

Risk Management Practices and Supply Chain Disruption Mitigation in Global Supply Networks

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Abstract

➤ Purpose:

This study examines the relationships between supply chain risk management (SCRM) practices and disruption mitigation effectiveness in global supply networks. Drawing on resource-based view (RBV) and dynamic capabilities theory, this study investigates how four core SCRM practices – risk identification, risk assessment, risk mitigation, and risk monitoring individually and collectively influence an organisation's ability to mitigate supply chain disruptions.

➤ Design/Methodology/Approach:

Cross-sectional survey data were collected from 487 organisations managing international supply chains across diverse industries between September 2023 and February 2024. Hypothesised relationships were tested using partial least squares structural equation modelling (PLS-SEM), with synergistic effects of integrated SCRM practices examined through hierarchical model comparison.

➤ Findings:

All four SCRM practices exert significant positive effects on disruption mitigation effectiveness. Risk mitigation demonstrates the strongest direct influence ($\beta = 0.284$, $p < .001$), followed by risk monitoring ($\beta = 0.212$), risk assessment ($\beta = 0.198$), and risk identification ($\beta = 0.176$). The integrated model explains 56.8% of variance in disruption mitigation effectiveness – a statistically significant 12.1 percentage-point improvement over the best individual practice model ($p < .001$), confirming synergistic effects. Mediation analyses reveal that risk assessment and risk monitoring partially mediate the relationship between risk identification and disruption mitigation effectiveness, with variance accounted for (VAF) of 43.4% and 42.9%, respectively.

➤ Practical Implications:

Organisations should develop holistic SCRM capabilities integrating all four practices rather than investing in isolated interventions. Risk mitigation practices represent the highest-priority improvement opportunity given their combination of high importance and relatively moderate current performance levels.

➤ Originality/Value:

This study provides robust empirical support for SCRM frameworks across diverse organisational contexts, demonstrating synergistic effects of coordinated SCRM practices and identifying specific mediating mechanisms that amplify disruption mitigation effectiveness.

Keywords: *Supply Chain Risk Management; Disruption Mitigation; Risk Identification; Risk Assessment; Risk Mitigation; Risk Monitoring; Supply Chain Resilience; Resource-Based View; Dynamic Capabilities; PLS-SEM.*

I. INTRODUCTION

The vulnerability of global supply chains has intensified substantially owing to increased network complexity and inter-organisational interconnectedness (Belhadi et al., 2021; Chowdhury et al., 2021). Recent disruptions precipitated by the COVID-19 pandemic, geopolitical instability, natural disasters, and cyber-attacks have exposed the inadequacies of conventional supply chain management approaches and underscored the strategic imperative of effective risk management (Sharma et al., 2022; Golan et al., 2020). The World Economic Forum (2020) estimates that supply chain disruptions result in average annual profit losses equivalent to 45% of one year's EBITDA over a decade for the typical organisation, highlighting the severe financial consequences of inadequate risk preparedness.

Supply chain risk management (SCRM) has emerged as a critical organisational competency, encompassing the systematic identification, evaluation, reduction, and monitoring of potential threats across the supply network (Fan et al., 2017; Pournader et al., 2019). Despite growing scholarly interest, significant gaps remain in understanding how specific SCRM practices translate into disruption mitigation outcomes in global supply networks (Paul et al., 2021; Scholten et al., 2019). Prior research has been predominantly conceptual or single-sector in nature, with limited empirical validation across diverse organisational contexts (Bier et al., 2020; Singh et al., 2020).

This study addresses these gaps by empirically examining the relationships between SCRM practices and supply chain disruption mitigation effectiveness. Grounded in RBV (Barney, 2018) and dynamic capabilities theory (Teece, 2018), this study conceptualises SCRM practices as organisational capabilities that enhance firms' adaptive capacity in the face of disruption. Specifically, this study examines four SCRM practices: risk identification, risk assessment, risk mitigation, and risk monitoring and their individual and collective effects on disruption mitigation effectiveness.

