to the environment, society, and the economy [11]. As a result, safe production has become the primary principle for sustainable development in chemical enterprises [12]. A recent study by Nawaz et al. [13] found that safety and sustainability are closely related, with security providing an operational command of sustainability. Because the two disciplines share the same pillars, including the economy, environment, and society, improving workplace safety and health management is essential to achieving sustainable development goals [14]. By prioritizing workplace safety and health, the chemical industry can create safe and healthy work environments, reduce the risk of accidents and environmental pollution, and contribute to sustainable development goals related to the economy, environment, and society. However, one of the most critical steps in achieving sustainability, increasing safety, and maintaining low incident rates is to perform a comprehensive, accurate, and detailed analysis of an organization's accidents and incidents [15].

The chemical industry is one of the sectors with the highest risk due to the catastrophic effects and outcomes caused by toxic, explosive, or flammable hazardous chemicals [7]. Chemical accidents may occur, releasing large amounts of dangerous chemicals in a plant during manufacturing, storage, utilization, and elimination or transportation [16]. Human and organizational factors, complex systems, process conditions, and improper management may lead to chemical accidents [7]. Although many regulations, standards, and policies apply in the chemical industries, accidents still happen [17]. Therefore, it is necessary to analyze the causes of chemical accidents to prevent incidents involving death or personal injury, provide safety, and reduce environmental and economic losses in the chemical industries [16]. Many studies have shown that human error is a significant factor in chemical accidents. For example, Dakkoune et al. [18] analyzed 169 events between 1974 and 2014 selected from a French database. The study shows that the causes were mainly related to human errors. Jung et al. [19] researched numerous chemical accidents in South Korea between 2008 and 2018, and human error was the reason for 76.1% of all chemical accidents. Zhang and Zheng [20] examined 1632 hazardous chemical accidents in China during 2006–2010 for statistical characteristics. The findings showed that human factors contributed to the most dangerous chemical accidents. According to another study, human factors were the leading cause of process accidents' unsafe behavior [4].

There are many human factors analysis models and theories to study the causation of accidents from the view of human behaviors or human errors. For example, Jens Rasmussen described human behavior in conformity with the levels of cognitive behavior in 1982 [21], and he suggested as based on skill, rule, and knowledge (SRK model) a model to describe the process of human cognitive behavior [22]. According to this theory, there are three levels of cognitive behavior: skill-based, rule-based, and knowledge-based. The skill-based level refers to automatic, unconscious actions without conscious thought or decision-making. The rule-based level involves conscious decision-making based on pre-learned rules and procedures. Finally, the knowledge-based level involves conscious decision-making based on understanding and problem-solving, requiring higher expertise [23,24].

One particularly revolutionary approach to the development of human error is the one proposed by James Reason [25]. It is called the "Swiss Cheese" model and is a widely used accident causation model. Reason identifies four levels of human failure, each influencing the next. Every level has a defect, and when unsafe factors pass through the holes represented in the cheese, they finally lead to accidents [26]. The model divided accident causes into two categories: active factors and latent factors, inclusive of organizational influences (latent), unsafe supervision (latent), preconditions for unsafe acts (latent), and unsafe acts (active). Active factors are those in which the impact is felt instantly. Latent factors tend to be inactive in the system, largely unnoticed until they combine with other factors and an accident occurs. The model provides a practical and valuable approach toward comprehending the causes of accidents and safety measures. The model emphasizes the significance of having several layers of defense to safeguard against accidents and recognizing potential weaknesses in each layer to prevent accidents [27,28]. The model is described diagrammatically in Figure 1. Due to the need to extend accident investigation beyond the scope of direct personnel action or inaction, Shappell and Wiegmann [26] developed the Human Factors Analysis and Classification System (HFACS) model in the aviation industry, based on Reason's Swiss cheese model. The HFACS model was designed to identify the underlying human factors contributing to accidents and provide a framework for understanding the root causes of accidents. Thus, active and latent categorizations of accidents helped in focusing more on a systemic approach to underlying contributing causes [28]. The HFACS is considered to be a comprehensive analysis model of human error that considers multiple causes of human failure [29].

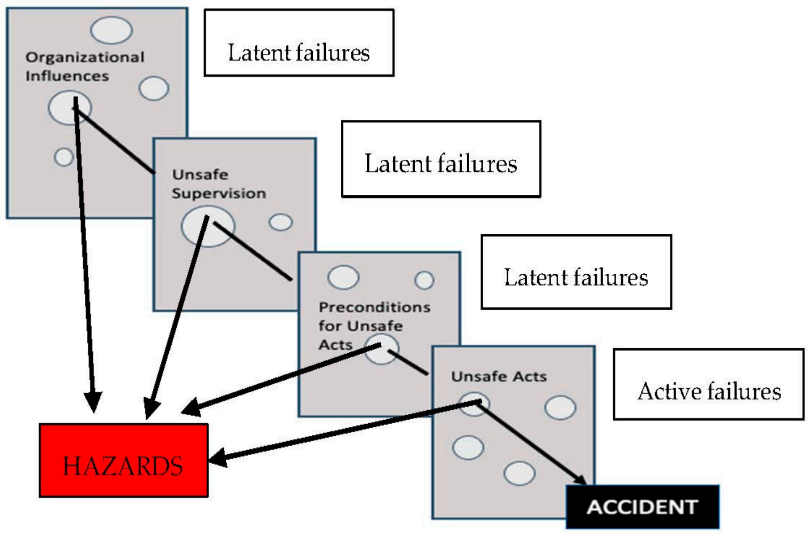

Figure 1. Reason's Swiss cheese model [25].

The HFACS model is a widely used and accepted method as a valid and reliable tool in accident research [7]. From this point of view, the HFACS model has been successfully extended to analyze and investigate the human error framework [30]. It is used in different industries such as maritime, mining, railway, construction, healthcare, nuclear power, chemical, and other industries [28,31]. For example, Xia et al. [32] used the HFACS model to conduct a statistical analysis of 120 fatal accidents involving confined space operations in China from 2008 to 2018. The results indicate that the causes of the accidents include inadequate safety culture, organizational process vulnerability, inadequate supervision, supervisory violations, decision errors, and operational violations. Liu et al. [33] developed a human factor analysis and classification system (HFACS-CM) for China's mines using data from 362 significant coal mine incidents between 2000 and 2016. Kandemir and Celik [34] defined the HFACS-MMO for marine engineering operations. Akyuz [35] introduced a novel hybrid approach for assessing potential operations whereby the hybrid accident analysis model integrates an analytical network process (ANP) method with the HFACS in the maritime transportation industry. With the aid of the HFACS, Zhou and Lei [36] investigated 611 accident/incident reports during the railway driving process. In the healthcare field, Cohen et al. [37] used the HFACS to classify 592 near-surgical near-misses reported via a hospital's incident reporting system over one year. As a result of the identification of 726 causal factors, most of the issues (n = 436, 60.00%) contained preconditions for unsafe actions. Karthick et al. [38] employed the fuzzy analytic hierarchy process (FAHP) in the HFACS framework to analyze and determine the critical human factors contributing to human errors in the nuclear control room application. In the chemical industry, Wang et al. [39] studied 101 accidents occurring in small and medium-sized enterprises from 2012 to 2016 using the HFACS framework. Li et al. [40] introduced the method of HFACS based on the Bayesian network to systematically investigate the factors influencing unsafe behavior according to the 39 investigation reports of hazardous chemical accidents in China. Theophilus et al. [41] proposed a new HFACS called the HFACS-OGI for the oil and gas industry and applied it by analyzing 11 accident reports from the US Chemical Safety Board.

