ISSN: 2617-4138
DOI: 10.32898/ibmj.01/8.2article03
www.ijarke.com

INTERNATIONAL JOURNALS OF ACADEMICS & RESEARCH
(IJARKE Business & Management Journal)

Supply Chain Risk Management Strategies and Logistics Operational Performance at Standard Gauge Railways – Nairobi, Kenya

Gideon Wamoyi, Technical University of Kenya, Kenya

Abstract

Globally, supply chains are facing increasing disruptions from pandemics, political instability, and infrastructure gaps. In Kenya, the Standard Gauge Railway (SGR), a Vision 2030 flagship, enhances cargo efficiency but remains vulnerable to operational risks. This study examined the effects of Supply Chain Risk Management Strategies (SCRMS) on logistics operational performance at the SGR Nairobi. The research focused on four dimensions, including risk identification, mitigation, assessment, and control and monitoring, with supply chain integration (SCI) as a moderator. Using Resource-Based View (RBV), Contingency Theory, and Information Processing Theory (IPT), a descriptive cross-sectional design targeted 250 staff, sampling 110 via stratified random sampling. Structured questionnaires collected data, which were analyzed in SPSS using descriptive and inferential statistics. Risk mitigation ($\beta = 0.419$, $p < .001$) and identification ($\beta = 0.272$, $p = .009$) significantly improved performance, while assessment had no effect ($\beta = -0.017$, $p = .812$) and control or monitoring was marginal ($\beta = 0.140$, $p = .059$). SCI had a direct effect ($\beta = 0.329$, $p = .002$) but no moderation. The findings demonstrate that risk mitigation and risk identification, supported by integration, are key to resilience. The study concludes that strengthening risk management practices and integration mechanisms is essential for sustainable logistics performance at the SGR. It recommends investment in advanced risk assessment tools, digital platforms, and collaborative frameworks to enhance resilience and operational excellence.

Key words: *Supply Chain Risk Management, Supply Chain Integration, Logistics Performance, Standard Gauge Railway*

1. Introduction

Over time, supply chain management has undergone extensive transformation driven by technological advancement, globalization, and shifting customer demands. However, the global risk landscape has equally evolved, exposing organizations to disruptions arising from pandemics, geopolitical tensions, cyber incidents, and climate events (Moreno, 2022). Such complexities have elevated the need for robust supply chain risk management (SCRM) strategies that enhance resilience and operational efficiency (Gurtu & Johny, 2021). The strength of any supply chain depends on its weakest link. As networks lengthen and interdependencies deepen, the probability of disruption increases (Ferreira de Araújo et al., 2020). Therefore, effective risk management and supply chain integration are vital to maintaining logistics continuity and minimizing losses. In Kenya, these global challenges are mirrored in the operations of the Standard Gauge Railway (SGR), a Vision 2030 flagship infrastructure designed to enhance logistics efficiency. While the SGR has improved regional connectivity, it still faces persistent risks linked to political, financial, and infrastructural uncertainties. Strengthening SCRM and integration mechanisms is thus central to the SGR's long-term sustainability and competitiveness.

1.1 Supply Chain Risk Management (SCRM)

SCRM is a systematic process for identifying, evaluating, mitigating, and monitoring potential disruptions in the supply chain (Aqlan & Lam, 2016). Historical shocks such as the Gulf War, the September 11 attacks, and the COVID-19 pandemic illustrate how unmitigated risks can paralyze logistics systems worldwide (Gurtu & Johny, 2021). Kenya's logistics sector has experienced similar vulnerabilities. The 2007–2008 post-election violence, the COVID-19 pandemic and periodic border closures have disrupted freight flows along the Northern Corridor, causing severe delivery delays. Moreover, region-specific issues like customs system failures, infrastructure gaps, and driver strikes continue to expose operational weaknesses. SCRM, therefore, demands collaboration among supply chain actors to identify and respond to risks collectively. Literature emphasizes that integrated risk approaches improve responsiveness, reduce uncertainty, and support sustainable logistics performance (Zhu et al., 2017). In Kenya's logistics landscape, particularly in the operations of the SGR, such collaboration is vital to ensure consistent service delivery, minimize disruptions, and support regional trade and economic development.

1.2 Supply Chain Integration (SCI)

Gonzalez (2022) defines integration as the degree to which the actions of different actors within an organization are systematically coordinated through established mechanisms to achieve common goals. Effective integration promotes visibility,

trust, and efficiency by linking procurement, production, and distribution into a seamless system. Drawing on Information Processing Theory (IPT), integration enhances a firm's ability to process and act on complex data, improving its response to uncertainty (Wasike et al., 2018). Al-Hajjim and Al-Salman (2021) note that integration capabilities enable firms to acquire and deploy resources efficiently toward shared strategic goals. For the SGR, SCI provides the structural cohesion necessary to coordinate multiple logistics stakeholders and ensure uninterrupted cargo operations.