This study makes four contributions to the SCRM literature. First, it provides robust multi-context empirical evidence on the direct relationships between SCRM practices and disruption mitigation effectiveness. Second, it identifies mediating mechanisms through which risk management practices amplify disruption outcomes. Third, it establishes the relative importance of different SCRM practices, informing resource allocation decisions. Fourth, it advances theoretical development by integrating RBV and dynamic capabilities theory to explain how organisations build and exercise risk management capabilities.

II. THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

➤ *Resource-Based View and Dynamic Capabilities Theory*

The resource-based view (RBV) provides a theoretical lens for understanding how competitive advantage arises from the strategic deployment of valuable, rare, inimitable, and non-substitutable organisational resources (Barney, 2018). In the context of SCRM, risk management practices may be understood as organisational capabilities and strategic resources that enable firms to respond effectively to environmental uncertainties (Ambulkar et al., 2016; Ralston et al., 2013).

Dynamic capabilities theory (Teece, 2018; Warner & Wäger, 2018) extends the RBV by emphasising the importance of organisational capacities to sense, seize, and reconfigure resources in response to changing environmental conditions. This perspective is particularly relevant to SCRM because supply chain disruptions constitute precisely the kind of dynamic contingency that demands rapid adaptive response and resource reallocation (Ambulkar et al., 2016; Beske et al., 2014).

The theoretical integration of RBV and dynamic capabilities offers a comprehensive explanatory framework for how SCRM practices contribute to disruption mitigation (Ali et al., 2021; Wieland & Durach, 2021). SCRM practices simultaneously represent static resources—the knowledge, systems, and processes organisations deploy to manage supply chain uncertainty and dynamic capabilities, reflecting organisations' abilities to adapt, learn, and restructure in response to disruptive events.

➤ *Supply Chain Risk Management Practices*

• *Risk Identification*

Risk identification is the foundational SCRM practice involving the systematic detection and documentation of potential disruption sources across the supply chain (Wieland & Durach, 2021). Effective risk identification requires organisations to conduct continuous internal and external environmental scanning to develop comprehensive knowledge of potential threats and their origins (Bier et al., 2020; Dolgui et al., 2020). Organisations with superior risk identification capabilities detect emerging threats earlier, affording greater anticipatory preparation time and enabling more targeted response design (Choi et al., 2016).

• *Risk Assessment*

Risk assessment involves the systematic evaluation of the likelihood and potential impact of identified risks to prioritise risk management resources (Kilubi, 2016; Paul et al., 2021). This practice requires organisations to develop systematic methods for analysing risk characteristics, including occurrence probability, potential severity, and impact propagation velocity (Ivanov & Dolgui, 2020). Contemporary approaches increasingly

incorporate quantitative modelling, scenario analysis, and simulation techniques to improve assessment precision (Hosseini & Ivanov, 2020).

• *Risk Mitigation*

Risk mitigation encompasses the proactive strategies and actions organisations implement to reduce the probability or severity of potential supply chain disruptions (Christopher & Holweg, 2017; Zsidisin & Wagner, 2010). Common strategies include supplier diversification, strategic safety stock positioning, production flexibility development, and business continuity planning (Chowdhury et al., 2021; Golan et al., 2020). Effective risk mitigation strategies are tailored to specific risk characteristics and aligned with organisational capabilities (Craighead et al., 2020).

• *Risk Monitoring*

Risk monitoring entails the ongoing surveillance of risk indicators and measurement of risk management performance (Fan et al., 2017; Scholten et al., 2019). This practice enables organisations to detect evolving risk profiles, assess the effectiveness of mitigation measures, and identify improvement opportunities in SCRM processes (Ali et al., 2021). Digital technologies

including IoT sensors, blockchain, and AI-based analytics have substantially expanded real-time monitoring capabilities, enabling dynamic risk surveillance across complex global networks (Queiroz et al., 2020).

➤ *Hypothesis Development*

Grounded in RBV and dynamic capabilities theory, this study hypothesises that each SCRM practice functions as an organisational capability that amplifies disruption mitigation performance by enabling firms to anticipate, prepare for, and respond to supply chain disruptions.

