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INTELLIGENCE-DRIVEN SUPPLY CHAIN RISK MANAGEMENT AND RESILIENCE STRATEGIES.

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ABSTRACT

This research article focuses on applying intelligence-driven strategies to enhance supply chain risk management and build resilience. The study utilizes secondary data analysis through SPSS software, with a sample size of 500 organizations operating in diverse industries. The objective is to provide a comprehensive understanding of the descriptive and inferential analysis of supply chain risks and the effectiveness of resilience strategies. The descriptive analysis explores various dimensions of supply chain risks, such as demand volatility, supplier reliability, transportation disruptions, and regulatory compliance. Additionally, it investigates the prevalence and impact of risks in different industries and geographical regions. This analysis aims to identify the critical risk factors that pose

significant challenges to supply chain operations. The inferential analysis assesses the relationships between risk factors and their influence on supply chain resilience. The research investigates the effectiveness of intelligence-driven strategies, including real-time monitoring, predictive analytics, and advanced technologies like artificial intelligence and machine learning, in mitigating risks and enhancing supply chain resilience. Furthermore, the study examines the role of collaboration among supply chain partners in improving resilience and reducing vulnerabilities. The findings from this research provide valuable insights into the current state of supply chain risk management practices and the effectiveness of resilience strategies in diverse industries. The results contribute to the existing body of knowledge by identifying best practices, key risk factors, and potential areas for improvement. Moreover, they assist practitioners and decision-makers in developing proactive risk management strategies and fostering resilience in their supply chain operations.

INTRODUCTION

In today's globalized and interconnected corporate environment, supply chain management is essential to firms' success and long-term viability. Supply chains, however, face several dangers due to the rising complexity and ambiguity in the market, which can negatively affect their operations, profitability, and reputation (Shen & Sun, 2023). Transportation interruptions, supplier dependability, fluctuating demand, regulatory compliance, natural disasters, geopolitical crises, and cyberattacks are just a few of these risks. Supply chain risk management has traditionally emphasized reactive techniques, relying on post-event research and historical data to mitigate disruptions and lessen their impact. However, this method frequently fails to effectively mitigate risks because it needs to pay attention to the dynamic and quickly changing nature of supply chain vulnerabilities (Can et al., 2021). As a result, businesses increasingly rely on intelligence-driven tactics to strengthen their supply chain risk management capacity and increase resilience. Using cutting-edge technologies, data analytics, and real-time monitoring for intelligence-driven supply chain risk management proactively identifies, evaluates, and addresses possible hazards (Wong et al., 2022). With the help of this method, companies may extract practical insights from enormous amounts of structured and unstructured data, empowering them to make wise decisions and take preventative action to avoid or lessen disruptions.

OBJECTIVE

This research paper aims to examine the efficacy of intelligence-driven supply chain risk management and resilience techniques in minimizing risks and improving the overall resilience of supply chain operations through the analysis of secondary data using SPSS software.

METHODOLOGY

The effectiveness of intelligence-driven supply chain risk management and resilience solutions is examined in this study using secondary data analysis. SPSS is used to conduct the analysis (Gupta et al., 2020). The dataset comprises secondary data gathered from 500 firms operating in various industries as a sample size. There are two steps in the methodology. First, secondary data is gathered from various sources, such as industry reports, scholarly journals, and pertinent databases (Wong et al., 2022). The data contains details on supply chain risks, resilience plans, business traits, and regional variables. The data is imported into the SPSS software for analysis in the second stage. The many aspects of supply chain risks, such as demand volatility, supplier dependability, transportation disruptions, and regulatory compliance, are examined using descriptive analysis. The incidence and impact of hazards in various industries and geographical areas are discussed in this report. Then, inferential analysis evaluates the connections between various risk factors and how they affect supply chain resilience (Dubey et al., 2021). In order to reduce risks and improve resilience, this analysis assesses the efficiency of intelligence-driven techniques like real-time monitoring, predictive analytics, and cutting-edge technologies like artificial intelligence and machine learning. In addition, resilience improvement is evaluated concerning supply chain partner collaboration. Best practices, major risk factors, and potential improvement areas in supply chain risk management and resilience methods are all identified using the data analysis results (Abeysekara et al., 2019). The research adds to the body of knowledge in the field. It offers practitioners and decision-makers helpful information for creating proactive risk management plans and promoting resilience in their supply chain operations.

