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Integrated Safety and Risk Management in Handling of Dangerous Goods

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Abstract: *This study examines the need for the integration of safety and risk management in the management of hazardous goods in the freight forwarding and logistics industry. Transport and storage. Types of dangerous goods include flammable liquids, toxic chemicals, corrosive substances, radioactive material and explosive cargo. They must be handled with care, employing rigorous safety protocols and strict regulatory compliance. Mistakes in handling such materials can result in serious accidents, environmental damage, financial loss and legal penalties. The aim of this research is to evaluate the influence of safety management systems, risk assessment procedures, employee training and technological support on the efficiency of safe handling of hazardous materials. The role of regulatory enforcement and organizational safety culture in improving overall operational safety performance is also examined. The primary data were collected from 50 employees working in dangerous goods operations using a structured questionnaire through census method. The secondary data were gathered from books, journals, company reports and industry sources. The data were analysed using SPSS Version 27 by percentage analysis, reliability analysis, Pearson correlation, ANOVA and multiple regression analysis. The results emphasize the importance of having robust safety systems, regular training, efficient risk assessment and technology-enabled monitoring to enhance safety performance. The study concludes with an integrated approach to safety management as a requirement to achieve safe, efficient and compliant dangerous goods handling operations. critical to the safe, efficient and compliant handling of dangerous goods.*

Introduction

Dangerous goods handling is a very important part of freight forwarding and logistics operations, especially in industries such as pharmaceuticals, chemicals, oil and gas, healthcare and manufacturing. Dangerous goods are flammable liquids, toxic substances, corrosive chemicals, radioactive materials and explosive cargo that require special care in their storage, transportation and delivery. If not handled properly these materials can also lead to serious accidents, environmental damage, financial loss and legal problems. Freight forwarding companies have an important role to play in ensuring the safe movement of dangerous goods through correct classification, packaging, labelling, documentation and regulatory compliance. To reduce risks and increase safety, companies need to comply with international regulations like the IATA DGR, IMDG Code and ICAO guidelines. Integrated safety and risk management incorporates safety systems, risk assessment, employee training and technology into one efficient process. The present study aims to examine the role of safety management systems, risk assessment practices, training and technological support in improving the safe handling effectiveness of dangerous goods. It also looks at the role of regulatory enforcement and organizational safety culture in maintaining strong safety standards.

Review of Literature

Guo & Luo (2022) reviewed three decades of literature on hazardous materials transport risk models and reported that road systems are relatively well established; rail and intermodal models are not well validated. They also refer to CVaR as a practical way forward for risk-averse planning.

Ren and Yang (2024) developed a life cycle-based accident risk model using a Tree Augmented Naive Bayesian network to capture the interactions among human, mechanical and environmental factors. Their method improved the accuracy of prediction and helped in better stage-wise control of risk.

Yu et al. (2022) proposed a real-time accident prediction model based on a GRU deep learning framework which combines traffic flow and weather data. The model showed important gains over traditional statistical methods.

A multi-objective routing model for electric vehicles hazardous materials transportation under uncertainty was developed by Zhang, Zhang and Ma (2025). They used an improved NSGA-II algorithm to obtain a trade-off between safety, cost and service performance.

Chen & Zhu (2025) proposed a multi-modal routing optimization model that simultaneously optimized cost, time and risk factors. Their genetic algorithm approach provided efficient routing solutions in complex transport networks.

Wang, Zhang, Liu & Zhao (2025) integrated bow-tie analysis and Bayesian networks to evaluate the accident probability in real-time. The hybrid structure allowed for dynamic updating and improved early warning capabilities.

Liu et al. (2021) used a combination of Gaussian plume dispersion modelling and population exposure data to evaluate the environmental consequences of hazmat incidents. They found that looking at injury risk alone grossly underestimates the overall effect.