1.3 Logistic Operation Performance

Logistics operational performance represents how effectively a firm delivers goods and services from origin to destination while optimizing time, cost, and quality (Ying et al., 2018). These services form the backbone of supply chain functionality, ensuring that products are efficiently and reliably delivered. It is typically assessed through key performance indicators (KPIs) such as delivery reliability, flexibility, customer satisfaction, and service quality (Oke, 2022). In this study, logistics performance is conceptualized as a second-order construct comprising quality, flexibility, delivery, and customer-service performance (Kauppi et al., 2016). Efficient logistics systems enhance competitiveness, reduce waste, and strengthen customer trust, all of which are essential for infrastructure-based entities like the SGR.

1.4 Standard Gauge Railways (SGR)

Kenya's Standard Gauge Railway is the most ambitious infrastructure project since independence, designed to connect Mombasa to the Great Lakes region and strengthen regional trade integration. The project supports Vision 2030's economic pillar by facilitating cargo mobility, reducing road congestion, and stimulating industrial growth (Githaiga & Bing, 2019). Despite its potential, the SGR faces operational and financial challenges, including high maintenance costs, limited cargo uptake, and insufficient inter-agency coordination. Continuous evaluation and integration with other transport networks thus remain vital to achieving long-term viability and regional economic transformation.

2. Statement of the Problem

Modern supply chains operate within a volatile environment characterized by political unrest, pandemics, and infrastructural gaps. Inadequate risk identification and fragmented mitigation frameworks undermine logistics efficiency and responsiveness (Zhang et al., 2020). At the SGR, the absence of coherent and integrated SCRM systems constrains its ability to sustain operations during disruptions, leading to delays, cost overruns, and reduced reliability. Although numerous studies highlight the importance of proactive risk management (Nair et al., 2024), empirical evidence specific to the SGR context is limited. Therefore, this study investigates the effects of SCRM strategies (risk identification, mitigation, assessment, and monitoring) on logistics operational performance, considering supply chain integration as a moderating factor.

3. Objective of the Study

The main objective of the study was to assess the Supply Chain Risk Management Strategies on Logistics operational performance at the Standard Gauge Railway in Kenya.

4. Literature Review

4.1 Theoretical Framework

4.1.1 Resource-Based Framework

The Resource-Based View (RBV) argues that internal resources and capabilities, when valuable, rare, inimitable, and non-substitutable, are the principal sources of sustained competitive advantage (Barney, 1991; Wernerfelt, 1984). Within the RBV, dynamic capabilities describe an organization's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments. For the SGR, risk identification, mitigation, assessment, and control/monitoring represents such strategic capabilities. Well-developed risk frameworks, contingency plans, and information-sharing systems function as resources that improve logistics operational performance. From this perspective, shortcomings in skills, technology, or funding reduce the effectiveness of SCRM and explain implementation gaps observed in infrastructure projects.

4.1.2 Information Processing Theory (IPT)

Information Processing Theory posits that organizational performance depends on matching information processing capacity to environmental uncertainty (Galbraith, 1973). In complex supply chains, IPT suggests that investments in real-time analytics, predictive models, and collaborative information platforms improve an organization's ability to detect and respond to disruptions. Applied to SGR, IPT implies that risk identification and mitigation are effective only when supported by adequate data flows and decision systems. Thus, IPT links directly to the study variables by explaining why integration (which enhances information flow) strengthens SCRM outcomes.

ISSN: 2617-4138
DOI: 10.32898/ibmj.01/8.2article03
www.ijarke.com

4.1.3 Contingency Theory

Contingency Theory holds that there is no universally best management approach as strategies must fit internal capabilities and external conditions (Donaldson, 2001). For SCRM, this means risk tools and mitigation measures must be tailored to the operating context (e.g., infrastructure maturity, regulatory environment, political risk). In the SGR setting, Contingency Theory explains variation in the success of high-tech solutions versus low-cost operational fixes. When contextual constraints (budget, skills, policy) are binding, adaptive and context-appropriate risk strategies outperform generic prescriptions.

Overall, RBV explains what internal capabilities matter (resources and dynamic capabilities), IPT explains how information and integration enable those capabilities to function under uncertainty, and Contingency Theory explains when and which strategies are appropriate given the operating environment. Together, these theories justify examining identification, mitigation, assessment, and control/monitoring as distinct SCRM constructs and testing supply chain integration as a moderator.

4.2 Empirical Studies

Empirical research on Supply Chain Risk Management (SCRM) and performance consistently affirms the critical role of risk identification, mitigation, and integration in driving resilience and operational efficiency. Kauppi et al. (2016) demonstrated that information-processing capabilities, enabled by advanced IT systems and collaborative platforms, enhance SCRM by allowing real-time risk detection and response. Similarly, Flynn, Huo, and Zhao (2010) found that firms with higher levels of supply chain integration are better positioned to manage risks through improved visibility and trust among partners.

Yang et al. (2021), in a large-scale study of Chinese manufacturers, confirmed that integration, supported by data analytics and blockchain, strengthens the link between information processing capability and risk management success. Rashid et al. (2022) expanded this evidence by showing that digitization enhances visibility and traceability, reducing uncertainty across the supply chain. These findings collectively underscore the importance of information quality, collaborative decision-making and digital transformation in sustaining logistics performance.

