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Supply Chain Analytics and Resilience in Roofing Sheet Manufacturing Firms in The Nairobi Metropolitan Area, Kenya

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Abstract

The global and local supply chains have faced many challenges, ranging from economic fluctuations to global pandemics. Political instability worsened Kenya's situation, resulting in a decline in manufactured goods exports to EAC partners. One of the most affected sub-sectors is roofing sheet manufacturing, hence the need to bolster supply chain resilience (SCR) among the players in the sub-sector. The study sought to examine the influence of demand analytics, logistics operations, inventory analytics, and supplier-related risks analytics on the supply chain resilience of roofing sheet manufacturing firms in NMA. Further, the study was anchored in Knowledge-based View, Systems Theory, Resource-based View, and Technology Acceptance Model. The study employed the cross-sectional survey research design and used a target population of 324 employees including 54 managers and 270 employees within procurement department (unit of observation) drawn from all 54 roofing sheet manufacturing firms in NMA (unit of analysis). Data were collected using a structured questionnaire designed in line with the independent and dependent variables. A pilot test involving 18 respondents assessed the instrument's validity and reliability. Data obtained from responses were coded and analyzed using SPSS Version 29. The data was analyzed and visualized using descriptive statistics, including mean and standard deviation. Correlation analysis was used to determine the strength and direction of the linear relationship between variables in the matrix. Regression analysis was used to find out how changes in the independent variable affect the dependent variable. The findings revealed that demand forecasting, logistics operations analytics, inventory management analytics, and supplier-related risk analytics significantly influence supply chain analytics in roofing sheet manufacturing firms within the NMA. Logistics operations had the greatest influence on supply chain resilience ($\beta = 0.142$, $p < 0.05$), followed by demand forecasting ($\beta = 0.093$, $p < 0.05$), inventory management analytics ($\beta = 0.035$, $p < 0.05$), and supplier-related risk analytics ($\beta = 0.033$, $p < 0.05$). The study concluded that supply chain analytics influences supply chain resilience. The study also recommends that firms effectively integrate supply chain analytics into their operations to enhance supply chain resilience.

Keywords: *Supply Chain Analytics, Resilience, Roofing Sheet Manufacturing Firms, Nairobi Metropolitan Area, Kenya*

1.1 Background of the Study

Supply chain resilience has become an important capability for manufacturing firms because modern supply chains are increasingly exposed to disruptions caused by economic fluctuations, pandemics, political instability, currency volatility, supplier failures, and logistics delays. A sound supply chain system should have the capacity to mitigate disruptions and sustain operations when unexpected shocks occur (Wairimu et al., 2023). In Kenya, the roofing sheet manufacturing sub-sector has experienced persistent delivery delays, unreliable supply of materials, and declining production output, with roofing sheet production falling from 290,283 metric tons in 2015 to 262,700 metric tons in 2017, while revenue fell by 40% in 2019 (Olieka

& Okello, 2020; Mutua & Yatich, 2024). These challenges show the need for roofing sheet manufacturing firms to strengthen supply chain resilience.

Supply chain analytics provides firms with data-driven tools for improving supply chain visibility, decision-making, responsiveness, and recovery from disruptions. It involves the use of statistical techniques, data mining, machine learning, artificial intelligence, software systems, and Internet of Things tools to analyze historical and current supply chain data (Wang & Aviles, 2023; Ugbebor et al., 2024). Through supply chain analytics, firms can forecast demand, identify possible supply chain disruptions, optimize logistics operations, manage inventory levels, and assess supplier-related risks. These capabilities help firms detect patterns, understand market trends, reduce uncertainty, and make informed decisions that strengthen supply chain resilience (Ikekwere, 2024).

Globally, supply chain analytics has become central to improving supply chain resilience in volatile markets. In the United States, firms use demand analytics and real-time technologies to predict customer behaviour, adjust production, and manage supplier risks (Enyejo et al., 2024; Hasan et al., 2025). In Asia, especially in high-tech and manufacturing industries, logistics operations analytics and machine learning are used to reduce production delays, transport interruptions, and demand uncertainty (Xiong et al., 2025; Wang et al., 2023). In Europe, manufacturers use statistical forecasting and inventory optimization techniques to respond to geopolitical uncertainties and strengthen network resilience (Adewusi et al., 2024). Regionally, African firms are increasingly adopting supply chain analytics to improve resilience in the face of market volatility, climate risks, weak infrastructure, and supplier uncertainty. In South Africa, big data tools have helped firms anticipate extreme weather events, forecast demand, optimize inventory, and improve logistics operations in the mining sector (Bag et al., 2022). In Nigeria, predictive models are used to assess supplier risks and support informed sourcing decisions in unstable business environments (Adesina et al., 2024). In Ethiopia, firms have integrated predictive tools into demand tracking, logistics optimization, supplier relationship management, and recovery planning (Bilal et al., 2024).

In Kenya, supply chain analytics is increasingly applied in sectors such as healthcare, retail, manufacturing, and logistics. Predictive models are used to anticipate inventory needs, reduce stock-outs, improve procurement cycles, respond to changes in consumer demand, optimize transport routes, and monitor supplier risks (Owich & Odero, 2023; Njehia, 2023). During the COVID-19 period, food and beverage firms in Nairobi used demand analytics to adjust production and distribution decisions, while retail chains and private hospitals used supplier-related risk analytics and agile procurement strategies to manage supply interruptions (Wairimu, 2023; Kuria & Ndeto, 2024).