A Severity Analysis of Road Transportation Crashes of Hazardous Material (2022) applied Random Forest and Bayesian Network methods to analyse crash severity patterns. The study identified driver behaviour, infrastructure quality and environmental conditions as critical determinants.

2021 Risk Assessment of Hazmat Road Transport Considering Environmental Risk. Combined atmospheric dispersion models and demographic exposure analysis in urban settings. The results highlighted the importance of taking environmental effects into account in risk assessment.

Hazardous Materials Route Optimization Railway Transportation based on CVaR and Equity (2025) proposed a railway routing model based on CVaR, taking into account the fairness of risk distribution. The study demonstrated that equitable routing could improve social acceptability without increasing overall risk.

Route Optimization for Transporting Hazardous Materials Risk Equity and Dynamic Wind Speeds (2025) developed a routing framework accounting for changing wind conditions and equity measures. The authors demonstrate that static models do not account for significant time-varying risk.

A three-objective multimodal routing model solved by an improved genetic algorithm was proposed by Chen & Zhu (2025). The method they used produced a number of practical Pareto-optimal routing alternatives.

Zou & Zhang (2024) developed a time-dependent routing model considering dynamic traffic and emission conditions. Their results showed the direct impact of departure time on safety and sustainability performance.

Mohammadi et al. (2021-2025) reviewed various risk equity approaches in hazardous material routing and questioned the practicality of strict threshold-based constraints. They proposed more flexible optimization approaches that balance between total risk and fairness.

Yang et al. (2025) researched the application of dynamic Bayesian networks in safety risk assessment frameworks. They argued that dynamic probability updating yields better predictions than static models.

Chai (2026) presented a hub-and-spoke model for multimodal transport of hazardous materials under uncertainty. The study found that coordinated mode transfers can reduce overall exposure risk.

Wang et al. (2025) proposed a possibility evaluation framework based on the logic of Bowtie and Bayesian inference. Their model improved the real-time estimation of the accident probability through a structured causal mapping.

Wang et al. (2025) further analysed accident chains based on a quantitative bow-tie Bayesian structure to understand risk evolution. The framework improved early detection but was reliant on consistent high-quality monitoring data.

Zhang, Zhang, and Ma (2025) tested their electric vehicle routing framework with urban case applications. The results indicated significant reductions in transportation risk and operating costs.

Yu et al. (2022) proved that the combination of real-time operational data and AI-based prediction models can significantly improve the accuracy of accident prediction. Their work emphasizes the increasing importance of intelligent systems to ensure safety in hazmat transport.

Research Gap

The existing literature is largely theoretical and fragmented, with a heavy focus on advanced modelling techniques such as CVaR-based optimization, genetic algorithms, dynamic Bayesian networks, bow-tie integrations, deep learning prediction models and multimodal routing under uncertainty. Most studies address routing optimization, accident probability modelling, environmental impact assessment, or equity considerations separately, with little integration of all these dimensions into a unified, practically deployable framework. However, real-time AI-based prediction models are proposed but rarely validated by actual field implementation in integration with operational decision-making systems in actual logistics firms. Likewise, equity-based and multimodal routing models are mathematically sophisticated but have not been empirically tested with real industry data, especially in the context of logistics in developing countries. There is also an absence of emphasis on organizational factors such as safety management systems, training effectiveness, compliance behaviour, and human decision making which significantly affect real-world risk outcomes. There is thus a large research gap in the development and empirical validation of an integrated, operationally feasible hazardous materials risk management framework that integrates routing optimization, real-time risk prediction, environmental exposure assessment and organizational safety practices in one practical decision-support system.

Research Questions

- How do safety management practices influence the safe handling of dangerous goods?
- What is the relationship between risk assessment and operational safety performance in dangerous goods handling?
- How does employee training and competency improve the safe handling effectiveness of dangerous goods?
- What role does technological integration play in reducing risks and improving dangerous goods safety operations?
- How do regulatory enforcement and organizational safety culture support effective dangerous goods handling?