Despite these insights, empirical work remains concentrated in manufacturing and retail sectors, often overlooking infrastructure-driven logistics systems such as rail networks. Limited studies have tested the moderating role of integration within the African context, where infrastructural and institutional challenges shape risk outcomes differently. Therefore, there is a research gap in contextualizing how SCRM and SCI jointly affect logistics operational performance in large-scale public transport systems like Kenya's SGR.

.

4.3 Conceptual Framework

The framework links SCRMS (identification, mitigation, assessment, control/monitoring) to performance, moderated by SCI.

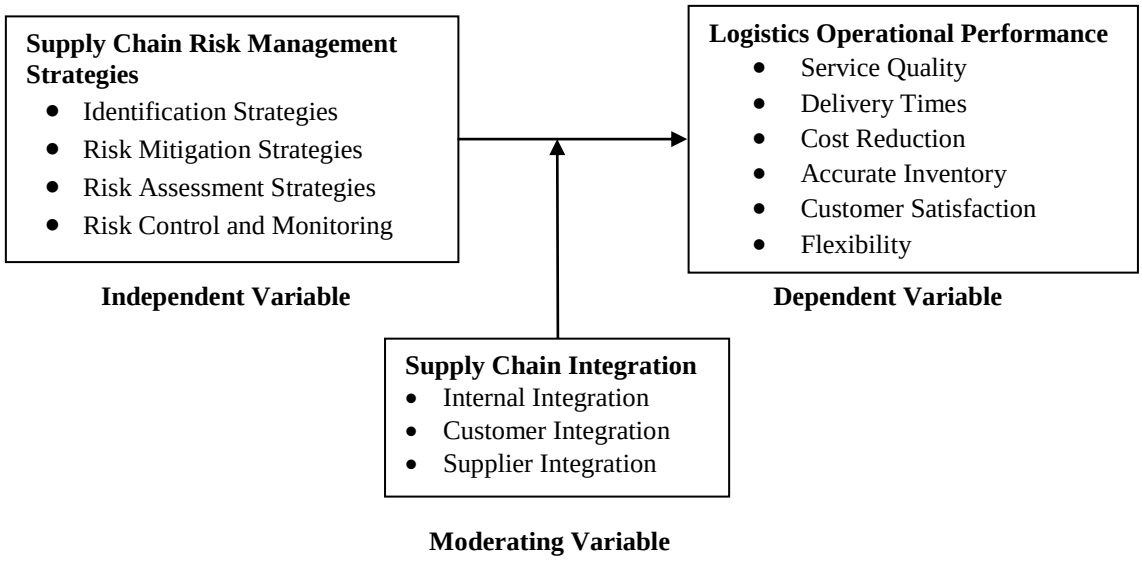

Fig. 1: Conceptual Framework

4.4 Literature Gaps and Contribution

Existing studies confirm the effectiveness of SCRM in improving operational performance, but rarely examine infrastructure projects within developing economies. Research focusing on manufacturing and retail does not capture the complexity of rail logistics networks, where public-private coordination and policy environments play a vital role. Furthermore, empirical investigations into the moderating effects of integration remain scarce, especially in the East African logistics sector.

ISSN: 2617-4138
DOI: 10.32898/ibmj.01/8.2article03
www.ijarke.com

This study bridges these gaps by focusing on the Standard Gauge Railway, a major public infrastructure under Kenya's Vision 2030. It provides evidence on how SCRM dimensions and SCI can collectively influence logistics operational performance and highlights the contextual challenges of implementing risk mitigation strategies within public-sector logistics operations. By integrating theoretical perspectives from RBV, IPT, and Contingency Theory, this study contributes both conceptually and empirically to supply chain risk management literature in emerging markets.

5. Research Design

This study adopted a descriptive quantitative research design, employing a cross-sectional survey to collect data from respondents at a single point in time. This approach is appropriate for examining relationships between variables using numerical data analyzed through statistical methods. The design enables efficient data collection from a large sample, offering representativeness and cost-effectiveness compared to longitudinal studies (Creswell & Creswell, 2017). This design aligns with the study's objective of assessing the effects of supply chain risk management strategies and supply chain integration on logistics operational performance at the Standard Gauge Railway (SGR).

The unit of analysis for this study was the organization, focusing on departments directly involved in supply chain and logistics operations at the SGR. The target population comprised 250 personnel distributed across four key departments: supply chain (49), operations (140), transporters (36), and senior administrative staff (25). These groups were selected because they oversee the movement of goods, procurement, warehousing, and policy implementation related to supply chain risk management and logistics performance (Hashmi et al., 2020).