RESULTS

Descriptive statistics

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Demand Volatility	500	.0081887613667675	99.8918405972797500	49.443738221861175	28.6296071559688 02
Supplier Reliability	500	.2091901183227440	99.5861078450772100	50.430867986189090	28.405256266264950
Transportation Disruptions	500	.0120101488974900	99.9644250811526000	49.219709936619864	30.771869904756045
Real-time Monitoring	500	.2390212344514531	99.9362592192450300	48.199239500102430	28.984409887174138
Predictive Analytics	500	.0067838312275081	99.4729211165785500	50.335977838377480	28.591645318190036
Regulatory Compliance	500	.0135942147207691	99.9474173296847800	50.803850869373946	29.249267394901846

Collaboration	500	.0556922842994467	99.316181533001 0900	51.425665164474 594	28.776561820212955
Valid N (listwise)	500				

The descriptive statistics highlight the key traits of the dataset's variables. Demand volatility, supplier dependability, transportation disruptions, real-time monitoring, predictive analytics, regulatory compliance, and collaboration are just a few of the elements that show different ranges and levels of variability (Kara et al., 2020). The standard deviations show the degree of dispersion around the means, whereas the mean values show the average levels of each variable. A deeper understanding of the patterns and properties of the variables in the dataset is made possible by these statistics, which shed light on the distribution and variability of the data.

CORRELATION ANALYSIS

Correlations								
		Demand Volatility	Supplier Reliability	Transportation Disruptions	Predictive Analytics	Real-time Monitoring	Regulatory Compliance	Collaboration
Demand Volatility	Pearson Correlation	1	0.054	-0.068	-.095*	0.055	-0.01	-0.027
	Sig. (2-tailed)		0.231	0.128	0.034	0.219	0.819	0.552
	N	500	500	500	500	500	500	500
Supplier Reliability	Pearson Correlation	0.054	1	0.023	0.022	-0.073	-0.026	-0.065
	Sig. (2-tailed)	0.231		0.612	0.62	0.104	0.565	0.144
	N	500	500	500	500	500	500	500
Transportation Disruptions	Pearson Correlation	-0.068	0.023	1	-0.03	-0.065	-0.008	0.013
	Sig. (2-tailed)	0.128	0.612		0.501	0.149	0.857	0.773
	N	500	500	500	500	500	500	500
Predictive Analytics	Pearson Correlation	-.095*	0.022	-0.03	1	0.058	-0.077	-0.056
	Sig. (2-tailed)	0.034	0.62	0.501		0.196	0.085	0.215
	N	500	500	500	500	500	500	500
Real-time Monitoring	Pearson Correlation	0.055	-0.073	-0.065	0.058	1	-0.057	0.027
	Sig. (2-tailed)	0.219	0.104	0.149	0.196		0.203	0.541
	N	500	500	500	500	500	500	500
Regulatory Compliance	Pearson Correlation	-0.01	-0.026	-0.008	-0.077	-0.057	1	-0.016
	Sig. (2-tailed)	0.819	0.565	0.857	0.085	0.203		0.723
	N	500	500	500	500	500	500	500
Collaboration	Pearson Correlation	-0.027	-0.065	0.013	-0.056	0.027	-0.016	1
	Sig. (2-tailed)	0.552	0.144	0.773	0.215	0.541	0.723	
	N	500	500	500	500	500	500	500
*. Correlation is significant at the 0.05 level (2-tailed).								

The correlation analysis shows the relationships between the variables in the dataset. Correlation coefficients between the variables range from -0.095 to 0.055, indicating a weak to moderate link. Demand volatility and Predictive Analytics have a weakly negative correlation (-0.095) and a weakly positive correlation (0.055). Real-time Monitoring and Collaboration have favourable relationships with Supplier Reliability (0.022 and 0.022, respectively). Predictive analytics and transportation disruptions have a slender negative connection (-0.030). The relationships are generally weak, but the correlations point to certain variables' interdependencies. It is crucial to remember that correlations do not imply causation, and more research is necessary to comprehend the underlying connections between the variables.

REGRESSION ANALYSIS

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.097[a]	.009	-.003	28.814949244709403
a. Predictors: (Constant), Transportation Disruptions, Regulatory Compliance, Supplier Reliability, Predictive Analytics, Real-time Monitoring, Demand Volatility				

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3878.624	6	646.437	.779	.587[b]
	Residual	409338.541	493	830.301		
	Total	413217.165	499			
a. Dependent Variable: Collaboration						
b. Predictors: (Constant) Transportation Disruptions, Regulatory Compliance, Supplier Reliability, Predictive Analytics, Real-time Monitoring, Demand Volatility						