Objectives of the Study

- To analyse the existing safety and risk management practices followed in handling dangerous goods operations.
- To examine the influence of safety management systems on the safe handling effectiveness of dangerous goods.

- To evaluate how risk assessment practices, employee training, and technological integration improve operational safety performance.
- To study the role of regulatory enforcement and organizational safety culture in maintaining safety standards.
- To provide suitable suggestions for improving safety performance and regulatory compliance in dangerous goods handling operations.

Conceptual Framework

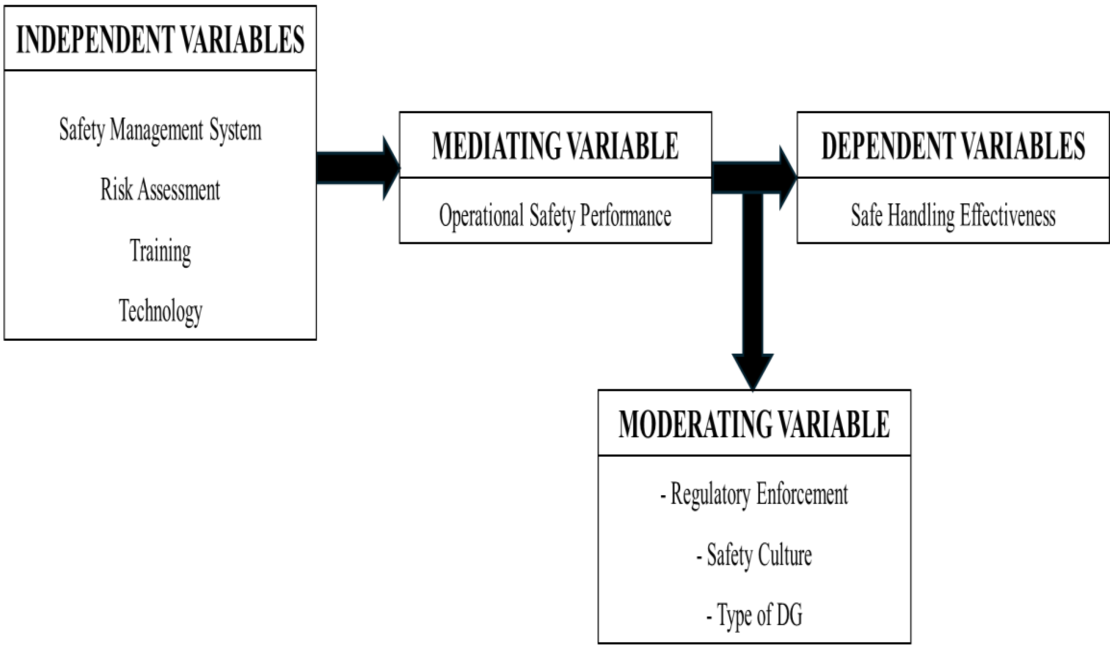

Figure 1

It shows that strong safety systems, adequate risk assessment, periodic training and the appropriate technology are not sufficient by themselves. These factors are only counted if they improve the way operations are run on the ground. What ultimately leads to safe and effective handling is the improvement of daily safety performance. Operational Safety Performance is the connection. When employees are procedurally correct, anticipate risks early and consistently adhere to safety standards, safe handling automatically becomes stronger and more dependable. This impact is affected by Regulatory Enforcement, Safety Culture and the type of Dangerous Goods. Strict enforcement of this and a culture that is committed to safety will improve the results. Weak oversight or very dangerous materials can make it more difficult to handle them safely.

Research Methodology

Research Design

The study adopted a descriptive research design, and a structured questionnaire was used to collect responses from the employees to assess their perception on safety practices and how effective they are in handling dangerous goods.

Sampling Technique

Sampling is normally based on taking a part of a population, but in this study, all 50 employees involved in dangerous goods handling were included. The Census Method was practical and also more accurate than selecting a sample as the workforce was small and was accessible in its totality. The study collects responses from all employees through a structured questionnaire. The method ensures that the findings of the study reflect the real situation of the organization’s safety practices, training, compliance and operational challenges.