Table 1: Target Population

Respondents	Frequency	% Frequency
Supply Chain	49	19.6
Operations	140	56
Transporters	36	14.4
Senior administrative staff	25	10
Totals	**250**	**100**

Sampling was conducted to ensure that the findings were representative of the population. Using Yamane's (1967) formula with a 95% confidence level and 5% margin of error, the study derived a sample size of 110 respondents from a total population of 250:

$$n = N/ (1 + N (e^2))$$

$$= 250 (1+ 250 (0.05)^2 = 110$$

Table 2: Sample Population

Respondents	Frequency	% Frequency
Supply Chain	21	19.4
Operations	62	55.9
Transporters	16	14.4
Senior administrative staff	11	9.9
Totals	**110**	**100.0**

A stratified random sampling technique was employed to ensure proportional representation from each department (Creswell & Creswell, 2018). Stratification enhanced the accuracy and reliability of the findings by ensuring that each group with distinct operational functions was fairly represented in the sample.

Data were collected using a structured questionnaire developed from relevant literature on supply chain risk management, integration, and logistics performance. The questionnaire included both closed-ended and Likert-scale items designed to capture respondents' perceptions consistently and quantitatively (Saunders et al., 2019).

Data were gathered using self-administered structured questionnaires, distributed physically and electronically to respondents in the supply chain, operations, transport, and administrative departments. Respondents were assured of confidentiality and anonymity to encourage honest feedback. Data collection occurred within a defined timeframe, and follow-ups were made to maximize response rates. This approach ensured comprehensive coverage and efficiency in obtaining insights on SCRM practices and their impact on logistics operational performance (Creswell & Creswell, 2018).

ISSN: 2617-4138
DOI: 10.32898/ibmj.01/8.2article03
www.ijarke.com

Both descriptive and inferential statistics were used to analyze the collected data. Descriptive statistics (mean, standard deviation, and percentages) summarized demographic characteristics and general responses. Inferential statistics, including correlation and multiple regression analysis, were employed to determine the relationships between supply chain risk management strategies, supply chain integration, and logistics operational performance. Data were analyzed using the Statistical Package for the Social Sciences (SPSS) software. The following multivariate regression models guided hypothesis testing:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \mu \ldots\ldots\ldots\ldots\ldots\ldots \text{ Model 1}$$

$$Y = \beta_0 + \beta_1 X_1 Z + \beta_2 X_2 Z + \beta_3 X_3 Z + \beta_4 X_4 Z + \mu \ldots\ldots\ldots\ldots\ldots \text{ Model 2}$$

Where,

Y = Logistics Operational performance
X_1 = Supply Chain Risk Management strategies
X_2 = Supply chain risk mitigation strategies
X_3= Risk Assessment
X_4 =Risk Control and Monitoring
Z_4 = Supply Chain Integration Management

In the model, β_0 = the constant term, while the coefficient β_i = 1, 2, 3, 4 was used to measure the sensitivity of the dependent variable (Y) to a unit change in the predictor variables X_1, X_2, X_3, and X_4. μ is the error term, which captures the unexplained variations in the model.

6. Research Findings and Discussion

6.1 Demographic Profile

A total of 110 respondents participated in the survey. Table 3 presents the demographic breakdown across gender, age, education, department, job level, and years of service based on frequency analysis.

Table 3: Demographic Profile of Respondents

Variable	Category	Frequency	Percentage (%)
Gender	Male	73	66.4
	Female	37	33.6
Age Group	20-24 Years	7	6.4
	25-29 Years	23	20.9
	30-34 Years	48	43.6
	Above 35 Years	32	29.1
	Certificate	6	5.5
	Diploma	42	38.2
	Undergraduate	45	40.9
	Postgraduate	17	15.5
Department	Supply Chain	19	17.3
	Operations	21	19.1
	Transport	37	33.6
	Procurement	21	19.1
	Senior Staff Admin	12	10.9
Job Level	Senior Management	25	22.7
	Middle Management	55	50.0
	Lower Management	30	27.3
Years in Department	<1 Year	4	3.6
	1-2 Years	20	18.2
	3-4 Years	26	23.6
	5-6 Years	17	15.5
	>6 Years	43	39.1

The sample was predominantly male (66.4%), consistent with employment trends in the logistics and transport industry in Kenya. The majority of respondents were aged 30-34 years (43.6%), followed by those above 35 years (29.1%), indicating a relatively youthful but experienced workforce. Educationally, 40.9% were undergraduates and 38.2% diploma holders, suggesting a fairly well-educated workforce. The largest department represented was transport (33.6%), which aligns with the operational focus of SGR. Regarding job levels, half of the respondents were in middle management (50%), indicating the survey captured insights from staff involved in day-to-day management of supply chain activities. Lastly, a large proportion of respondents (39.1%) had more than six years of experience, showing substantial institutional knowledge within the workforce.

ISSN: 2617-4138
DOI: 10.32898/ibmj.01/8.2article03
www.ijarke.com

6.2 Descriptive Statistics

Table 4 presents the descriptive statistics for the six-studies constructs, each measured using multiple items averaged into composite scores.