The Nairobi Metropolitan Area is a major hub for roofing sheet manufacturing firms due to its active construction and real estate sectors. The region hosts several roofing sheet manufacturers, including Mabati Rolling Mills, Imarisha Mabati, Royal Mabati, Capital Mabati, and Maisha Mabati, with many firms concentrated in Nairobi, Machakos, and Kiambu counties (KAM, 2025). However, intense competition, dependence on imported raw materials, logistics challenges, supplier uncertainty, and customer delivery expectations expose these firms to serious supply chain risks. This study therefore examined the influence of supply chain analytics on supply chain resilience among roofing sheet manufacturing firms in the Nairobi Metropolitan Area, focusing on demand forecasting, logistics operations analytics, inventory management analytics, and supplier-related risk analytics.

1.2 Statement of the Problem

In the era of global volatility, achieving supply chain resilience remains critical to the operations of manufacturing firms. Evidence from Orlando *et al*. (2022) suggests that firms with resilient supply chains are 2.5 times more likely to achieve high performance and can cut down recovery time from disruption by up to 42%. Recently, Kenya's NMA emerged as an industrial hub for roofing sheet manufacturing, driven by the expanding construction sector that grew at an annual rate of 6.4% between 2018 and 2023 (Kenya National Bureau of Statistics, 2024). Today, NMA hosts 60% of all roofing sheet manufacturing firms in Kenya (KAM, 2025). Despite the rise in the entries, NMA does not produce raw materials for roofing sheet manufacturing, including galvanized steel coils, coating compounds, and aluminum, compelling manufacturers to source from countries such as China, exposing the manufacturers to global logistics disruptions caused by currency volatility, natural disasters, and supplier-related risks (KAM, 2024). For instance, in 2023, the Kenyan shilling depreciated against the U.S. dollar, increasing importation costs (CBK, 2024). Concurrently, political instability every 5 years, COVID-19 disruptions, and poor infrastructure in the far-flung regions of Nyanza, Western, and Northern Kenya further complicated the firms' domestic supply chains. The impact of these challenges is evident in KAM's (2022) report, which found that 79% of NMA's new, small, and medium-sized roofing sheet manufacturers suffered severe effects from supply chain disruptions, causing delays and losses of up to 3.8 billion Kenya shillings.

Although studies such as Orlando *et al*. (2022) suggest that supply chain analytics offers significant potential for supply chain departments to enhance SCR among firms, its influence among roofing sheet manufacturers in NMA during such supply chain disruptions remains unclear. Without clear empirical insights into the influence of supply chain analytics on the firms' supply chains, new setups and small and medium-sized roofing sheet manufacturing firms in NMA will continue to suffer the challenges of compromised supply chain operations. It is in view of the foregoing that this study aims to establish the influence of supply chain analytics on resilience among roofing sheet manufacturing firms in NMA.

1.3 Objectives of the Study

i. To assess the influence of demand forecasting on the supply chain resilience of sheet manufacturing firms in NMA.
ii. To find out the influence of logistics operations analytics on the supply chain resilience of roofing sheet manufacturing firms in NMA.
iii. To examine the influence of inventory management analytics on the supply chain resilience of roofing sheet manufacturing firms in NMA.
iv. To assess the influence of supplier-related risk assessment on the supply chain resilience of roofing sheet manufacturing firms in NMA.

2.0 Literature Review

This chapter reviews existing theories and a model for variables relevant to the study. Further, the chapter presents the conceptual framework from which the study measures specific variables. The study also reviews literature on supply chain analytics and supply chain resilience relevant to roofing sheet manufacturing firms in NMA. A good literature review provides the context within which to focus the study.

2.1 Theoretical Framework

According to Mosquera *et al*. (2022), the theoretical framework includes concepts, their definitions, and their applications in scholarly literature. The Knowledge-Based View (KBV) was used to inform the variable of demand forecasting. The theory, developed by Kogut and

Zander (1992), views knowledge as one of the firm's most valuable and scarce resources. In this study, KBV supports the argument that roofing sheet manufacturing firms can use intellectual capital, historical sales data, market knowledge, and customer behaviour information to forecast demand and make better supply chain decisions (Mariano, 2023). Since demand forecasting depends on the firm's ability to collect, interpret, and apply knowledge, the theory explains how data-driven knowledge helps firms anticipate market changes, reduce uncertainty, and improve supply chain resilience (Mubarik et al., 2021).

The Systems Theory was used to inform the variable of logistics operations analytics. The theory, associated with Ludwig von Bertalanffy (1971), explains that an organization operates as a system made up of interrelated and interdependent parts. In this study, the theory supports the view that logistics operations, inventory management, demand forecasting, and supplier risk management are connected and must work together to enhance supply chain resilience (Wilkinson et al., 2014). Logistics operations analytics depends on real-time data, route optimization, transport monitoring, and coordination of supply chain activities; therefore, Systems Theory explains how effective coordination of internal and external supply chain subsystems improves visibility, reduces delays, and strengthens resilience (Punia & Shankar, 2022; Jain et al., 2022).

The Resource-Based View (RBV) was used to inform the variable of inventory management analytics. The theory, proposed by Wernerfelt (1984) and refined by Barney (1991), argues that firms achieve competitive advantage by using valuable, rare, and difficult-to-imitate resources and capabilities. In this study, RBV explains how roofing sheet manufacturing firms can use internal resources such as skilled employees, information technology, supplier networks, logistics infrastructure, and inventory systems to build resilient supply chains (Henry, 2021). Inventory management analytics is therefore viewed as a strategic capability that helps firms monitor inventory levels, reduce stock-outs and overstocks, improve turnover, and recover from disruptions more effectively (Komakech et al., 2025).