Data Collection Methods

The credibility of any research depends on the quality of the data used for analysis. If the data is unreliable, the conclusions will be weak. Therefore, this study uses both primary and secondary data to ensure accuracy, relevance, and contextual depth.

Primary Data

Primary data was collected from respondents directly to get real operational insights and not assumptions. A structured questionnaire was administered to 50 employees working in Dangerous Goods handling operations. The questionnaire was developed to assess specific operational variables related to the safe handling of DG. These included safety management systems, standard operating procedures, risk assessment practices, preventive control measures, employee training and certification, use of technological systems (e.g. digital documentation and cargo tracking), incident reporting mechanisms, regulatory compliance practices, and organizational safety culture. It also looked at the effect of various classes of dangerous goods on operational complexity. Data was collected directly from the operational staff. This ensured that the findings are representative of the real ground level practices and not the theoretical expectations.

Secondary Data

Primary findings were supported and validated by secondary data. The data was collected from academic textbooks, peer-reviewed research articles, industry reports, regulatory guidelines, and credible online databases on logistics and dangerous goods transportation. This data provided theoretical backing, industry benchmarks and regulatory views. It also made comparisons of practical operations and setting standards easier and increased the depth of the study from an analytical perspective.

Data Analysis

Statistical tools were used to organize, analyse, and interpret the collected data. All statistical analyses were performed using IBM SPSS 27 Version Software.

Reliability Analysis using Cronbach's Alpha

This tool was used to measure the internal consistency of each construct and confirm that the survey instrument is reliable and suitable for analysis.

Table 1: Reliability Analysis

Constructs	No. of Items	Cronbach's Alpha
Safety Management System	3	0.939
Risk Assessment	3	0.900
Training	3	0.942
Technology	3	0.943
Operational Safety Performance	4	0.893
Regulatory Enforcement	3	0.891
Safety Culture	3	0.916
Type of Dangerous Goods	3	0.815
Safe Handling Effectiveness	5	0.882
Overall (30 items)	30	

The reliability analysis shows that all the constructs recorded Cronbach's Alpha values above the recommended threshold of 0.70 as suggested by Nunnally (1978). The values ranged from 0.815 to 0.943, showing strong consistency among the measurement items. Technology (α = 0.943), Training (α = 0.942) and Safety Management System (α = 0.939) have very high reliability. Internal consistency is also high for Safety Culture (α = 0.916) and Risk Assessment (α = 0.900). The reliability of Operational Safety Performance (α=0.893), Regulatory Enforcement (α=0.891), Safe Handling Effectiveness (α=0.882) and Type of Dangerous Goods (α=0.815) is good. The questionnaire instrument is statistically reliable and suitable for further analysis in general.

Percentage Analysis

Table 2: Percentage Analysis

Variable	Category	No. of Respondents	Percentage
Designation	Operations Staff	16	32%
	Supervisor	13	26%
	Safety / DG Officer	8	16%
	Manager	7	14%
	Others	6	12%
	Total	**50**	**100%**
Years of Experience	Less than 2 years	21	42%
	2 – 5 years	11	22%
	5 – 8 years	8	16%
	8 – 10 years	6	12%
	More than 10 years	4	8%
	Total	**50**	**100%**
Department	Documentation	15	30%
	Warehouse Handling	11	22%
	Cargo Operations	11	22%
	Safety / Compliance	9	18%
	Others	4	8%
	Total	**50**	**100%**
DG Handling Frequency	Daily	17	34%
	Weekly	11	22%
	Occasionally	10	20%
	Monthly	7	14%
	Rarely	5	10%
	Total	**50**	**100%**

Mean and Standard Deviation

These measures were used to understand the central tendency and the spread of respondents' perceptions across all research variables.