Table Error! No text of specified style in document.**: Descriptive Statistics for Study Constructs**

	N	Mean	Std. Deviation	Skewness	
	Statistic	Statistic	Statistic	Statistic	Std. Error
Risk Identification Strategies (RIS)	110	4.0091	.77974	-.959	.230
Risk Assessment (RA)	110	3.7255	.56818	-.379	.230
Risk Mitigation Strategies (RMS)	110	4.1473	.70212	-1.048	.230
Risk Control and Monitoring Strategies (RCMS)	110	4.0564	.77915	-1.519	.230
Supply Chain Integration (SCI)	110	4.1309	.75050	-1.065	.230
Logistics Operational Performance (LOP)	110	4.0109	.52591	-.329	.230
Valid N (listwise)	110				

All constructs had means above 3.7, indicating general agreement that SGR employs effective SCRMS and SCI, leading to a strong LOP. RMS (M = 4.15, SD = 0.70) and SCI (M = 4.13, SD = 0.75) had the highest means, reflecting robust mitigation like supplier diversification and integration, such as partner coordination. RA had the lowest mean (M = 3.73, SD = 0.57), suggesting less agreement on risk assessment practices.

Logistics operational performance itself had a mean of 4.01 (SD = 0.53), suggesting respondents generally agreed that SGR's operations are reliable, cost-efficient, and responsive. Negative skewness for most constructs indicates clustering at the higher end of the scale, reinforcing the perception that respondents largely viewed risk management practices and integration positively.

6.3 Inferential Statistics

6.3.1 Correlation Analysis

Pearson's correlation coefficients were computed to examine relationships between variables.

Table 5: Correlation Matrix

		RIS	RA	RMS	RCMS	SCI	LOP
RIS	Pearson Correlation	1					
	Sig. (2-tailed)						
	N	110					
RA	Pearson Correlation	-.097	1				
	Sig. (2-tailed)	.313					
	N	110	110				
RMS	Pearson Correlation	.725**	-.035	1			
	Sig. (2-tailed)	.000	.718				
	N	110	110	110			
RCMS	Pearson Correlation	.240*	.001	.319**	1		
	Sig. (2-tailed)	.012	.989	.001			
	N	110	110	110	110		
SCI	Pearson Correlation	.648**	-.103	.659**	.390**	1	
	Sig. (2-tailed)	.000	.282	.000	.000		
	N	110	110	110	110	110	
LOP	Pearson Correlation	.611**	-.057	.661**	.339**	.667**	1
	Sig. (2-tailed)	.000	.551	.000	.000	.000	
	N	110	110	110	110	110	110

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

ISSN: 2617-4138
DOI: 10.32898/ibmj.01/8.2article03
www.ijarke.com

Risk mitigation strategies (r = .661, p < .01), supply chain integration (r = .667, p < .01), and risk identification strategies (r = .611, p < .01) showed strong positive correlations with logistics performance. On the other hand, Risk control and monitoring strategies were moderately correlated with performance (r = .339, p < .01), suggesting they play a smaller but still positive role. Risk assessment, however, was weakly and negatively correlated with performance (r = -0.057), indicating that assessment practices as currently implemented do not translate into operational improvements.

6.3.2 Regression Analysis for Model 1: Effect of SCRMS on Logistic Performance

Table 6: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.701[a]	.492	.472	.38203	1.967

a. Predictors: (Constant), Risk Control and Monitoring Strategies, Risk Assessment, Risk Identification Strategies, Risk Mitigation Strategies

b. Dependent Variable: Logistics Operational Performance

Table 7: ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14.823	4	3.706	25.391	.000[b]
	Residual	15.324	105	.146		
	Total	30.147	109			

a. Dependent Variable: Logistics Operational Performance

b. Predictors: (Constant), Risk Control and Monitoring Strategies, Risk Assessment, Risk Identification Strategies, Risk Mitigation Strategies

Table 8: Regression Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.648	.360		4.573	.000
	Risk Identification Strategies	.183	.069	272.000	2.673	.009
	Risk Assessment	-.015	.065	-.017	-.238	.812
	Risk Mitigation Strategies	.314	.078	.419	4.042	.000
	Risk Control and Monitoring Strategies	.095	.050	.140	1.909	.059

a. Dependent Variable: Logistics Operational Performance

This model is significant F (4,105) = 25.391, p < .001), and explains 49.2% of the variance in logistics performance. The regression equation is:

LOP = 1.648 + 0.183RIS + 0.314RMS + 0.095RCMS.

Risk mitigation strategies (β = 0.419, p < .001) and risk identification strategies (β = 0.272, p < .01) were significant positive predictors of logistics performance. This indicates that effective mitigation (such as supplier diversification and technology use) and systematic risk identification significantly improve delivery reliability, cost efficiency, and responsiveness. Risk control and monitoring strategies were marginally significant (β = 0.140, p = .059), suggesting limited influence. Risk assessment was not significant (β = -0.017, p = .812), indicating no measurable impact on performance.

6.3.3 Regression Analysis for Model 2: Moderating Role of SCI.

A hierarchical regression was conducted to test whether SCI moderated the relationship between SCRMS and LOP. Variables were centered to reduce multicollinearity, and interaction terms were created.