Although some research has been performed on the effect of chemical accident prevention, there need to be more studies on which human factors are more effective in chemical operations and that examine the relationship between the causes. Therefore, this study aims to investigate the human factors in the five operations of accidents in the chemical industry: maintenance repair, process, loading unloading, storage, and shutdown startup. In the study, the following research hypotheses were established:

H1. *The HFACS framework levels differ in five operations (maintenance repair, process, loading unloading, storage, and shutdown startup).*

H2. *In chemical accidents, there is a significant relationship between the five operations and organizational influences, unsafe supervision, preconditions for unsafe acts, and unsafe acts.*

H3. *The significantly correlated factors of organizational influences, unsafe supervision, preconditions for unsafe acts, and unsafe acts significantly affect chemical accident operations.*

Section 2 of the research briefly reviews the test hypothesis tools and describes the methods applied. Then, in Section 3 are the results of the hypothesis, and in Section 4, there is a discussion according to the results. Finally, the concluding remarks on the HFACS, some limitation notes, and suggestions for future research are given.

2. Materials and Methods

This section briefly overviews the study tools and provides a detailed description of the applied methodology.

2.1. Data Collection Tools

The 251 investigation accident reports were collected from various online data in the chemical industry. These databases are the European Commission's Major Accident Reporting System (MARS) [42], France's Analysis, Research and Information on Accidents database (ARIA) [43], The Central Reporting and Evaluation Office for Major Accidents and Incidents in Process Engineering (ZEMA) [44], Germany's network of engineering chemistry and biotechnology expert DECHEMA [45], and Tukes' VARO registry of chemical accidents in Finland [46]. Industrial accident databases are created and maintained to achieve some goals; they assist in evaluating safety management and safety policy, create statistical trends and estimates, and verify probabilistic safety assessment or consequence assessment results, models, and assumptions [47]. Additionally, using incident databases as a management tool allows a company to evaluate its performance, learn from its errors, and enhance its risk management [48]. Many studies are carried out using such databases [18,49,50].

The selected text resources in accident reports include accident records, accident causes, accident analysis results, and prevention strategies. Unfortunately, the information offered in some cases is restricted. Due to the difficulties in drawing valid inferences on the causes or effects of the accidents, some accidents that did not meet the selection criteria were left out of the analysis. The selected reports contain at least one cause of human error. In addition, they have one of the five operations of the chemical industry: maintenance repair (n = 66), process (n = 91), loading unloading (n = 53), storage (n = 17), and shutdown startup (n = 24). Understanding the causes of past similar accidents and deficiencies in the performed processes can help to better understand similar chemical operations [51]. From this point of view, accidents are divided into five operations. In this study, the causes of accidents were classified according to the operations, and the error-producing conditions of accidents were analyzed based on statistical data.

2.2. The HFACS Model

The HFACS is a conceptually clever technique for analyzing how human factors contribute to accidents. The method's primary purpose is to give users a conceptual framework while looking into and analyzing instances of human error in accidents [35]. The combined system investigating active and latent factors has increased the reliability of the HFACS in accident investigation applications [52]. According to the HFACS model framework, many deficiencies that lead to accidents are identified within four levels of human failures: organizational influences, unsafe supervision, preconditions for unsafe acts, and unsafe acts [26].

(1) The organizational influences level is divided into three categories: resource management (contains top management decision-making about the utilization of resources such as equipment, facilities, money, and personnel), organizational climate (refers to the factors that affect employee performance, such as organizational structure, culture, and policies), and organizational process (relates to the decision-making that determines how an organization conducts its daily business, including its operations, procedures, and oversight).

(2) The unsafe supervision level, which is divided into four categories, deals with the actions and decisions of managers and supervisors that may have an impact on the performance of front-line personnel: Planned inappropriate operations (which involve circumstances in which managers fail to assess the risk involved in a task, putting personnel at an unacceptable level of risk. These include insufficient personnel, missions that do not adhere to norms or regulations, and insufficient opportunities for personnel rest), failure to correct the problem (refers to situations when inadequate equipment, training, or behavior is found but is left unchecked, implying that managers are failing to take corrective action or report such unsafe conditions), supervisory violations (the willful violation of the established laws and regulations by individuals in positions of authority), and inadequate supervision (involves those instances where supervision either fails to give advice, oversight, or training or does it incorrectly or improperly).

(3) The preconditions for unsafe acts level is divided into three categories: Environmental factors are the physical and technological factors that impact people's behaviors, conditions, and activities that can lead to harmful situations or human error. Condition of operators refers to the adverse mental state, physiological state, and physical/mental limitation factors that impact individual actions, needs, or behaviors and cause harmful situations or human error. Finally, personnel factors include personal readiness and crew resource management factors that affect behaviors, conditions, or individual decisions that cause a situation to be unsafe or lead to human error.

(4) The unsafe acts level is divided into two categories: errors and violations. Errors (decision, skill-based, perceptual errors) are unintentional behaviors and operator activities that fail to provide the desired results. Violations (routine violations, exceptional violations) are a deliberate disregard for the regulations. Skill-based errors are described as skills that occur without considerable conscious thought. Decision errors are intentional actions that go as planned, but the strategy is ineffective or wrong for the situation. Perceptual errors can often occur when one's perception of the world differs from reality. Routine violations tend to be habitual and usually tolerated by the leading authority. Exceptional violations are departures from a rule that is neither indicative of a person's usual behavior pattern nor approved by management [26]. In this context, the HFACS model framework is shown in Figure 2.