- H1: Risk identification practices positively influence supply chain disruption mitigation effectiveness.
- H2: Risk assessment practices positively influence supply chain disruption mitigation effectiveness.
- H3: Risk mitigation practices positively influence supply chain disruption mitigation effectiveness.
- H4: Risk monitoring practices positively influence supply chain disruption mitigation effectiveness.
- H5: Integrated SCRM practices (risk identification, assessment, mitigation, and monitoring) collectively explain greater variance in disruption mitigation effectiveness than individual practices in isolation.

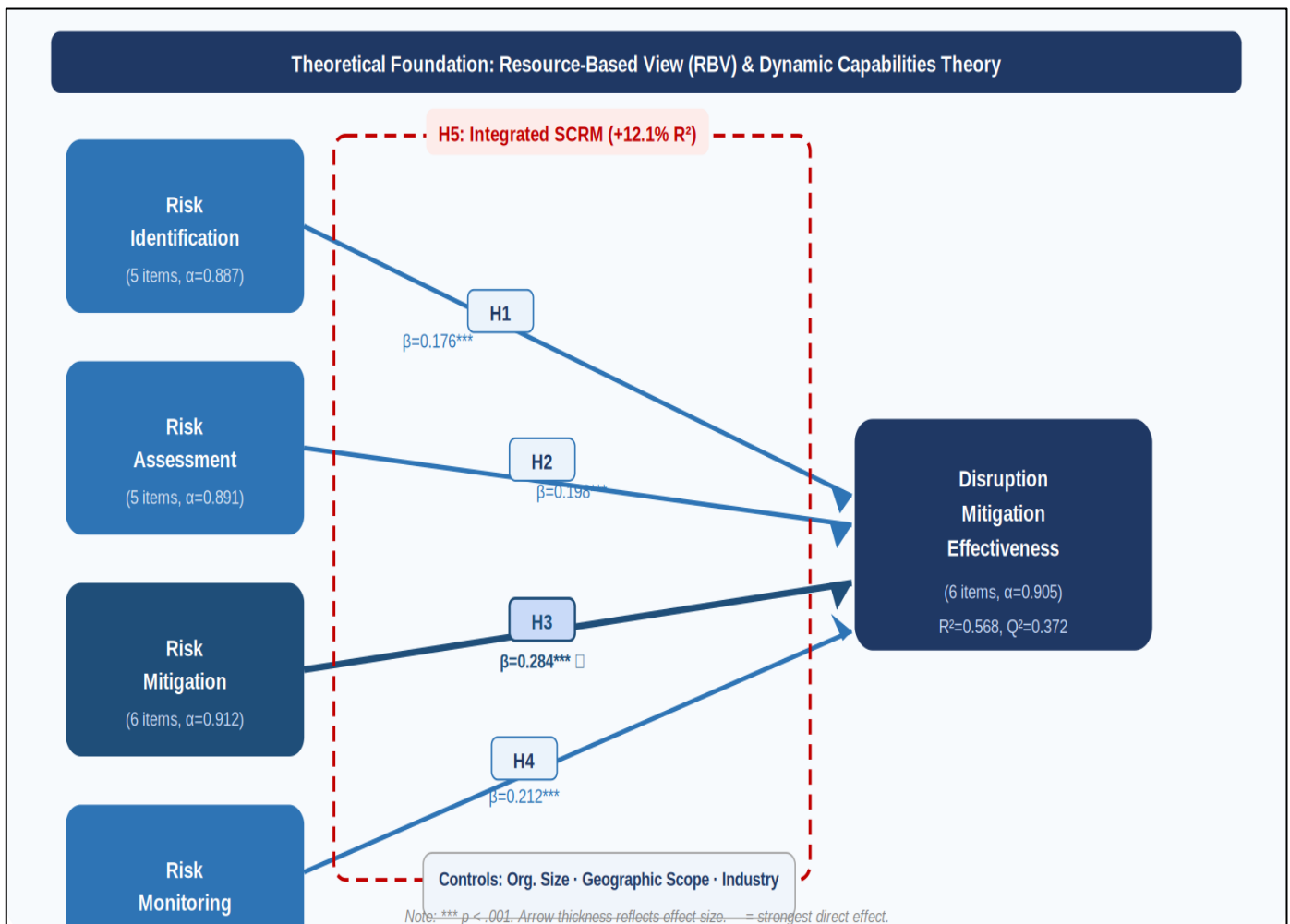


Fig 1 Conceptual framework illustrating the hypothesised relationships between SCRM practices and disruption mitigation effectiveness (DME). Arrow thickness reflects relative effect size. Dashed border = integrated SCRM model (H5). Theoretical foundation: Resource-Based View (Barney, 2018) and Dynamic Capabilities Theory (Teece, 2018).

III. RESEARCH METHODOLOGY

➤ *Research Design and Data Collection*

This study employs a cross-sectional survey design to examine the relationships between SCRM practices and disruption mitigation effectiveness. The target population comprised organisations managing international supply chains across multiple industries, with eligibility criteria of annual revenues exceeding US\$50 million and operations in at least three countries. The sampling frame was constructed from the Dun & Bradstreet and Bloomberg commercial databases, supplemented by industry association membership lists, to ensure broad organisational representation across industries, geographic regions, and firm sizes. Stratified random sampling was applied to balance representation across these strata (Cycyota & Harrison, 2006).

Data collection was conducted via an online survey administered to senior supply chain executives between September 2023 and February 2024. Survey invitations were sent to 2,850 eligible organisations; 487 usable responses were received, yielding a response rate of 17.1% consistent with established benchmarks for executive surveys (Cycyota & Harrison, 2006). Non-response bias was assessed by comparing the survey responses of early and late respondents on key firm characteristics following Armstrong and Overton (1977); no significant differences were detected (all $p > .05$), indicating non-response bias is unlikely to confound findings.