ISSN: 2617-4138
DOI: 10.32898/ibmj.01/8.2article03
www.ijarke.com

Table 9: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.738[a]	.545	.523	.36311	
2	.746[b]	.556	.516	.36570	1.975

a. Predictors: (Constant), SCI centered, RA centered, RCMS centered, RIS centered, RMS centered

b. Predictors: (Constant), SCI centered, RA centered, RCMS centered, RIScentered, RMS centered, Int_RA, Int_RCMS, Int_RIS, Int_RMS

c. Dependent Variable: Logistics Operational Performance

Table 10: ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	16.435	5	3.287	24.930	.000[b]
	Residual	13.712	104	.132		
	Total	30.147	109			
2	Regression	16.774	9	1.864	13.936	.000[c]
	Residual	13.373	100	.134		
	Total	30.147	109			

a. Dependent Variable: Logistics Operational Performance

b. Predictors: (Constant), SCI centered, RA centered, RCMS centered, RIS centered, RMS centered

c. Predictors: (Constant), SCI centered, RA centered, RCMS centered, RIS centered, RMS centered, Int_RA, Int_RCMS, Int_RIS, Int_RMS

Table 11: Regression Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	3.999	.035		114.878	.000
	RIS centered	.105	.069	.155	1.516	.133
	RA centered	.003	.062	.003	.046	.964
	RMS centered	.227	.078	.303	2.908	.004
	RCMS centered	.049	.049	.073	1.011	.315
	SCI centered	.237	.068	.339	3.497	.001
2	(Constant)	3.972	.042		95.699	.000
	RIS centered	.097	.074	.144	1.311	.193
	RA centered	-.018	.065	-.020	-.281	.779
	RMS centered	.260	.084	.348	3.090	.003
	RCMS centered	.063	.059	.094	1.071	.287
	SCI centered	.230	.074	.329	3.115	.002
	Int_ RIS	.047	.087	.071	.543	.588
	Int RA	.101	.108	.077	.934	.353
	Int_ RMS	.032	.108	.046	.300	.765
	Int _RCMS	.004	.093	.006	.047	.963

a. Dependent Variable: Logistics Operational Performance

The first regression model, which included the centered independent variables and the centered moderator, explained 54.5% of the variance in logistic performance, $R^2 = .545$, $F(5,104) = 24.930$, $p < .001$. The second model, which added the interaction terms, explained an additional 1.1% of the variance, bringing the total variance explained to 55.6%, but this change was not significant, $R^2 = .545$, $F(5,104) = 13.94$, $p < .001$. The coefficients indicated that in the first model, RMS ($\beta = 0.348$, $p < .01$) and SCI ($\beta = 0.329$, $p < .01$) were significant predictors of performance.

In Model 2, no interaction terms were significant ($p > .05$), indicating that SCI did not moderate the relationships between SCRMS and performance. However, SCI remained a strong independent predictor, alongside RMS. This result suggests that while integration directly enhances logistics outcomes by improving coordination and responsiveness, it does not necessarily amplify or boost the effects of risk management strategies. Therefore, SCI works as a parallel driver rather than a moderator.

ISSN: 2617-4138
DOI: 10.32898/ibmj.01/8.2article03
www.ijarke.com

6.4 Hypothesis Testing Summary

The results for the five hypotheses (H_{01}-H_{05}) are summarized below, based on the regression and moderation analyses.

Table12: Hypothesis Testing Summary

Hypothesis	Description	Result	Evidence
H_{01}	Risk identification strategies do not have any statistical influence on Logistics operational performance	Rejected	β = .272, p=.009, r=.61, p< .01
H_{02}	Supply chain risk mitigation strategies do not have any statistical effects on logistics operational performance	Rejected	β=.419, p<.001, r=.66, p< .01
H_{03}	Supply Chain risk assessment has no statistical effects on Logistics operational performance	Not Rejected	β= -.017, p = .812, r = -.06, p = .551
H_{04}	Risk control and monitoring do not have any statistical effects on logistics operational performance	Not Rejected	β=.140, p = .059, r = .34, p < .01
H_{05}	Supply chain integration does not have any statistically significant moderating effects on the relationship between SCRM and Logistics operational performance	Not Rejected	ΔR^2=.011, p=.0, interaction p-values > 0.05

6.5 Discussion of Findings

The results showed that risk mitigation strategies were the strongest and most consistent predictors of logistics operational performance (β = 0.419, p < .001). This highlights that SGR's proactive measures, such as supplier diversification, technology adoption, and contingency planning, are crucial in ensuring delivery reliability and cost efficiency. These results align with resilience theory, which emphasizes adaptive capacity and flexibility as core factors in maintaining performance during disruptions (Ivanov & Dolgui, 2021). Similar conclusions by Chowdhury et al. (2021) confirm that firms with robust mitigation frameworks recover faster from external shocks like pandemics or geopolitical disruptions.