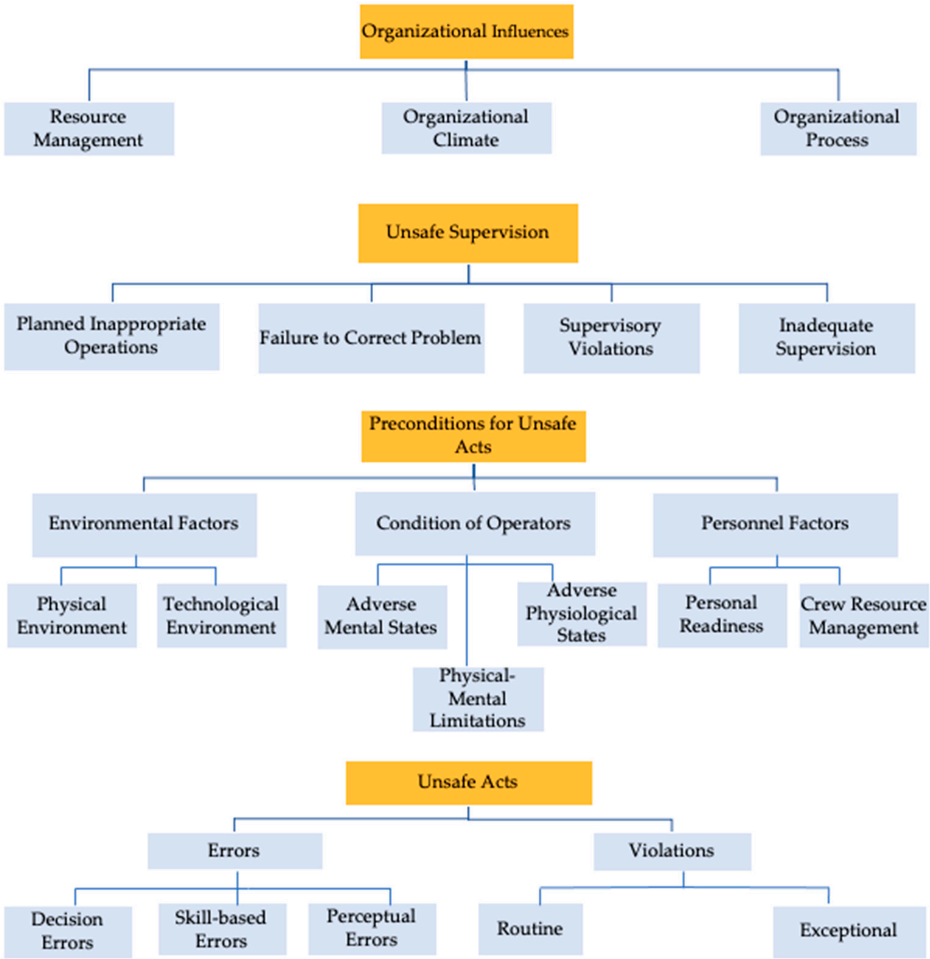

Figure 2. The HFACS model framework [26].

2.3. Statistical Methods

The accident reasons were categorized and statistically examined after the analysis. Under the HFACS framework, the frequency of each accident caused was determined. Frequency analysis was used to describe the nominal and ordinal parameters in the study. The chi-square test and Fisher's exact test were utilized in difference analysis. Spearman's rho analysis was used in relational scanning analysis. Spearman's rho test was chosen because the accident operations act as the dependent variables and the presence of accidents are the categorical variables. Generalized linear model (logit model) analyses were used in causality analysis. In this method, the significant parameters in the correlation analysis were converted into dummy variables, and therefore the ordinal logit method was used. All analyses were performed in SPSS 25.0 of the Windows program at a 95% confidence interval and 0.05 significance level.

The Fisher exact test is one of modern data analysis's most widely utilized techniques. It examines contingency tables with small sample sizes where the predicted frequency in one or more cells is less than five. Contingency tables are used to summarize the relationship between two categorical variables. If the p-value obtained from the test is below a predetermined significance level, it is concluded that there is a significant difference between the variables [53]. Fisher's exact test uses the following formula [54]:

$$Pr(\{x_{ij}\}) = \frac{\binom{m_1}{x_{11}}\binom{m_2}{n_1 - x_{11}}}{\binom{N}{n_1}}$$

Here, x states cell counts, m_1 and m_2 are row totals, n_1 and n_2 are column totals, and N states the table total [54].

Spearman's rho correlation coefficient expresses the strength and direction of the association between two variables. The relationship will be weak or strong on one side and negative or positive on the other. For example, if we suppose that the variables A and B have ranks of (RA) and (RB), respectively, and that (d) reflects the difference between the two ranks, then (d = RA − RB), and Spearman's is used to determine the correlation of ranks. Spearman's rho correlation analysis coefficient is calculated as follows. Here, d states two rank differences, and n displays the number of ordered pairs [55].

$$r_s = 1 - 6\sum d^2/n\left(n^2 - 1\right)$$

The generalized linear model (GLM) is an extension of the linear regression model that allows it to handle a variety of response variables, including binary and categorical variables. The logit model is a type of GLM that is a valuable tool for modeling binary response variables. The generalized linear (logit) model formula is given below [56].

$$P(Y = y; \pi) = \binom{n}{yn}\pi^{ny}(1-\pi)^{n(1-y)}$$

where

$$\pi = \frac{e^{\alpha+\beta_1 x_1+\ldots+\beta_n x_n}}{1+e^{\alpha+\beta_1 x_1+\ldots+\beta_n x_n}}$$

Here, β is the regression coefficient, X is the independent parameter, Y is the dependent parameter, and n is a number of independent parameters [56].

3. Results

The results of the causation analysis show that 66 maintenance repair accidents resulted in a total of 289 accident manifestations, 91 process accidents resulted in a total of 341 accident manifestations, 17 storage accidents resulted in a total of 67 accident manifestations, 24 shutdown startup accidents resulted in a total of 109 accident manifestations, and 53 loading unloading accidents resulted in a total of 190 accident manifestations. Finally, 996 accident manifestations were gathered as a result for this study. When calculating the percentage rates, the frequencies were divided by the number of accidents in operations in the chemical industry. Thus, the percentage weight of the number of causes per accident was found. Table 1 displays the frequency sequences of images in each level in the HFACS. The percentages show the proportion of manifestations for each accident number.

Among the causes of the maintenance repair accidents, technic errors (55.55%) are the most frequent manifestations within skill-based errors. Among the organizational process errors that depend on process accidents, the most common are errors related to the lack of procedures (51.72%). Similarly, the lack of procedures in organizational process accidents is one of the most common errors in storage (58.33%) and in shutdown startup (36.36%). Finally, attention failures (60%) are the most common in loading unloading due to skill-based errors.

According to the analysis, the six manifestations of the HFACS framework levels differed in accident operations (maintenance repair, process, loading unloading, storage, and shutdown startup). The details of these differences are presented in Tables 2–5. Additionally, after mapping the manifestations to the causes in the HFACS, the percentage of the failure paths consisting of each cause by chemical operations was acquired.

Table 1. The HFACS model's frequency statistics for chemical operations.