The Technology Acceptance Model (TAM) was used to inform the variable of supplier-related risk analytics and the overall adoption of supply chain analytics tools. Developed by Davis (1989), TAM explains technology adoption through perceived usefulness and perceived ease of use. In this study, the model supports the argument that roofing sheet manufacturing firms are more likely to adopt analytics tools when managers believe that such tools can improve supplier risk assessment, enhance decision-making, and strengthen supply chain resilience (Julianto & Daniawan, 2022). Supplier-related risk analytics depends on the use of technology to identify supplier risks, monitor supplier performance, assess delivery reliability, and support timely mitigation; therefore, TAM explains how acceptance of analytics technologies improves the firm's ability to manage supplier disruptions and sustain resilient supply chains.

2.2 Conceptual Framework

According to Shields and Rangarajan (2013), a conceptual framework defines the way in which a researcher organizes ideas by defining relationships between variables. A conceptual framework offers the foundation for interpreting the phenomena under study; hence, it outlines the hypotheses. The figure depicts the conceptual framework for the study.

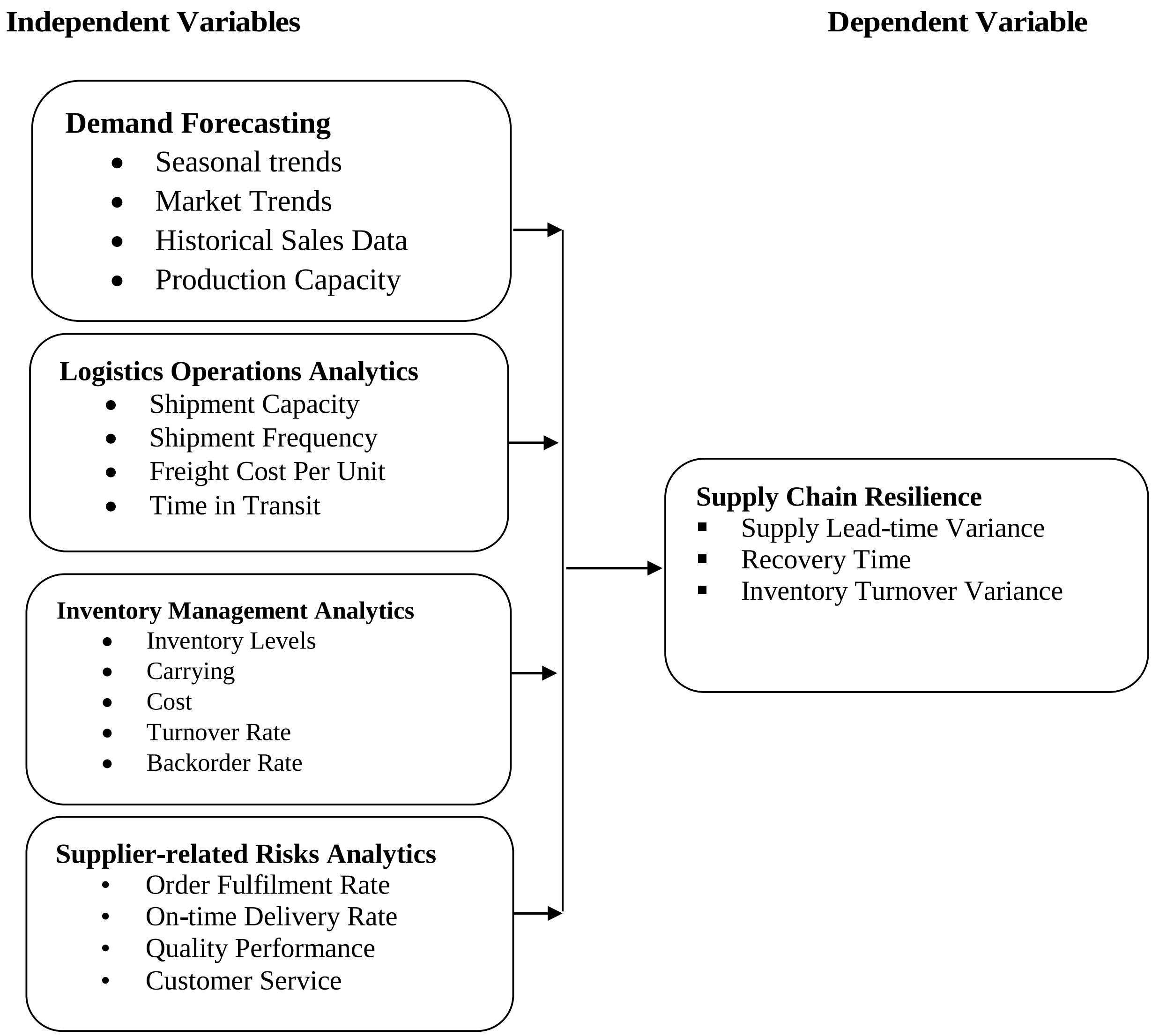

Figure 1: Conceptual Framework

2.3 Empirical Review

Fu and Chien (2019) examined the role of data-driven demand forecasting using machine learning in managing uncertainties and disruptions in supply chain networks. The study found that demand forecasting enables firms to proactively adjust production levels, supplier relationships, and inventory management in response to unexpected events. Similarly, Ikekwere (2024) found that demand analytics technologies improve supply chain resilience by helping firms anticipate demand shifts and adopt sector-specific predictive models. Kiplagat (2024) also established that artificial intelligence and machine learning improve demand forecasting accuracy by identifying patterns that traditional methods may fail to detect. These studies show that demand forecasting strengthens supply chain resilience by enabling firms to anticipate market fluctuations, reduce uncertainty, and respond flexibly to disruptions.