Table 3: Mean and Standard Deviation

Variables	Mean	Std. Deviation
Safety Management System	3.347	1.373
Risk Assessment	3.240	1.278
Training	3.327	1.380
Technology	3.253	1.303
Operational Safety Performance	3.500	1.289
Regulatory Enforcement	3.367	1.287
Safety Culture	3.460	1.287
Type of Dangerous Goods	3.367	1.240
Safe Handling Effectiveness	3.480	1.314

The above table shows the mean values and standard deviation values on a five-point Likert scale. All variables reported means above the midpoint of 3.0 indicating generally good perceptions of dangerous goods handling practices. The highest mean was Operational Safety Performance (3.500) followed by Safe Handling Effectiveness (3.480) and Safety Culture (3.460). Risk Assessment had the lowest mean (3.240) indicating relatively less agreement in that area. The standard deviation values range from 1.240 to 1.380, indicating moderate variation in responses among respondents.

ANOVA

This tool was conducted to test whether demographic variables such as Designation, Years of Experience, Department, and Frequency of DG Handling create significant differences in Safe Handling Effectiveness. In all four cases (H01–H04), the significance values were greater than 0.05. This indicates that the differences between groups are not statistically significant. Therefore, all null hypotheses were accepted, confirming that demographic factors do not significantly influence Safe Handling Effectiveness.

H_{01}: There are no significant differences between Designation and Safe Handling Effectiveness of Dangerous Goods

Table 4: ANOVA (Designation)

ANOVA	Sum of Squares	df	Mean Square	F	Sig.
Designation					
Between Groups	14.618	9	1.624	1.487	.186
Within Groups	43.702	40	1.093		
Total	58.320	49			

The one-way ANOVA result shows an F-value of 1.487 with a significance level of 0.186, which is greater than 0.05. This indicates that differences in designation do not lead to statistically significant differences in Safe Handling Effectiveness. The variation observed between groups is minimal and likely due to random factors. Therefore, the null hypothesis is accepted. Designation does not significantly influence safe handling performance.

H_{02}: There are no significant differences between Years of Experience and Safe Handling Effectiveness of Dangerous Goods

Table 5: ANOVA (Years of Experience)

ANOVA	Sum of Squares	df	Mean Square	F	Sig.
Years of Experience					
Between Groups	7.055	4	1.764	1.548	.205
Within Groups	51.265	45	1.139		
Total	58.320	49			

The analysis produced an F-value of 1.548 and a p-value of 0.205, exceeding the 0.05 threshold. This means employees with different experience levels do not differ significantly in Safe Handling Effectiveness. The group differences are statistically insignificant. Hence, the null hypothesis is accepted. Years of experience do not have a measurable impact on safe handling effectiveness.

H_{03}: There are no significant differences between Department and Safe Handling Effectiveness of Dangerous Goods

Table 6: ANOVA (Department)

ANOVA	Sum of Squares	df	Mean Square	F	Sig.
Department					
Between Groups	9.195	7	1.314	1.123	.367
Within Groups	49.125	42	1.170		
Total	58.320	49			

The ANOVA result shows an F-value of 1.123 with a significance value of 0.367. Since the p-value is well above 0.05, the differences across departments are not statistically significant. Employees from various departments demonstrate comparable levels of Safe Handling Effectiveness. Therefore, the null hypothesis is accepted. Department does not significantly affect safe handling practices.

H_{04}: There are no significant differences between Frequency of DG Handling and Safe Handling Effectiveness of Dangerous Goods

Table 7: ANOVA (DG Handling)

ANOVA	Sum of Squares	df	Mean Square	F	Sig.
Frequency of DG Handling					
Between Groups	10.237	4	2.559	2.395	.064
Within Groups	48.083	45	1.069		
Total	58.320	49			

The F-value of 2.395 with a p-value of 0.064 is slightly above 0.05. Although there is minor variation among groups, it is not statistically significant. The differences observed may be due to sampling variation rather than a real effect. Hence, the null hypothesis is accepted. Frequency of DG handling does not significantly influence Safe Handling Effectiveness.