Categories in the HFACS Framework			Maintenance Repair		Process		Storage		Shutdown Startup		Loading Unloading	
			n	*** (%)**	***n***	*** (%)**	***n***	*** (%)**	***n***	*** (%)**	***n***	*** (%)**
Organizational Influences	Resource Management		2	3.03	20	21.97	4	23.52	5	20.83	11	20.75
	Organizational Climate		3	4.54	11	12.08	2	11.76	2	8.33	3	5.66
	Organizational Process		46	69.69	58	63.73	12	70.58	22	91.66	26	49.05
Unsafe Supervision	Planned Inappropriate Operations		4	6.06	5	5.49	0	0	2	8.33	5	9.43
	Failure to Correct Problem		3	4.54	2	2.19	0	0	2	8.33	2	3.77
	Supervisory Violations		15	22.72	4	4.39	5	29.41	1	4.16	4	7.54
	Inadequate Supervision		24	36.36	41	45.05	7	41.17	11	45.83	27	50.94
Preconditions for Unsafe Acts	Environmental Factors	Physical Environment	14	21.21	11	12.08	6	35.29	3	12.50	4	7.54
		Technological Environment	26	39.39	49	53.84	5	29.41	19	79.16	18	33.96
	Condition of Operators	Adverse Mental States	6	9.09	13	14.28	1	5.88	1	4.16	3	5.66
		Physical-Mental Limitations	1	1.51	0	0	0	0	0	0	0	0
	Personnel Factors	Personal Readiness	12	18.18	5	5.49	0	0	0	0	5	9.43
		Crew Resource Management	9	13.63	12	13.18	2	11.76	3	12.50	6	11.32
Unsafe Acts	Errors	Decision Errors	20	30.30	4	4.39	1	5.88	5	20.83	5	9.43
		Skill-Based Errors	54	81.81	55	60.43	11	64.70	14	58.33	35	66.03
		Perceptual Errors	14	21.21	16	17.58	8	47.05	4	16.66	11	20.75
	Violations	Routine	28	42.42	19	46.34	1	5.88	10	41.66	16	30.18
		Exceptional	8	12.12	16	17.58	2	11.76	5	20.83	9	16.98

* The total percentages of accident causes under the HFACS framework are higher than 100% because there are several reasons for one accident.

Table 2. Difference in of organizational influence levels in operations.

	Resource Management		Organizational Climate		Organizational Process	
	n	%	*n*	%	*n*	%
Maintenance repair	2	4.8	3	14.3	46	28.0
Process	20	47.6	11	52.4	58	35.4
Loading unloading	11	26.2	3	14.3	26	15.9
Storage	4	9.5	2	9.5	12	7.3
Shutdown startup	5	11.9	2	9.5	22	13.4
Test value	12.231		1.980		13.149	
p value	0.013		0.746		0.010	

Table 3. Difference in unsafe supervision levels in operations.

	Planned Inappropriate Operations		Failure to Correct Problem		Supervisory Violations		Inadequate Supervision	
	n	%	*n*	%	*n*	%	*n*	%
Maintenance repair	4	25.0	3	33.4	15	51.7	24	21.8
Process	5	31.3	2	22.2	4	13.8	41	37.3
Loading unloading	5	31.3	2	22.2	4	13.8	27	24.5
Storage	-	-	-	-	5	17.2	7	6.4
Shutdown startup	2	12.4	2	22.2	1	3.4	11	10.0
Test value	1.759		2.336		16.542		8.552	
p value	0.810		0.673		0.001		0.070	

Table 4. Difference in preconditions for unsafe act levels in operations.

	Physical Environment		Technological Environment		Adverse Mental States		Personal Readiness		Crew Resource Management	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%
Maintenance repair	14	36.8	26	22.2	6	25.0	12	54.6	9	28.1
Process	11	28.9	49	41.9	13	54.2	5	22.7	12	37.5
Loading unloading	4	10.5	18	15.4	3	12.5	5	22.7	6	18.8
Storage	6	15.8	5	4.3	1	4.2	-	-	2	6.3
Shutdown startup	3	7.9	19	16.2	1	4.2	-	-	3	9.4
Test value	8.876		11.157		2.655		10.700		0.590	
p value	0.055		0.025		0.615		0.019		0.975	

Table 5. Difference in unsafe act levels in operations.

	Decision Errors		Skill-Based Errors		Perceptual Errors		Routine Violations		Exceptional Violations	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%
Maintenance repair	20	57.1	54	32.0	14	26.4	28	37.8	8	20.0
Process	4	11.4	55	32.5	16	30.2	19	25.7	16	40.0
Loading unloading	5	14.3	35	20.7	11	20.8	16	21.6	9	22.5
Storage	1	2.9	11	6.5	8	15.1	1	1.4	2	5.0
Shutdown startup	5	14.3	14	8.3	4	7.5	10	13.5	5	12.5
Test value	12.304		2.296		7.772		5.849		4.680	
p value	0.011		0.681		0.093		0.207		0.308	

The difference in the organizational influence levels in the five operations is shown in Table 2. The results indicate that resource management, organizational climate, and organizational-process-related accidents are the most common areas for process operation. According to the results of the differences, the resource management ($p < 0.05$) and organizational process ($p < 0.05$) levels differ in operations (maintenance repair, process, loading unloading, storage, and shutdown startup). On the other hand, there is no difference in the organizational climate level ($p > 0.05$) in operations.

In the case of accidents caused by unsafe supervision levels in Table 3, planned inappropriate operations-related accidents are the most common area for process and loading unloading operations; failure to correct problems and supervisory violations-related accidents are the most common area for maintenance repair operations; and inadequate supervision-related accidents are the most common in process operations. The result of the difference analysis revealed that the supervisory violations level differs in operations ($p < 0.05$). The other three manifestations of unsafe supervision, planned inappropriate operation ($p > 0.05$) level, failure to correct the problem ($p > 0.05$) level, and inadequate supervision ($p > 0.05$) level, showed no difference in the accident operations.

As seen in Table 4, accidents due to physical environment and personal readiness occur mainly in maintenance repair operations, while technological environment, adverse mental state, personal readiness, and crew resource management-related accidents are primarily seen in the process operations. Levels of preconditions for unsafe acts indicated that the two differed in operations ($p < 0.05$), technological environment, and personal readiness. The other three manifestations in this level, physical environment, adverse mental states, and crew resource management, showed no difference in operations ($p > 0.05$). Finally, the other two manifestations in this level were not analyzed because of images being 0 and 1.

Decision errors and routine violations in the maintenance repair operations and skill-based errors, perceptual errors, and exceptional violations in the process operation are more common in terms of the probability of an accident, as seen in Table 5. In the level of the unsafe acts, the decision error ($p < 0.05$) level differs in operations. The other four manifestations in the group, skill-based errors ($p > 0.05$), perceptual errors ($p > 0.05$), routine violations ($p > 0.05$), and exceptional violations ($p > 0.05$), showed no difference in operations.