Mathews and Rajab (2024) examined the use of data-driven insights in warehouse operations and found that real-time analytics significantly improves firms' ability to withstand supply chain disruptions. The study showed that logistics operations analytics supports route optimization, delay reduction, and uninterrupted operations. Muoki and Moronge (2021) further found that logistics management requires rapid responses to changing operational conditions, which can be achieved through real-time data collection, route optimization, transport capacity optimization, warehouse optimization, and vehicle maintenance analytics.

Nagarajan (2022) also emphasized that routing, scheduling, vehicle loading software, and real-time tracking help firms avoid disruptions such as traffic congestion, poor roads, vehicle breakdowns, and delivery delays. These studies imply that logistics operations analytics enhances supply chain resilience by improving freight efficiency, shipment reliability, transport visibility, and recovery from logistics disruptions.

Sugut and Ondara (2023) examined the relationship between inventory management practices and supply chain performance in Nairobi County and found that inventory management supports supply chain resilience by addressing demand uncertainty and supply fluctuations. Their findings showed that predictive techniques such as reorder point analysis and safety stock analysis help firms maintain service continuity. Ndemo and Achuora (2020) also found that inventory management models such as ABC analysis improve operational performance by guiding firms on efficient inventory control. Enyejo et al. (2024) further established that inventory management analytics technologies help firms understand past inventory trends, analyze customer demand, monitor available stock, and recommend adjustments for stock safety. These studies show that inventory management analytics improves supply chain resilience by reducing stock-outs, overstocks, backorders, carrying costs, and inventory-related disruptions.

Liu and Wei (2022) analyzed the moderating role of supplier-related risk assessment and analytics capabilities in the relationship between supply chain disruption orientation and supply chain resilience. The study found that supplier-related risk assessment and analytics capabilities strengthen resilience in digital supply chains. Bag et al. (2024) also found that supply chain technologies such as advanced analytics, Internet of Things, blockchain, and artificial intelligence improve supply chain flexibility by predicting disruptions, optimizing resources, and supporting quick responses to geopolitical, pandemic-related, and natural disaster risks. Kuranovic (2022) further emphasized that firms should conduct supplier risk assessment to identify, analyze, prioritize, and mitigate risks linked to supplier shortages, compliance issues, economic fluctuations, and natural calamities. These studies suggest that supplier-related risk analytics enhances supply chain resilience by helping firms assess supplier reliability, monitor delivery performance, identify vulnerabilities, and develop targeted mitigation strategies.

3.1 Research Methodology

The study adopted a cross-sectional survey research design to examine the relationship between supply chain analytics and supply chain resilience among roofing sheet manufacturing firms in the Nairobi Metropolitan Area. The design was appropriate because it enabled the collection of qualitative and quantitative data at one point in time and supported the analysis of relationships between the independent variables and the dependent variable (Creswell, 2021; Thomas & Zebkov, 2023). The target population comprised 324 respondents drawn from roofing sheet manufacturing firms, including 54 managers and 270 employees working in supply chain departments, while the sampling frame consisted of 54 roofing sheet manufacturing firms listed by the Kenya Association of Manufacturers. The study used Yamane's formula to obtain a sample size of 179 respondents, comprising 29 managers and 150 other employees, selected through stratified random sampling to ensure representation of different respondent categories. Primary data were collected using semi-structured questionnaires administered mainly through Google Forms, while physical drop-off-and-pick-up questionnaires were used where online administration was not possible (Jaiswal, 2024). A pilot test was conducted using 18 respondents from six roofing sheet manufacturing firms to assess the validity and reliability of the research instrument, in line with the 5% to 10% pilot testing recommendation by Teresi et al. (2021).

Face validity was confirmed using six raters, with an overall face validity score of 9.16, while content validity was confirmed using the Scale-Level Content Validity Index, which recorded an S-CVI average of 0.91, above the acceptable threshold (Roy et al., 2023; Hakim et al., 2025). Reliability was tested using Cronbach's alpha, and all variables achieved acceptable reliability after adjustment, including demand forecasting (α = .732), logistics operations analytics (α = .736), inventory management analytics (α = .769), supplier-related risk analytics (α = .717), and supply chain resilience (α = .718). Ethical approval was obtained from NACOSTI under Ref No. 796026, and informed consent, confidentiality, anonymity, and voluntary participation were observed. Data were analyzed using IBM SPSS Version 29 through descriptive statistics, Pearson correlation analysis, and multiple regression analysis to test the effect of demand forecasting, logistics operations analytics, inventory management analytics, and supplier-related risk assessment on supply chain resilience.

4.0 Results and Findings

This study used various statistical analysis techniques in SPSS V.29 to examine the influence of supply chain analytics variables on supply chain resilience among roofing sheet manufacturing firms in NMA. This chapter describes the response rate, the various data analysis techniques employed, and the key findings aimed at answering the research questions.

4.1 Response Rate

According to Beehr *et al*. (2022), the response rate is an important indicator of survey quality. This study suggests that the higher the response rate, the more accurate the study. This study administered 179 questionnaires, out of which 162 questionnaires were returned and used for the data analysis. A 90.5% response rate satisfied the rule of thumb recommending at least a 75% response rate as suggested by Holtom *et al*. (2021). Table 1 shows the distribution of the questionnaires administered.