Risk identification strategies also emerged as a significant predictor of logistics performance (β = 0.272, p = .009). This underscores the importance of mapping potential threats, maintaining visibility, and establishing early warning systems. Proactive identification enables timely response and coordination, reducing the severity of disruptions. This aligns with Fan and Stevenson (2018) and Christopher and Peck (2020), who emphasize that accurate identification forms the foundation of any effective supply chain risk management system.

Contrary to expectations, risk assessment had no significant impact on logistics operational performance (β = -0.017, p = .812). This suggests that while risk scoring and prioritization exist conceptually, they may not be effectively implemented at SGR. Limited analytical capacity and reliance on subjective judgment could explain this weak relationship, as noted by Mwangi & Kariuki (2021) in similar developing-economy contexts.

Risk control and monitoring strategies were only marginally significant (β = 0.140, p = .059), implying that monitoring mechanisms exist but are not dynamic or technology-driven enough to influence outcomes strongly. This finding echoes Ghadge et al. (2020), who observed that static monitoring systems often lag in rapidly evolving logistics environments.

A major contribution of this study is the finding that supply chain integration has a strong direct effect on logistics performance (β = 0.329, p = .002), but does not moderate the relationship between SCRMS and performance. This means that integration contributes independently to outcomes but does not significantly strengthen or weaken the effect of risk management strategies. This result diverges from some studies that have found integration to play a moderating or mediating role (Zhang et al., 2020). Instead, it suggests that at SGR, integration functions as a separate driver of performance. Integration practices such as real-time communication with partners, joint planning, and information sharing create efficiency gains that are valuable regardless of the quality of risk management practices.

7. Summary of Findings, Conclusions and Recommendations

The study sought to examine how Supply Chain Risk Management Strategies (SCRMS) influence logistics operational performance at the Standard Gauge Railway (SGR), focusing on risk identification, mitigation, assessment, and control, with supply chain integration (SCI) as a moderating variable.

Findings revealed that risk identification (β = 0.272, p = .009) and risk mitigation (β = 0.419, p < .001) significantly improved logistics performance by enhancing delivery reliability and efficiency. Risk assessment had no significant effect (β = -0.017, p = .812), suggesting weak analytical links to operations, while risk control and monitoring showed marginal significance (β = 0.140, p = .059). SCI had a strong direct effect (β = 0.329, p = .002) but no moderating influence, indicating it acts as an independent driver of operational efficiency. Overall, mitigation and identification emerged as the most critical determinants of SGR's logistics performance.

The study implies that effective supply chain risk management strategies, particularly risk identification and mitigation, are essential for enhancing logistics operational performance at SGR. It highlights that while integration directly improves efficiency, risk assessment and monitoring practices need further development. The findings suggest that managers should strengthen proactive risk measures and data-driven decision-making, while policymakers should support standardized frameworks that promote resilience and coordination across logistics systems. Overall, the study reinforces the importance of combining strategic risk management and integration to achieve sustainable operational performance.

The study concludes that SCRMS are critical in shaping logistics performance at SGR, though their effectiveness varies across strategies. Risk identification and mitigation stand out as the most impactful, while risk assessment and monitoring require further strengthening. Supply chain integration directly enhances performance but does not amplify the effects of SCRMS. This suggests that resilience in railway logistics relies both on robust risk management strategies and on efficient integration practices operating in parallel.

References

1. Al-Hajjim, H. N., & Al-Salman, H. A. (2021). The role of sustainable production in achieving sustainable competitive advantage through the mediating variable of dynamic capabilities. *Economic Sciences*, *16*(61), 24-51.
2. Aqlan, F., & Lam, S. S. (2016). Supply chain risk modeling and mitigation. International Journal of Production Research, 54(21), 6234–6249.
3. Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108.
4. Christopher, M., & Peck, H. (2020). Mitigating supply chain risk through resilience strategies. International Journal of Physical Distribution & Logistics Management, 50(9), 821-840. https://doi.org/10.1108/IJPDLM-04-2020-1128.
5. Chowdhury, P., Paul, S. K., Kaisar, S., & Moktadir, Md. A. (2021). COVID-19 pandemic-related supply chain studies: A systematic review. *Transportation Research Part E: Logistics and Transportation Review*, *148*(102271), 102271. NCBI. https://doi.org/10.1016/j.tre.2021.102271.
6. Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approach*. Sage Publications.
7. Donaldson, L. (2001). *The Contingency Theory of Organizations. Sage Publications, Inc., New York. – References-Scientific Research Publishing*. Www.scirp.org. https://www.scirp.org/reference/referencespapers?referenceid=1365575.
8. Fan, Y., & Stevenson, M. (2018). A review of supply chain risk management: Definition, theory, and research agenda. *International Journal of Physical Distribution & Logistics Management*, *48*(3), 205–230. Emerald. https://doi.org/10.1108/ijpdlm-01-2017-0043.
9. Flynn, B. B., Huo, B., & Zhao, X. (2010). The impact of supply chain integration on performance: A contingency and configuration approach. *Journal of Operations Management*, *28*(1), 58-71. https://doi.org/10.1016/j.jom.2009.06.001.
10. Ferreira de Araújo Lima, P. F., Crema, M., & Verbano, C. (2020). Risk management in SMEs: A systematic literature review and future directions. *European management journal*, *38*(1), 78-94. https://doi.org/10.1016/j.emj.2019.06.005.
11. Galbraith, J. (1973). *Designing Complex Organizations. Addison-Wesley, Boston. - References - Scientific Research Publishing*. Www.scirp.org. https://www.scirp.org/reference/referencespapers?referenceid=1404747.
12. Ghadge, A., Er Kara, M., Moradlou, H., & Goswami, M. (2020). The impact of Industry 4.0 implementation on supply chains. *Journal of Manufacturing Technology Management*, *31*(4), 669-686. https://dspace.lib.cranfield.ac.uk/bitstreams/fa9f9bc9-9100-4bf0-baa2-26f05c0a9e22/download
13. Githaiga, W., & Bing, X. (2019). Kenya Vision 2030 and the Standard Gauge Railway: An analysis of national development goals. Journal of African Development, 22(1), 45–67.
14. Gonzalez, R. V. D. (2022). Innovative performance of project teams: the role of organizational structure and knowledge-based dynamic capability. Journal of Knowledge.
15. Gurtu, A., & Johny, J. (2021). Supply chain risk management: Literature review. Risks, 9(1), 16.
16. Hashmi, A. R., Amirah, N. A., & Yusof, Y. (2020). Mediating effect of integrated systems on the relationship between supply chain management practices and public healthcare performance: Structural