The results of Spearman's rho correlation analysis for the relationship between the operations and organizational influences, unsafe supervision, preconditions for unsafe acts, and unsafe acts are shown in Table 6. According to this, there is a significant relationship between the five operations and the resource management factors of organizational influences ($p < 0.05$), the technological environment factor of preconditions for unsafe acts ($p < 0.05$), and the personal readiness factor of preconditions for unsafe acts ($p < 0.05$). These results mean that resource management, technological environment, and personal readiness variables were significantly correlated with the five operations.

Table 6. Spearman's rho correlation analysis results for the relationship between the operations and organizational influences, unsafe supervision, preconditions for unsafe acts, and unsafe acts.

The Operations	**r**	***p***
Organizational Influences		
Resource Management	0.139 *	0.036
Organizational Climate	0.006	0.923
Organizational Process	−0.125	0.060
Unsafe Supervision		
Planned Inappropriate Operations	0.017	0.833
Failure to Correct Problem	0.012	0.876
Supervisory Violations	−0.144	0.066
Inadequate Supervision	0.100	0.202
Preconditions for Unsafe Acts		
Physical Environment	−0.028	0.674
Technological Environment	0.146 *	0.025
Adverse Mental States	−0.040	0.539
Physical Mental Limitations	−0.084	0.199
Adverse Physiological States	-	-
Personal Readiness	−0.164 *	0.012
Crew Resource Management	0.008	0.909
Unsafe Acts		
Decision Errors	−0.098	0.059
Skill-Based Errors	−0.009	0.862
Perceptual Errors	0.065	0.210
Routine Violations	−0.026	0.618
Exceptional Violations	0.067	0.200

Note: * $p < 0.05$.

Finally, the generalized linear model (logit model) was utilized to identify the effects of resource management, technological environment, and personal readiness variables on operations at the multivariable level. There were correlations and dependent variables, the operation was non-parametric, and the logit model was used for analysis. Table 7 reports the generalized linear model results. Spearman's rank correlation is used to evaluate a monotonic association's direction and strength and is unsuitable for a linear association interpretation [57]. For the multivariate level and drawing a linear association for non-parametric variables, generalized linear models are used. Promoting the likelihood function's central position in inference is one of the GLM's most significant achievements [58]. Therefore, the results of correlation analysis and GLM analysis differ. While correlation analysis examines the relationship between two variables, GLM analysis examines the effect of more than one variable on the dependent variable. Each significant parameter in the correlation analysis is included in the GLM analysis. Overall, the "B" results provide information about the strength and direction of the associations between the predictor variables and the response variable. According to this, although in univariate analysis variables of resource management, technological environment, and personal readiness were effective on operations in the correlation analysis, these effects were not significant in multivariate analysis because of $p > 0.05$. These results show that resource management, technological environment, and personal readiness variables affect operations only at the univariate level.

Table 7. Effects of resource management, technological environment, and personal readiness variables on operations.

Parameter Name	B	Std. Error	95% Wald Confidence Interval		Test of Hypothesis		
			Min.	Max.	Wald Chi-Square	df	p
Resource Management	0.248	0.170	−0.085	0.580	2.126	1	0.145
Technological Environment	−0.118	0.182	−0.476	0.240	0.417	1	0.518
Personal Readiness	0 [a]						
Dummy	−0.284	0.169	−0.615	0.046	2.843	1	0.092
Value = 1.00	0						
(Scale)	1						

a: Set to zero because this parameter is redundant.

4. Discussion

In this study, the main goal was to research whether accidents caused by human factors may occur in different operations in the chemical industry. First, the causes were determined using the HFACS model. Then, the relationships and effects of these parameters were examined using univariate and multivariate statistical analysis techniques.

The knowledge of the causes of accidents is the most significant material when drawing lessons from them [51]. The efficiency of accident learning depends on in-depth cause analysis [17]. A combination of many different causes leads to significant chemical accidents. For example, in this study, 251 accidents were investigated, and a total of 996 reasons were obtained, showing an average of 3.96 causes for each accident. For this reason, it is seen that more than one human factor affects the accidents that occur in the chemical industry. Therefore, it is important to take a holistic approach to accident prevention and consider all of the potential factors when developing safety plans and protocols.

Skill-based errors usually consist of attention, memory, and technical errors. Memory failures frequently appear as omitted items in a checklist or forgotten goals, and attention failures link to many factors such as the breakdown in visual scan patterns, task fixation, the accidental activation of controls, the misordering of steps in a procedure, and technical failures that develop depending on an employee's training experience, educational background, perspective, and approach to events [26]. The study revealed that skill-based errors mainly cause maintenance repair and loading unloading accidents. It has been determined that technical errors in maintenance repair and attention errors in loading unloading are more common and frequent. Similarly, Patterson and Shappell examined 508 coal mine incidents using the HFACS-mining industry (HFACS-MI) model and found that skill-based errors constitute the most frequent unsafe acts [59].

According to the study results, the organizational process is the main reason for process, storage, and shutdown startup accidents with the highest weight values. Procedural errors are the most widespread in all three operations. These procedural errors refer to a lack of procedures, unclear procedures, or an insufficiency of procedures. In such operational accidents, procedural manifestations such as "emergency operating procedures", "operational procedures", "maintenance procedures", "training procedures", "safety procedures", and "work permit system procedures" are frequently encountered. A lack of or inadequate safety operation procedures are the important causes of casualty accidents [60]. Similarly, in the shipping industry, the International Safety Management (ISM) Code mandates that shipping companies establish procedures that allow seafarers to take part in risk identification, assessment, and mitigation, and report safety lapses and issues. The Code, in principle, encourages a safe place strategy [61]. Therefore, the procedures in the chemical plants should be fit for purpose, written, and up-to-date to prevent errors.

After identifying the order of importance of causes in five operations using HFACS analysis, the significant relationships between each HFACS level and operations and HFACS level differences in operations were determined. The results show that resource management ($p < 0.05$), organizational process ($p < 0.05$), and technological environment ($p < 0.05$) cause differences in operations. Accordingly, it has been confirmed that forecited procedural errors, and those exceedingly foreseen in the organizational process, are more significant in operations. It has been observed that resource management causes, such as lack of machinery spare parts, alarm systems, or safety equipment, and defective design of plants are frequently involved in operation accidents. Similarly, Li et al. [40] found that resource management impacts operation violations in hazardous chemical accidents. Furthermore, Rostamabadi et al. [7] determined that resource management was one of the most influential factors contributing to process accidents. The study of [62] showed that adequate resources were one of the primary safety motivators for employees. The organizational process describes how chemical operations are standardized and managed using various procedures and frameworks. Therefore, vulnerabilities in operational management are likely caused by poor organizational processes. Xia et al. [32] have shown that one of the factors affecting China's confined space operation accidents is organizational process vulnerability. Therefore, it is essential to prioritize resource management issues and organizational processes in every operation. Poor technological environments include things such as defective equipment and facilities, a lack of safety precautions, a lack of electronic monitoring tools, irrational control layouts, etc. As a result, if issues are not identified or resolved quickly, or risks are not sufficiently addressed, a poor technological environment can easily increase the risks of accidents.