Table 1: Response Rate

Responses	No.	Percentage (%)
Administered Questionnaires	179	100
Returned Questionnaires and Used	162	90.5

Source: Research Data (2026)

4.2 Descriptive Statistics

This section highlights the various descriptive analysis responses based on specific items for the dependent and independent variables. The study used mean scores and standard deviation to organize the responses for easy understanding. The descriptive results provided an understanding of the implementation of supply chain analytics among roofing sheet manufacturing firms in NMA and the effect of its implementation on the supply chain resilience of the firms. The responses were obtained on the 5-point Likert scale, which ranges between 1 = Strongly Disagree and 5 = Strongly Agree. In order to effectively interpret the aggregate means and standard deviation in a standardized manner, the study relied on a framework by Chito and Wachiuri (2025), where scores 1.00 - 1.79 (Strongly Disagree), 1.80 - 2.59 (Disagree), 2.60 - 3.39 (Neutral), 3.40 - 4.19 (Agree), and 4.20 - 5.00 (Strongly Agree). The subsequent section explores descriptive statistics results.

Demand Forecasting and Supply Chain Resilience

The first objective sought to assess the influence of demand forecasting on the supply chain resilience of roofing sheet manufacturing firms in the Nairobi Metropolitan Area. The descriptive findings showed that respondents agreed that demand forecasting practices were used in the firms, with an aggregate mean score of 3.78 and a standard deviation of 0.575. The highest mean was recorded for the use of historical sales data to predict demand volatility for proactive demand planning during disruptions (M = 3.85, SD = 0.571). Respondents also agreed that market trends for similar products affected product demand (M = 3.78, SD = 0.565), while seasonal demand patterns and production scheduling both recorded a mean of 3.77. These findings imply that roofing sheet manufacturing firms use seasonal trends, market trends, historical sales data, discount patterns, and production capacity analytics to anticipate demand changes and strengthen supply chain resilience. The findings agree with Dhanalakshm and Prabhu (2025), who noted that demand forecasting strengthens resilience in competitive global supply chains.

Logistics Operations Analytics and Supply Chain Resilience

The second objective sought to find out the influence of logistics operations analytics on the supply chain resilience of roofing sheet manufacturing firms in the Nairobi Metropolitan Area. The findings showed strong agreement on the use of logistics operations analytics, with an aggregate mean score of 3.94 and a standard deviation of 0.552. The highest mean was recorded for monitoring delivery vehicle health to minimize breakdown-related delays (M = 3.99, SD = 0.546). Monitoring changes in shipment frequency and monitoring time in transit both recorded a mean of 3.95, while ensuring timely delivery to reduce customer complaints and managing shipment capacity during vehicle breakdowns both recorded a mean of 3.94. These findings suggest that roofing sheet manufacturing firms use logistics analytics to monitor shipment capacity, shipment frequency, freight efficiency, time in transit, and vehicle performance in order to reduce delivery delays and maintain operational continuity. This supports Adeniran et al. (2024), who found that advanced logistics analytics improves firms' ability to adapt quickly to disruptions.

Inventory Management Analytics and Supply Chain Resilience

The third objective examined the influence of inventory management analytics on the supply chain resilience of roofing sheet manufacturing firms in the Nairobi Metropolitan Area. The findings showed that respondents agreed on the use of inventory management analytics, with an aggregate mean score of 3.83 and a standard deviation of 0.579. The highest mean was recorded for the ability of inventory management systems to track inventory levels in real time and predict stock-outs (M = 3.89, SD = 0.579). Predictive insights guiding inventory restocking recorded a mean of 3.86, while keeping backorder rates in check to reduce lost sales recorded a mean of 3.84. These findings imply that inventory management analytics helps firms monitor stock levels, manage carrying costs, control backorders, track turnover rates, and guide restocking decisions. The findings align with Kelka (2024), who found that resilient inventory management practices improve supply chain visibility and help firms navigate disruptions.

Supplier-Related Risk Analytics and Supply Chain Resilience

The fourth objective examined the influence of supplier-related risk analytics on the supply chain resilience of roofing sheet manufacturing firms in the Nairobi Metropolitan Area. The findings showed strong agreement on the use of supplier-related risk analytics, with an aggregate mean score of 4.11 and a standard deviation of 0.585. The highest mean scores were recorded for using supplier order fulfilment records to identify service delays and monitoring the timeliness of suppliers' responses to complaints, both with a mean of 4.15. Tracking supplier lead time inconsistencies recorded a mean of 4.09, while using historical quality data to anticipate supplier compliance issues recorded a mean of 4.07. These findings show that roofing sheet manufacturing firms use supplier analytics to monitor on-time delivery, quality performance, order fulfilment, lead time reliability, and supplier responsiveness. The findings support Mudunuri (2023), who noted that data analytics helps manufacturing firms identify predictive measures for supplier-related risks.

Supply Chain Resilience

The descriptive findings on supply chain resilience showed that roofing sheet manufacturing firms had strong resilience capabilities, with an aggregate mean score of 4.07 and a standard deviation of 0.552. The highest mean was recorded for sorting quality concerns as soon as possible (M = 4.14, SD = 0.540), followed by maintaining stable inventory turnover despite changes in supply conditions (M = 4.09, SD = 0.516). Recovery of supply chain operations within predictable timeframes recorded a mean of 4.07, while quick restoration of sales volume after interruptions recorded a mean of 4.04. These findings imply that the firms are able to maintain lead times, recover from disruptions, stabilize inventory turnover, restore sales volumes, and address quality concerns. The findings agree with Adewusi et al. (2024), who established that predictive analytics strengthens supply chain resilience by mitigating risks and optimizing operations.

4.3 Diagnostic Tests

In an attempt to establish the relationship between the dependent and independent variables, the study first tested several critical assumptions of the data obtained. These tests are essential before conducting correlation and multiple linear regression analysis.