ISSN: 2617-4138
DOI: 10.32898/ibmj.01/8.2article03

Equation Modeling. *International Journal of Management and Sustainability*, *9*(3), 148-160. https://doi.org/10.18488/journal.11.2020.93.148.160.

17. Ivanov, D., & Dolgui, A. (2021). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control*, *32*(9), 775–788. https://doi.org/10.1080/09537287.2020.1768450.
18. Kariuki, M. C., & Dr. Samuel Wabala. (2021). Influence Of Procurement Planning on The Procurement Performance of Selected County Governments In Kenya. *International Research Journal of Business and Strategic Management*, *2*(2). https://www.irjp.org/index.php/irjbsm/article/view/39.
19. Kauppi, K., Longoni, A., Caniato, F., & Kuula, M. (2016). Managing Country Disruption Risks and Improving Operational Performance: Risk Management along Integrated Supply Chains. *International Journal of Production Economics*, *182*, 484-495. https://doi.org/10.1016/j.ijpe.2016.10.006.
20. Moreno, J. P. (2022). International Trade and the Rise of Digital Borders. *Trade, Law & Development*, *16*(1).
21. Nair, A., Jayaram, J., & Roth, A. V. (2024). Dynamic capabilities and risk management under environmental turbulence. Journal of Operations Management, 83, 143–156.
22. Oke, A. E. (2022). Operational performance: A measure of project success. In Measures of Sustainable Construction Projects Performance (pp. 129–134). Emerald Publishing Limited.
23. Rashid, A., Rasheed, R., Ngah, A., Jayaratne, M., Rahi, S., &Tunio, M. N. (2024). Role of information processing and digital supply chain in supply chain resilience through supply chain risk management. Journal of Global Operations and Strategic Sourcing, 17(1). https://doi.org/10.1108/JGOSS-12-2023-0106
24. Saunders, M., Lewis, P., & Thornhill, A. (2019, May). *Saunders, Research Methods for Business Students, 8/E*. Www.pearson.com. https://www.pearson.com/se/Nordics-Higher-Education/subject-catalogue/business-and-management/Research-methods-for-business-students-8e-saunders.html
25. Wasike, S., Sagwa, E., & Sakwa, M. (2018). Supply chain integration on the performance of public universities in Kenya.
26. Wernerfelt, B. (1984). A Resource-Based View of the Firm. *Strategic Management Journal*, *5*(2), 171–180. http://web.mit.edu/bwerner/www/papers/AResource-BasedViewoftheFirm.pdf.
27. Yang, J., Xie, H., Yu, G., & Liu, M. (2021). Antecedents and consequences of supply chain risk management capabilities: An investigation in the post-coronavirus crisis. *International Journal of Production Research*, *59*(5), 1573-1585. https://doi.org/10.1080/00207543.2020.1856958.
28. Ying, F., Tookey, J., & Seadon, J. (2018). Measuring the invisible: A key performance indicator for managing construction logistics performance. *Benchmarking: an international journal*, *25*(6), 1921-1934.
29. Zhang, Q., Fan, W., Lu, J., Wu, S., & Wang, X. (2020). Research on Dynamic Analysis and Mitigation Strategies of Supply Chains under Different Disruption Risks. *Sustainability*, *13*(5), 2462. https://doi.org/10.3390/su13052462.
30. Zhu, Q., Krikke, H., & Caniëls, M. C. (2017). Integrated supply chain risk management: a systematic review. *The International Journal of Logistics Management*, *28*(4), 1123-1141. https://doi.org/10.1108/IJLM-09-2016-0206.