The identified manifestations were mainly different in supervisory violations ($p < 0.05$), personal readiness ($p < 0.05$), and decision errors ($p < 0.05$) in operations. Supervisory violation is frequently defined as the manager or supervisor disregarding the established operating procedures. An insufficient safety culture can be regarded as one of the contributing factors to supervisory violations [32]. It has been observed that non-compliance with actions of permit-to-work, allowing not using personal protective equipment (PPE), violated procedures, and willful disregard for authority by supervisors would be classified as supervisory violations in operations. Therefore, it would be beneficial to focus on management violations in operations to minimize the accidents resulting from management violations. These consist of personal readiness, not wearing PPE, inadequate training, and lack of information. It can be inferred that adequate personal readiness influences doing the job safely. According to a study in the maritime industry [63], safety training was the second most significant predictor of safety supervision. The same study's results indicated that the quality of the safety inspection would be high if crew members were well-trained in following safety rules and procedures or could use appropriate PPE. The decision errors in unsafe acts are wrong judgment and wrong response to an emergency, decisions due to poor practice, and decisions on using incorrect tools.

Based on the hypotheses, the study's results suggest that five operations differed in the six manifestations of the HFACS framework levels (resource management, organizational process, supervisory violations, personal readiness, technological environment, and decision errors). In addition, the study found a significant relationship between five operations and three manifestations of the HFACS framework resource management, personal readiness, and technological environment. Regardless of these factors' effect, efficient control can reduce the frequency and severity of accidents in the identified operations. For example, effective resource management can ensure that the equipment, materials, and personnel are available to carry out the operations safely and efficiently. In addition, a favorable technological environment can reduce the likelihood of equipment failures and malfunctions, leading to accidents. Finally, personal readiness can ensure that the personnel involved in the operations are adequately trained, experienced, and prepared to handle any unexpected situations. Overall, identifying these critical factors can provide valuable insights into the causes of accidents in specified chemical operations and can serve as a basis for developing effective interventions and strategies to improve safety and prevent accidents. It can also affect how employees and managers handle potential changes in the workplace, along with their ability to make decisions based on the risk perception profile. Where limited resources are involved in an industry, extra attention must be paid to identified causes of accidents to prevent them from having more severe consequences. In addition, it will help organizations to better understand the factors contributing to safety incidents and develop targeted interventions to prevent them from occurring. The study highlights the importance of considering multiple factors when designing interventions to improve safety outcomes in chemical operations.

5. Conclusions

Chemical accidents occur from different accident causes in chemical industry operations. Therefore, clarifying the relationship between the factors affecting the accident and the accidents occurring in various operations is an effective way to prevent similar accidents. Thus, this study was divided into five operations: maintenance repair, process, loading unloading, storage, and shutdown startup of the chemical industry. In this study, 251 accidents in five operations were analyzed. The primary purpose was to commit to plant safety, to understand hazards and risks, to manage risks, and to learn from experience.

Based on the research results, resource management, technological environment, and personal readiness are more significant accident causes in operations. This finding emphasizes the importance of understanding the specific causes of accidents in each type of operation and tailoring interventions and strategies accordingly. Furthermore, the high-frequency accident causes under the HFACS framework were identified. This result is useful for developing targeted interventions and remedial strategies that focus on the most significant factors contributing to accidents rather than attempting to address the entire system as a whole.

A detailed analysis of chemical plant accidents from cause to effect was obtained to better understand and evaluate the root causes of chemical accidents in terms of occupational health and safety. A reliable result was provided by the ability to thoroughly analyze the interactions and uncertainties of various accident factors and review them with expert experience. However, a detailed comparison of the operational levels in chemical industries within the framework of the HFACS has clearly shown which operations human error will occur more in.

From this point of view, in chemical plants, the HFACS method provides a valuable decision support framework to identify and address the human factors that contribute to incidents and accidents in the plant. To use the HFACS in a chemical plant, a team of experts should be established including human factor specialists, safety professionals, and chemical engineers. The team should thoroughly review each of the plant's five operations.

The unit can then use the HFACS framework to categorize the human factors contributing to incidents or accidents in the plant's operations. By identifying and addressing these factors, the plant can improve its overall safety performance, prevent future incidents, and develop strategies to mitigate their effects.

Some limitations should be noted and handled in future research: This study was based on a limited number of public chemical accident reports suffering from extensive plant damage or at least one fatality. These were obtained from different accident databases. The quality of the accident reports significantly impacts the accuracy and integrity of the accident studies. Even if the data collected provided a thorough account of the accidents, certain information might still be lacking.

The study focused on only five operations, regardless of the type of chemical industry. Further research on crashes and near misses related to the industry will help to identify specific accident causes for that industry. By analyzing and understanding the root causes of accidents, organizations can develop targeted interventions to improve workplace safety and health management components. Thus, organizations can create safe and healthy work environments, reduce the risk of accidents and environmental pollution, and contribute to sustainable development goals related to the economy, environment, and society.