Normality Test

Statistically, this study used skewness and kurtosis to evaluate data normality. While skewness measures the departure from horizontal symmetry, kurtosis measures the central peak's sharpness relative to a standard bell curve. The normality test assumes that skewness and kurtosis z-values should be between -1.96 and 1.96 for normally distributed data.

Table 2: Skewness and Kurtosis Results

Variable	Skewness			Kurtosis		
	Statistic	df	Sig.	Statistic	df	Sig.
Demand Forecasting	-.001	162	.019	.427	162	.038
Inventory Management Analytics	-.231	162	.019	.063	162	.038
Logistics Operations Analytics	-.364	162	.019	-.387	162	.038
Supplier-related Risk Analytics	1.28	162	.019	.012	162	.038

H_0: The data come from a normally distributed population.

Based on the test results for the skewness and kurtosis test, all the variables exhibited a z score of between -364 and 1.28, which falls within the -1.96 and 1.96 margin. These findings show that all the variable in the current study depicted normal distributions.

Autocorrelation Test

The test confirms independence of observation, a critical requirement for regression analysis. Independence of observation means that one observation value does not predict another observation. Autocorrelation was tested using the Durbin-Watson test with a test statistic ranging between 0 and 4. In this test, values close to 2 suggest less autocorrelation, while values close to 0 and 4 suggest positive and negative autocorrelation, respectively.

Table 3: Durbin-Watson Test

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.173[a]	.030	.005	.231	1.928

a. Predictors: (Constant), SR, DF, IM, LO

b. Dependent Variable: SCR

H_0: Errors are independent.

Based on the test results above, the Durbin-Watson Statistic of 1.929 suggests no presence of autocorrelation.

Heteroscedasticity

The current study performed a test for heteroscedasticity to avoid the risk of bias in parameter estimates. This tests the assumption that the residual values do not increase with increasing values of independent variables. The study used the Breusch-Pagan test and obtained results shown in Table 4.

Table 4: Breusch-Pagan Test

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.003	4	.001	148	.964[b]
	Residual	.796	157	.005		
	Total	.799	161			

a. Dependent Variable: SQR_RES

b. Predictors: (Constant), SR, DF, IM, LO

H_0: Residuals do not exhibit heteroscedasticity.

With the significance level of 5%, the test obtained a p-value of 0.964, which is greater than the level of significance of 0.05; the test failed to reject the null hypothesis to conclude the residuals do not exhibit heteroscedasticity, satisfying the homoscedasticity assumption.

Multicollinearity Test

Multicollinearity explains a situation where independent variables in a multiple regression are correlated. This test assumes that no independent variable has a perfect linear relationship with another independent variable, an essential assumption for regression analysis. This assumption is tested using the Variable Inflation Factor (VIF) and Tolerance. VIF values between 1 and 10 suggest no multicollinearity. On the other hand, values less than 1 and more than 10 indicate multicollinearity concerns. Accordingly, being the inverse of VIF, a Tolerance value greater than 0.1 indicates no multicollinearity concerns.

Table 5: Multicollinearity Test

Coefficients[a]

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics	
1	(Constant)	2.884	.604	.092	4.777	.001	Tolerance	VIF
	DF	.093	.080	.039	1.170	.044	.996	1.005
	IM	.035	.071	.134	.498	.019	.992	1.008
	LO	.142	.184	.134	1.691	.043	.988	1.012
	SR	.033	.071	.036	.459	.047	.998	1.002

a. Dependent Variable SCR

Based on the results obtained, all the independent variables exhibited a tolerance of between .988 and .998 and a VIF of between 1.002 and 1.012, suggesting no multicollinearity concerns. This test result indicates that each variable uniquely contributes to the regression model; hence, it is reliable for analyzing the impact of each variable on supply chain resilience among roofing sheet manufacturing firms in NMA, Kenya.

4.4 Correlation Analysis

The study used correlation analysis to measure both the strength and direction of the linear relationship between any two variables in the matrix. These variables are continuous in nature. Specifically, the study used Pearson's r correlation statistic to measure the degree of correlation with a 95% confidence level. The analysis results are presented in table 6.

Table 6: Correlation Matrix

Variables		DF	IM	LO	SR	SCR
DF	Pearson Correlation	1.000				
	N	162				
IM	Pearson Correlation	0.018	1.000			
	Sig. (2-tailed)	0.000				
	N	162	162			
LO	Pearson Correlation	0.063	0.087	1.000		
	Sig. (2-tailed)	0.002	0.003			
	N	162	162	162		
SR	Pearson Correlation	0.016	0.025	0.028	1.000	
	Sig. (2-tailed)	0.015	0.000	0.002		
	N	162	162	162	162	
SCR	Pearson Correlation	0.099	0.025	0.137	0.037	1.000
	Sig. (2-tailed)	0.000	0.014	0.000	0.002	
	N	162	162	162	162	162

Demand forecasting was found to be positively and significantly correlated with supply chain resilience ($r = .099$, $p < .05$); the correlation between inventory management and supply chain resilience was also positive and significant ($r = .025$, $p < .05$). Besides, the correlation between logistics operations and supply chain resilience was positive and significant ($r = .137$, $p < .05$). Finally, the correlation between supplier-related risk analytics and supply chain resilience was also positive and significant ($r = .037$, $p < .05$). These results imply that there exists a statistical association between the variables.

4.5 Regression Analysis

Regression analysis is a statistical tool for establishing relationships among research variables. The study conducted a multiple regression analysis to jointly examine the relationship between the study variables affecting supply chain analytics and supply chain resilience among roofing sheet manufacturing firms in NMA, Kenya. Done at a 0.05 significance level, the multiple regression analysis provided the model summary.