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	58.240	5.847		9.961	.000
	Demand Volatility	-.030	.046	-.030	-.661	.509
	Predictive Analytics	-.060	.046	-.060	-1.322	.187
	Real-time Monitoring	.027	.045	.028	.610	.542
	Supplier Reliability	-.062	.046	-.061	-1.361	.174
	Regulatory Compliance	-.020	.044	-.021	-.460	.646

	Transportation Disruptions	.011	.042	.012	.268	.789
a. Dependent Variable: Collaboration						

A regression study on the independent variable (Collaboration) and the independent variables (Demand Volatility, Predictive Analytics, Real-time Monitoring, Supplier Reliability, Regulatory Compliance, and Transportation Disruptions) reveals a poor overall model fit (Chu et al., 2020). The model's R-squared value is 0.009, meaning that the independent variables can only account for 0.9% of the variation in collaboration. The model does not adequately match the data, according to the corrected R-squared value of -0.003.

The regression model as a whole does not appear to be statistically significant, according to the ANOVA table, which shows an F-value of 0.779 and a corresponding p-value of 0.587. This implies that the independent factors' combined effects on collaboration could be more noteworthy. According to the coefficient analysis, none of the independent factors have statistically significant effects on Collaboration (Wong et al., 2022). All of the variables' p-values are higher than the usual significance threshold of 0.05. As a result, there is insufficient data to prove that collaboration and the independent variables are significantly related.

DISCUSSION

Regression analysis was performed on the variables (Demand Volatility, Predictive Analytics, Real-time Monitoring, Supplier Reliability, Regulatory Compliance, and Transportation Disruptions) concerning the dependent variable (Collaboration), and the results offer important insights into the relationship between these variables in the context of intelligence-driven supply chain risk management and resilience strategies. The regression analysis showed a weak model fit; the R-squared value indicated that only 0.9% of the variation in collaboration could be attributed to the independent components (Baryannis et al., 2019). Modified R-squared, which accounts for sample size and predictors, indicates that the model does not match the data well. These findings suggest that the selected independent variables may not adequately account for the observed variation in collaboration. The regression model's overall ANOVA findings showed that it was not statistically significant, indicating that the independent variables did not collectively have a meaningful effect on collaboration. The observed results could be the result of chance since the p-value for the F-statistic was higher than the usual significance level of 0.05.

None of the independent variables had a statistically significant impact on collaboration when the individual coefficients were examined (Kamalahmadi et al., 2022). Because there was insufficient data to demonstrate a significant association between the independent variables and collaboration, the p-values attached to each coefficient were higher than 0.05. These findings suggest that, in the specific context of intelligence-driven supply chain risk management and resilience strategies, factors like demand volatility, predictive analytics, real-time monitoring, supplier dependability, regulatory compliance, and transportation disruptions, as considered in this analysis, may not be strong predictors of collaboration. It is crucial to evaluate these findings cautiously and consider any potential limitations. Five hundred instances comprised the sample size, and the analysis was based on a specific set of variables. Different outcomes could have been obtained with a bigger sample size or other unmeasured variables (Ivanov, 2018). Additionally, the selected variables might not have captured all the pertinent variables influencing collaboration, and the research might not have considered additional contextual or organizational characteristics.

The relationship between intelligence-driven supply chain risk management and resilience strategies and collaboration merits further investigation, consideration of various analytical trajectories, and the inclusion of qualitative techniques (Gupta et al., 2020). This would improve the efficiency of supply chain risk management and resilience methods and aid in identifying other essential aspects that lead to collaboration.

CONCLUSION

The regression analysis results indicate that in the context of intelligence-driven supply chain risk management and resilience strategies, the selected variables (Demand Volatility, Predictive Analytics, Real-time Monitoring, Supplier Reliability, Regulatory Compliance, and Transportation Disruptions) do not significantly affect collaboration. None of the independent variables displayed a statistically significant association with collaboration, and the model's fit was poor (Gupta et al., 2020). These results underline the necessity for more investigation into other variables and the consideration of different analytical strategies in order to comprehend the aspects influencing collaboration in supply chain management.

RECOMMENDATION

Based on the investigation findings, several suggestions can be made to enhance collaboration in intelligence-driven supply chain risk management and resilience strategies. First, it is crucial to investigate other factors affecting collaboration, like information-sharing habits and technological adoption. Qualitative research techniques might be applied to learn more about the variables influencing collaboration. Furthermore, a deeper comprehension of the complexity of supply chain dynamics will be possible thanks to collecting more extensive and varied data. Collaboration and decision-making in supply chain management will also be improved by promoting cooperative activities among stakeholders, implementing continuous monitoring and improvement processes, and embracing technological solutions. Organizations can improve their risk management and resilience strategies through efficient collaboration by implementing these tips.

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