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References

1. Alexander, T.M. A case based human reliability assessment using HFACS for complex space operations. *J. Space Saf. Eng.* **2019**, *6*, 53–59. [CrossRef]
2. Xie, X.; Guo, D. Human factors risk assessment and management: Process safety in engineering. *Process Saf. Environ. Prot.* **2018**, *113*, 467–482. [CrossRef]
3. Kumar, A.M.; Rajakarunakaran, S.; Prabhu, V.A. Application of Fuzzy HEART and expert elicitation for quantifying human error probabilities in LPG refuelling station. *J. Loss Prev. Process Ind.* **2017**, *48*, 186–198. [CrossRef]
4. Zarei, E.; Yazdi, M.; Abbassi, R.; Khan, F. A hybrid model for human factor analysis in process accidents: FBN-HFACS. *J. Loss Prev. Process Ind.* **2019**, *57*, 142–155. [CrossRef]
5. Shokria, S.; Varmazyar, S.; Heydari, P. A cognitive human error analysis with CREAM in control room of petrochemical industry. *Biotechnol. Health Sci.* **2016**, *1*, 13–21. Available online: http://eprints.qums.ac.ir/6452/1/bhs-04-02-38592.pdf (accessed on 20 January 2022).
6. Gupta, J.P. The Bhopal gas tragedy: Could it have happened in a developed country? *J. Loss Prev. Process Ind.* **2002**, *15*, 1–4. [CrossRef]
7. Rostamabadi, A.; Jahangiri, M.; Zarei, E.; Kamalinia, M.; Banaee, S.; Samaei, M.R. A Novel Fuzzy Bayesian Network-HFACS (FBN-HFACS) model for analyzing human and organizational factors (HOFs) in process accidents. *Process Saf. Environ. Prot.* **2019**, *132*, 59–72. [CrossRef]
8. Darabont, D.C.; Badea, D.O.; Trifu, A. Comparison of four major industrial disasters from the perspective of human error factor. *MATEC Web Conf.* **2020**, *305*, 00017. [CrossRef]
9. Zarei, E.; Khan, F.; Abbassi, R. Importance of human reliability in process operation: A critical analysis. *Reliab. Eng. Syst. Saf.* **2021**, *211*, 107607. [CrossRef]
10. Jahangiri, M.; Hoboubi, N.; Rostamabadi, A.; Keshavarzi, S.; Hosseini, A.A. Human Error Analysis in a Permit to Work System: A Case Study in a Chemical Plant. *Saf. Health Work.* **2016**, *7*, 6–11. [CrossRef]
11. Liao, M.H.; Wang, C.T. Using enterprise architecture to integrate lean manufacturing, digitalization, and sustainability: A lean enterprise case study in the chemical industry. *Sustainability* **2021**, *13*, 4851. [CrossRef]
12. Tong, L.; Pu, Z.; Ma, J. Maintenance supplier evaluation and selection for safe and sustainable production in the chemical industry: A case study. *Sustainability* **2019**, *11*, 1533. [CrossRef]
13. Nawaz, W.; Linke, P.; Koç, M. Safety and sustainability nexus: A review and appraisal. *J. Clean. Prod.* **2019**, *216*, 74–87. [CrossRef]

14. Jilcha, K.; Kitaw, D. Industrial occupational safety and health innovation for sustainable development. *Eng. Sci. Technol. Int. J.* **2017**, *20*, 372–380. [CrossRef]
15. Delikhoon, M.; Zarei, E.; Banda, O.V.; Faridan, M.; Habibi, E. Systems thinking accident analysis models: A systematic review for sustainable safety management. *Sustainability* **2022**, *14*, 5869. [CrossRef]
16. Zhou, L.; Fu, G.; Xue, Y. Human and organizational factors in Chinese hazardous chemical accidents: A case study of the '8.12' Tianjin Port fire and explosion using the HFACS-HC. *Int. J. Occup. Saf. Ergon.* **2018**, *24*, 329–340. [CrossRef]
17. Wang, J.; Fan, Y.; Niu, Y. Routes to failure: Analysis of chemical accidents using the HFACS. *J. Loss Prev. Process Ind.* **2022**, *75*, 104695. [CrossRef]
18. Dakkoune, A.; Vernières-Hassimi, L.; Leveneur, S.; Lefebvre, D.; Estel, L. Risk analysis of French chemical industry. *Saf. Sci.* **2018**, *105*, 77–85. [CrossRef]
19. Jung, S.; Woo, J.; Kang, C. Analysis of severe industrial accidents caused by hazardous chemicals in South Korea from January 2008 to June 2018. *Saf. Sci.* **2020**, *124*, 104580. [CrossRef]
20. Zhang, H.D.; Zheng, X.P. Characteristics of hazardous chemical accidents in China: A statistical investigation. *J. Loss Prev. Process Ind.* **2012**, *25*, 686–693. [CrossRef]
21. Rasmussen, J. Human errors. A taxonomy for describing human malfunction in industrial installations. *J. Occup. Accid.* **1982**, *4*, 311–333. [CrossRef]
22. Bolt, H.; Morris, J.; Pedrali, M.; Antão, P. Techniques for human reliability evaluation. In *Safety and Reliability of Industrial Products, Systems and Structures*; CRC Press: Boca Raton, FL, USA, 2010; pp. 141–156. Available online: https://scholar.google.com.tr/scholar?q=Techniques+for+human+reliability+evaluation.+In+Safety+and+Reliability+of+Industrial+Products,+Systems+and+Structures%3B&hl=tr&as_sdt=0&as_vis=1&oi=scholart (accessed on 15 January 2022).
23. Malone, T.B. Human factors and human error. *Proc. Hum. Factors Soc. Annu. Meet.* **1990**, *34*, 651–654. [CrossRef]
24. Zhang, L.; He, X.; Dai, L.C.; Huang, X.R. The simulator experimental study on the operator reliability of Qinshan nuclear power plant. *Reliab. Eng. Syst. Saf.* **2007**, *92*, 252–259. [CrossRef]
25. Reason, J. *Human Error*; Cambridge University Press: New York, NY, USA, 1990.
26. Shappell, S.A.; Wiegmann, D.A. *The Human Factors Analysis and Classification System-HFACS*; U.S. Department of Transportation Office Aviation Medicine: Washington, DC, USA, 2000; pp. 1–15. Available online: https://commons.erau.edu/publication/737/ (accessed on 20 January 2022).
27. Ferlin, A.; Qiu, S.; Bon, P.; Sallak, M.; Dutilleul, S.C.; Schon, W.; Cherfi-Boulanger, Z. An automated method for the study of human reliability in railway supervision systems. *IEEE Trans. Intell. Transp. Syst.* **2018**, *19*, 3360–3375. [CrossRef]
28. Nwankwo, C.D.; Arewa, A.O.; Theophilus, S.C.; Esenowo, V.N. Analysis of accidents caused by human factors in the oil and gas industry using the HFACS-OGI framework. *Int. J. Occup. Saf. Ergon.* **2022**, *28*, 1642–1654. [CrossRef]
29. Alexander, T.M. *Human Error Assessment and Reduction Technique (Heart) and Human Factors Analysis and Classification System (Hfacs)*; Collaboration on Quality in the Space and Defense Industries Forum; NASA: Washington, DC, USA, 2017. Available online: https://ntrs.nasa.gov/archive/nasa/casi.ntrs.nasa.gov/20170002279.pdf (accessed on 15 February 2022).
30. Akyuz, E.; Celik, M.; Cebi, S. A phase of comprehensive research to determine marine-specific EPC values in human error assessment and reduction technique. *Saf. Sci.* **2016**, *87*, 63–75. [CrossRef]
31. Hulme, A.; Stanton, N.A.; Walker, G.H.; Waterson, P.; Salmon, P.M. What do applications of systems thinking accident analysis methods tell us about accident causation? A systematic review of applications between 1990 and 2018. *Saf. Sci.* **2019**, *117*, 164–183. [CrossRef]
32. Xia, J.; Liu, Y.; Zhao, D.; Tian, Y.; Li, J.; Zhong, Y.; Roy, N. Human factors analysis of China's confined space operation accidents from 2008 to 2018. *J. Loss Prev. Process Ind.* **2021**, *71*, 104480. [CrossRef]
33. Liu, R.; Cheng, W.; Yu, Y.; Xu, Q. Human factors analysis of major coal mine accidents in China based on the HFACS-CM model and AHP method. *Int. J. Ind. Ergon.* **2018**, *68*, 270–279. [CrossRef]
34. Kandemir, C.; Celik, M. Determining the error producing conditions in marine engineering maintenance and operations through HFACS-MMO. *Reliab. Eng. Syst. Saf.* **2021**, *206*, 107308. [CrossRef]
35. Akyuz, E. A marine accident analysing model to evaluate potential operational causes in cargo ships. *Saf. Sci.* **2017**, *92*, 17–25. [CrossRef]
36. Zhou, J.L.; Lei, Y. A slim integrated with empirical study and network analysis for human error assessment in the railway driving process. *Reliab. Eng. Syst. Saf.* **2020**, *204*, 107148. [CrossRef]
37. Cohen, T.N.; Francis, S.E.; Wiegmann, D.A.; Shappell, S.A.; Gewertz, B.L. Using HFACS-healthcare to identify systemic vulnerabilities during surgery. *Am. J. Med. Qual.* **2018**, *33*, 614–622. [CrossRef]
38. Karthick, M.; Robert, T.P.; Kumar, C.S. HFACS-based FAHP implementation to identify critical factors influencing human error occurrence in nuclear plant control room. *Soft Comput.* **2020**, *24*, 16577–16591. [CrossRef]
39. Wang, J.; Fan, Y.; Gao, Y. Revising HFACS for SMEs in the chemical industry: HFACS-CSMEs. *J. Loss Prev. Process Ind.* **2020**, *65*, 104138. [CrossRef]
40. Li, X.; Liu, T.; Liu, Y. Cause analysis of unsafe behaviors in hazardous chemical accidents: Combined with HFACs and bayesian network. *Int. J. Environ. Res. Public Health* **2020**, *17*, 11. [CrossRef] [PubMed]
41. Theophilus, S.C.; Esenowo, V.N.; Arewa, A.O.; Ifelebuegu, A.O.; Nnadi, E.O.; Mbanaso, F.U. Human factors analysis and classification system for the oil and gas industry (HFACS-OGI). *Reliab. Eng. Syst. Saf.* **2017**, *167*, 168–176. [CrossRef]