Model Summary

The model shows that the correlation coefficient (R) was .773, suggesting a strong positive linear relationship between supply chain analytics and supply chain resilience. The coefficient of determination, R^2, was 0.598, indicating that a combination of demand forecasting, inventory management, logistics operations, and supplier-related risk analytics explains 59.8% of the variance in supply chain resilience in roofing sheet manufacturing firms in NMA. As such, 40.2% of the variance in supply chain resilience is occasioned by other factors not included in the study. The relatively high adjusted R-squared of .588 suggests that the model's independent variables contribute more to explaining the variance in the dependent variable. Also, the standard error of the estimate of 0.0230 explains a relatively small deviation of the dependent variable (supply resilience) outputs from the line of best fit.

Table 7: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.773[a]	.598	.588	.0230

a. Predictor (Constant), DF, IM, LO, SR

b. Dependent Variable: SCR

Goodness of Fit (ANOVA)

Using Analysis of Variance (ANOVA), the analysis also summarizes the results for two sources of variation, including accounted-for values (regression) and unaccounted-for values (residual) in table 8.

Table 8: ANOVA Statistics

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	0.257	4	0.064	1.207	.000[b]
	Residual	8.341	157	0.053		
	Total	8.598	161			

a. Dependent Variable: SCR

b. Predictors: (Constant), SR, DF, IM, LO

For the accounted-for value, the sum of squares is 0.257, the mean square is 0.064, and the degrees of freedom is 1.207. On the other hand, for the values not accounted for, the sum of squares is 8.341; then the mean square is 0.064, and the degrees of freedom are 157. Also, the F statistic, which explains the regression mean square divided by the residual mean square, is 1.207. The relationship obtained is $F1{,}161 = 1.207$, $p < 0.05$. Importantly, with a significance level of 0.000, there is zero chance of obtaining the regression results from events other than the true relationship. As a result, the model is a good fit for the data and is proper for predicting the influence of supply chain analytics on supply chain resilience among roofing sheet manufacturing firms in NMA, Kenya. The ANOVA table suggests that the regression model was statistically significant (p-value is 0.00, which is less than 0.05). As such, the data obtained was ideal for making conclusions about the study population.

Optimal Regression Coefficients

A regression model depicts a cause-and-effect relationship between the explanatory and predicted variables. It is therefore necessary to calculate the coefficients of estimation for the regression model. The study also established regression coefficients and obtained the results as shown in table 9.

Table 9: Regression Coefficients Results

Coefficients[a]						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
		B	**Std. Error**	**Beta**		
1	(Constant)	2.884	0.604		4.777	.001
	Demand Forecasting	0.093	0.08	0.092	2.171	.024
	Inventory Management	0.035	0.071	0.039	2.498	.041
	Logistics Operations	0.142	0.084	0.134	2.691	.033
	Supplier-related Risk	0.033	0.071	0.036	3.459	.023

a. Dependent Variable: SCR

Coefficients of each independent variable explain their importance in the regression model. Although the table highlights both the standardized and unstandardized coefficients, the discussion was only based on the unstandardized coefficients. Based on the regression coefficients obtained,

Optimal Model

$\mathbf{Y = 2.884 + 0.093X_1 + 0.035X_2 + 0.142X_3 + 0.033X_4 + \varepsilon}$; where the error term ε is negligible.

Based on the results of the regression analysis, the constant 2.884 suggests the expected baseline supply chain resilience in the absence of all predictive analytics variables factored into the model. The analysis shows that demand forecasting has a positive and significant influence on supply chain resilience (B = 0.093, $p < .05$), suggesting that holding the other factors constant, a unit increase in demand forecasting leads to a 0.093-unit increase in supply chain resilience. The t value of 2.171 also implies that the variation in supply chain resilience attributed to demand forecasting was significantly greater than that attributed to the standard error. There also exists a positive and significant influence of inventory management analytics on supply chain resilience (B = 0.035, $p < .05$). Meaning that for every unit increase in inventory management analytics, there exists a 0.532-unit increase in supply chain resilience. A t-value of 2.498 also implies that the variation in supply chain resilience attributed to inventory management analytics was significantly greater than that attributed to the standard error. Again, there is a positive and significant influence of logistics operations analytics on supply chain resilience (B = 0.142, $p < .05$). This means that for a unit increase in logistics operations analytics, there will be a 0.142-unit increase in supply chain resilience. Furthermore, the calculated t-value of 2.691 indicates that the variation in supply chain resilience attributed to logistics operations analytics was significantly twice that attributed to the standard error.

Finally, there is a positive and significant influence of supplier-realted risk analytics on supply chain resilience (B = 0.033, $p < .05$). Also, this means that for every one-unit increase in supplier-related risk analytics, there is a 0.033-unit increase in supply chain resilience. The t-value of 3.459 also suggests that the variation in supply chain resilience attributed to supplier-related risk analytics was significantly more than twice that attributed to the standard error.

4.6 Qualitative Data Analysis

Through open-ended questionnaire items, the study also collected qualitative data to gain a better understanding of the firms' embraced supply chain analytics and their role in enhancing supply chain resilience among roofing sheet manufacturing firms in NMA. The current study manually recorded and coded the data for key words. The keywords were used to generate sub-themes, and finally main themes were obtained.

Demand Forecasting Theme

The study aimed to understand the impact of the seasonal trends, market trends, and production capacity in predicting demand in the firm. A majority of the firms surveyed did not effectively use seasonal and market trends to make demand forecasting decisions. As such, the firms focused on dealing with the short-term demand variations with no consideration for long-term forecasting systems. One of the respondents indicated that:

“We have not effectively embraced the alignment between production capacity and forecasted demand, resulting in mismatches between the supplies and the predicted market demands.”