Pearson Correlation Analysis

H_{05}: There is no significant relationship between Safety Management System, Risk Assessment, Training, Technology, Operational Safety Performance, Regulatory Enforcement, Safety Culture, and Type of Dangerous Goods with Safe Handling Effectiveness.

Correlation analysis is used to test the relationships between quantitative variables. The Pearson correlation test was used to find r, where values range from +1 to -1. A value of 0 indicates no association, a value greater than 0 implies a positive association, and a value lesser than 0 means a negative association.

Table 8: Correlation Matrix

Correlations		Safety Management System	Risk Assessment	Training	Technology	Operational Safety Performance	Regulatory Enforcement	Safety Culture	Type of Dangerous Goods	Safe Handling Effectiveness
Safety Management System	Pearson Correlation	1	.790**	.861**	.627**	.777**	.660**	.662**	.663**	.692**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	50	50	50	50	50	50	50	50	50
Risk Assessment	Pearson Correlation	.790**	1	.816**	.645**	.729**	.675**	.732**	.687**	.657**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	50	50	50	50	50	50	50	50	50
Training	Pearson Correlation	.861**	.816**	1	.685**	.746**	.705**	.587**	.594**	.681**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001
	N	50	50	50	50	50	50	50	50	50
Technology	Pearson Correlation	.627**	.645**	.685**	1	.717**	.760**	.707**	.665**	.773**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001
	N	50	50	50	50	50	50	50	50	50
Operational Safety Performance	Pearson Correlation	.777**	.729**	.746**	.717**	1	.796**	.772**	.726**	.787**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001
	N	50	50	50	50	50	50	50	50	50
Regulatory Enforcement	Pearson Correlation	.660**	.675**	.705**	.760**	.796**	1	.743**	.721**	.745**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001
	N	50	50	50	50	50	50	50	50	50
Safety Culture	Pearson Correlation	.662**	.732**	.587**	.707**	.772**	.743**	1	.835**	.713**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001
	N	50	50	50	50	50	50	50	50	50
Type of Dangerous Goods	Pearson Correlation	.663**	.687**	.594**	.665**	.726**	.721**	.835**	1	.807**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001
	N	50	50	50	50	50	50	50	50	50
Safe Handling Effectiveness	Pearson Correlation	.692**	.657**	.681**	.773**	.787**	.745**	.713**	.807**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	
	N	50	50	50	50	50	50	50	50	50

Pearson correlation analysis shows that all independent variables have a strong and positive relationship with Safe Handling Effectiveness ($r = 0.657$ to 0.807, $p < 0.001$). Since all correlations are significant at the 0.01 level, the null hypothesis ($r = 0$) is rejected. Type of Dangerous Goods ($r = 0.807$) demonstrates the strongest association, followed by Operational Safety Performance and Technology. The consistent positive pattern confirms that improvements in safety systems, training, compliance, culture, and operational controls directly enhance handling effectiveness. Therefore, H05 is fully supported.

Multiple Regression Analysis

H_{06}: There is no significant collective association between Safety Management System, Risk Assessment, Training, Technology, Regulatory Enforcement, and Safety Culture with Safe Handling Effectiveness.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.838	.702	.660	.63591

a. Predictors: (Constant), Safety Culture, Risk Assessment, Training, Technology, Safety Management System, Regulatory Enforcement

ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	40.932	6	6.822	16.870	<.001
Residual	17.388	43	.404		
Total	58.320	49			

a. Dependent Variable: Safe Handling Effectiveness

Coefficients

Table 9: Multiple Regression Analysis

Model	B	Std. Error	Beta	t	Sig.
(Constant)	.673	.303		2.224	.031
Safety Management System	.192	.151	.229	1.276	.209
Risk Assessment	-.035	.162	-.037	-.214	.831
Training	.021	.175	.025	.119	.906
Technology	.326	.126	.369	2.576	.014
Regulatory Enforcement	.183	.143	.196	1.279	.208
Safety Culture	.154	.146	.168	1.056	.297

a. Dependent Variable: Safe Handling Effectiveness

Based on multiple regression analysis, Strong associations between all 6 safety constructs exist and Safe handling effectiveness ($R = 0.838$). The model accounts for 70.2% of the variance in safe handling effectiveness ($R^2 = 0.702$), making it a very powerful explanatory model. The overall model is statistically significant ($F = 16.870$, $p < 0.001$), providing evidence that the variables operate together with reliability rather than being due to random chance. Of the 6 variables, only technology ($\beta = 0.369$, $p = 0.014$) has a statistically significant independent contribution to improving safe handling effectiveness; the other variables most likely did not have significant independent contributions due to some overlap of related safety constructs. Since the overall model was statistically significant, we reject the null hypothesis (H06).

Equation

$$\mathbf{y = a + bx}$$

$$y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6$$

$$y = 0.673 + 0.192X_1 + (-0.035)\,X_2 + 0.021X_3 + 0.326X_4 + 0.183X_5 + 0.154X_6$$

$$y = 0.673 + 0.192(3.347) + (-0.035)\,(3.240) + 0.021(3.327) + 0.326(3.253) + 0.183(3.367) + 0.154(3.460)$$

$$y = 0.673 + 0.643 - 0.113 + 0.070 + 1.060 + 0.616 + 0.533$$

$$\mathbf{y = 3.482}$$

Suggestions

- To improve the handling of dangerous goods and minimize the risk of accidents, companies need to invest in real-time monitoring systems, automated tracking tools and digital compliance platforms.
- Regular refresher courses, simulation-based drills, competency certification programs should be introduced to keep the employees updated & minimize the errors in handling.
- A proactive safety mindset should be created by leadership commitment, open incident reporting and regular awareness campaigns at all operational levels.
- We need to embed structured hazard identification protocols and routine risk audits in the daily routine, not a periodic compliance activity.
- To ensure uniform adherence to safety standards, dedicated compliance teams should be formed and internal audits carried out in accordance with IATA DGR, IMDG Code and ICAO guidelines.

Limitations of the Study

- The study is limited and may not be representative of the entire DG sector.
- The research is mostly based on primary data collected from employees and the answers might contain subjective opinions.
- The short length of the study restricted the collection of a large amount of data and detailed analysis.

Future Scope

This research is a good start but there is much more to explore. If you run this test with multiple freight forwarding companies in different regions the findings will be much more reliable and relatable. Technology was the biggest gamechanger, so future research into AI, IoT and blockchain in dangerous goods safety would be worthwhile. A longitudinal study would provide more insight than a single snapshot into how safety practices and workplace culture evolve over time. The research model would also be strengthened if other factors such as leadership style, quality of equipment and safety budgets were incorporated. And if you took that framework and applied it to industries like oil and gas, pharmaceuticals, chemical manufacturing, you'd get some really valuable comparisons across high-risk sectors.

Conclusion

The conclusion of this research is that the secure management of dangerous goods is achieved through a combination of several components working together as one. These include; strong safety systems, a thorough risk assessment, consistent training, smart use of technology, compliance with regulations, and a real safety culture. Of all the elements which were measured, technology was determined to be the largest contributing factor, suggesting that both digital tools and real-time monitoring are now essential to perform logistics operations rather than something that is optional. Based on the full model, 70.2% of variations in safe handling effectiveness were explained, thereby revealing that an integrated approach does indeed make a significant, real difference at a practical level. There were two specific areas of concern that had notably lower scores than the others: risk assessments and training, which indicate there is still an opportunity for organizations to do much better in those two areas. This study makes it clear that developing safer dangerous goods operations is not simple matter of meeting regulatory requirements; but involves the entire organization creating an environment where everyone practices, values, supports safety.

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