42. E-MARS. Available online: https://emars.jrc.ec.europa.eu/en/emars/accident/search (accessed on 16 February 2022).
43. ARIA. Available online: https://www.aria.developpement-durable.gouv.fr/ (accessed on 20 May 2022).
44. ZEMA. Available online: https://www.infosis.uba.de/index.php/en/site/13947/zema/ (accessed on 28 May 2022).
45. DECHEMA. Available online: https://processnet.org/ereignisdb.html (accessed on 30 March 2022).
46. VARO. Available online: https://varo.tukes.fi/ (accessed on 17 April 2022).
47. Papadakis, G.A.; Amendola, A. Learning from Experience: The Major Accident Reporting System (MARS) in the European Union. *Probabilistic Saf. Assess. Manag.* **1996**, *96*, 101–106. [CrossRef]
48. Nivolianitou, Z.; Konstandinidou, M.; Kiranoudis, C.; Markatos, N. Development of a database for accidents and incidents in the Greek petrochemical industry. *J. Loss Prev. Process Ind.* **2006**, *19*, 630–638. [CrossRef]
49. Cozzani, V.; Campedel, M.; Renni, E.; Krausmann, E. Industrial accidents triggered by flood events: Analysis of past accidents. *J. Hazard. Mater.* **2010**, *175*, 501–509. [CrossRef]
50. Chebila, M. Predicting the consequences of accidents involving dangerous substances using machine learning. *Ecotoxicol. Environ. Saf.* **2021**, *208*, 111470. [CrossRef] [PubMed]
51. Sales, J.; Mushtaq, F.; Christou, M.D.; Nomen, R. Study of major accidents involving chemical reactive substances: Analysis and lessons learned. *Process Saf. Environ. Prot.* **2007**, *85*, 117–124. [CrossRef]
52. Celik, M.; Cebi, S. Analytical HFACS for investigating human errors in shipping accidents. *Accid. Anal. Prev.* **2009**, *41*, 66–75. [CrossRef] [PubMed]
53. Zhao, G.; Yang, H.; Yang, J.; Zhang, L.; Yang, X.A. Data-based adjustment for fisher exact test. *Eur. J. Stat.* **2021**, *1*, 74–107. [CrossRef]
54. Mehta, C.R.; Patel, N.R. *IBM SPSS Exact Tests*; IBM Corporation: Armonk, NY, USA, 2011; pp. 23–24.
55. Ali Abd Al-Hameed, K. Spearman's correlation coefficient in statistical analysis. *Int. J. Nonlinear Anal. Appl.* **2022**, *13*, 3249–3255. [CrossRef]
56. Levy, R. Probabilistic models in the study of language. Online Draft. 2012. Available online: https://pages.ucsd.edu/~rlevy/pmsl_textbook/book_draft.pdf (accessed on 16 May 2023).
57. Sedgwick, P. Spearman's rank correlation coefficient. *BMJ* **2014**, *349*, g7327. [CrossRef]
58. Lindsey, J.K. *Applying Generalized Linear Models*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2000.
59. Patterson, J.M.; Shappell, S.A. Operator error and system deficiencies: Analysis of 508 mining incidents and accidents from Queensland, Australia using HFACS. *Accid. Anal. Prev.* **2010**, *42*, 1379–1385. [CrossRef]
60. Zhao, L.; Qian, Y.; Hu, Q.M.; Jiang, R.; Li, M.; Wang, X. An analysis of hazardous chemical accidents in China between 2006 and 2017. *Sustainability* **2018**, *10*, 2935. [CrossRef]
61. Xue, C.; Tang, L. Organisational support and safety management: A study of shipboard safety supervision. *Econ. Labour Relat. Rev.* **2019**, *30*, 549–565. [CrossRef]
62. Teperi, A.M.; Lappalainen, J.; Puro, V.; Perttula, P. Assessing artefacts of maritime safety culture—Current state and prerequisites for improvement. *WMU J. Marit. Aff.* **2019**, *18*, 79–102. [CrossRef]
63. Mišković, D.; Ivče, R.; Hess, M.; Koboević, Ž. The influence of shipboard safety factors on quality of safety supervision: Croatian seafarer's attitudes. *J. Mar. Sci. Eng.* **2022**, *10*, 1265. [CrossRef]