Logistics Operations Theme

The study also attempted to determine the effect of shipment capacity and shipment frequency on the efficiency of logistics operations analytics of the firms. The findings indicated that the majority of the firms failed to effectively balance shipment capacity and shipment frequency. The companies only focus on fulfilling the minimal needs of deliveries without optimizing logistics processes. The respondents disagreed that their firms use shipment capacity optimally to ensure economically viable logistical operations. The findings also indicated that the companies have not been successfully adopting a coordinated approach in planning shipments, which has led to inefficiencies, delays, and increased costs. One respondent suggested:

“One of the causes of shipment delays in our firm has been a lack of clear plans on the right time to make shipments. This has often resulted in unfulfilled customer demands.”

Inventory Management Theme

The study also investigated the impact of carrying cost and inventory turnover rate on inventory management efficiency at the company. The results indicate that most firms did not adequately monitor carrying costs, causing unprecedented increases in operational costs. The respondents also disagreed that their firms have maximized the rates of inventory turnover to optimize performance. The results also indicate that the companies have not been successfully adopting data-driven inventory management systems, which have resulted in unbalanced inventory levels and reduced operational efficiencies. A respondent stated:

“In a long time, we haven’t maximized our inventory turnover rates to optimize performance. We envision a data-driven inventory management system that guarantees balanced inventory levels for operational efficiency.”

Supplier-Related Risk Analytics

The qualitative study also evaluated the extent to which delivery rates and on-time delivery affected supplier reliability and supply chain resilience. The findings indicated that most firms surveyed did not strictly monitor suppliers' on-time delivery performances. The respondents disagreed that their firms strictly examined supplier performance but maintained close supplier relationships. One of the respondents indicated that,

"Although our firm encourages suppliers to strictly adhere to delivery timelines, suppliers occasionally missing delivery deadlines causes stoppages in production processes. This often causes serious challenges in meeting customers' urgent demands."

The results also indicate that the companies have not been successfully harnessing supplier-related risk analytics, putting the companies' operations at risk of delays, quality variability, and general disruption of the supply chain.

5.1 Conclusion

This study concludes that supply chain analytics has a positive influence on supply chain resilience among roofing sheet manufacturing firms in NMA. The findings show that when firms analyze their demand, logistics operations, inventory, and supplier-related risks, they are more likely to anticipate, withstand, and recover from the associated risks. However, descriptive statistics suggest that most of its actors failed to adapt supply chain analytics technologies in their operations. As a result, most firms are experiencing significant delays, quality variabilities, and supply chain disruptions, leading to increased customer complaints and lawsuits related to delivery terms.

More specifically, the study concludes that although demand forecasting has a positive and significant influence on supply chain resilience among roofing sheet manufacturing firms in NMA, most of the firms are yet to fully adopt demand analytics, analyzing seasonal trends, market trends, historical sales data, and firms' production capacity for managing unexpected demands. Most of these firms fail to survive unexpected supply chain disruptions, exposing them to online complaints and lawsuits. The study also concludes that although logistics operations analytics has a positive and significant influence on supply chain resilience, as suggested by regression analysis, it is yet to be fully embraced in their operations. Many firms face unprecedented challenges with their inbound and outbound logistics, especially when raw materials used in their production processes are imported. Therefore, analyzing firms' shipment capacity, shipment frequency, freight cost per unit, and time-in-transit can help maintain optimum production and distribution levels, even during supply chain disruptions.

The study also concludes that inventory management analytics has a positive and significant influence on supply chain analytics among surveyed firms. However, most of these firms face challenges such as inaccurate stock tracking and high storage costs as they fail to fully adopt inventory management analytics practices. The study concludes that by monitoring and managing inventory levels, carrying costs, turnover rates, and backorder rates, firms can ensure the right amount of stock at any given time to minimize the impact of supply chain disruptions.

Most importantly, the study concludes that most roofing sheet manufacturing firms in the NMA face challenges with order fulfilment rates and on-time delivery, even from their most trusted suppliers. Although inferential statistics suggest that supplier-related risk analytics and supply chain resilience have a positive and significant relationship, most of these firms only partially engage in supplier-related risk analytics in their daily operations, exposing them to supply chain vulnerabilities such as poor-quality products.

6.1 Recommendations of the Study

This study makes several recommendations to the management of roofing sheet manufacturing firms in NMA. First, the study recommends that firms should embrace demand forecasting practices such as analyzing seasonal trends, historical data, and market trends to understand demand gaps for improved supply chain resilience. Identifying risks associated with demand will help the firms meet demands even in the most hostile supply disruptions. The study also recommends the use of logistics operations analytics by undertaking vigorous processes for understanding and optimizing shipment capacity and time-in-transit against odd weather patterns and traffic congestion to bolster supply chain resilience. Firms should also ensure optimum shipment frequency on materials and finished products to avoid challenges that come with overstocking and understocking.

Additionally, this study recommends innovation in the manner in which roofing sheet manufacturing firms manage their inventory. Some of the key innovative practices include keeping track of the backorder rates and turnover rates. They may supply chain visibility for improved supply chain resilience during downturns and surges in demand.The study also recommends that firms stress on supplier-related risk analytics, given that it has a huge bearing on quality standards and customer service. The firms should institutionalize supplier-related risk analytics by tracking suppliers' metrics on order fulfilment, on-time delivery, and quality performance to identify and resolve supply chain issues quickly. This desire may demand close collaboration with the suppliers.

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