Common method bias was assessed using two procedures: Harman's single-factor test, in which the largest extracted factor accounted for 38.7% of total variance below the 50% threshold (Podsakoff et al., 2003) and the full collinearity variance inflation factor (VIF) test (Kock, 2015), which yielded no values exceeding conventional thresholds. Both assessments indicate common method variance is unlikely to represent a material threat to the validity of findings.

➤ *Measurement Instruments*

All constructs were operationalised using multi-item scales adapted from previously validated instruments, with responses captured on seven-point Likert scales (1 = strongly disagree, 7 = strongly agree). Risk Identification was assessed using five items adapted from Wieland and Wallenburg (2012) and Fan et al. (2017), measuring systematic risk detection and documentation. Risk Assessment was measured with five items adapted from Manuj and Mentzer (2008) and Ambulkar et al. (2016), assessing risk analysis and prioritisation capabilities. Risk Mitigation was operationalised using six items adapted from Christopher and Holweg (2017) and Chowdhury et al. (2021), capturing strategies to reduce risk probability and severity. Risk Monitoring was assessed using four items adapted from Fan et al. (2017) and Scholten et al. (2019), measuring continuous risk surveillance and SCRM performance evaluation. Disruption Mitigation Effectiveness was measured with six items adapted from

Ambulkar et al. (2016) and Belhadi et al. (2021), assessing organisations' ability to sustain operations and minimise adverse impacts during disruption events.

Control variables included organisational size (log-transformed annual revenue and employee count), industry sector (dummy-coded), geographic scope (number of countries of operation), and supply chain complexity (number of tier-1 suppliers).

➤ *Analytical Approach*

Data were analysed using partial least squares structural equation modelling (PLS-SEM) in SmartPLS 4.0 (Ringle et al., 2022). PLS-SEM was selected for three reasons: (1) the research model incorporates multiple constructs with complex relationships; (2) the study is orientated toward prediction and theory development; and (3) PLS-SEM accommodates both formative and reflective measurement models (Hair et al., 2018). Missing data, comprising less than 2% of values, were addressed through listwise deletion in the final structural model estimation.

Analysis proceeded in two stages. In the first stage, the measurement model was evaluated for indicator reliability (loadings), internal consistency reliability (Cronbach's α , composite reliability), convergent validity (AVE), and discriminant validity (Fornell–Larcker criterion, HTMT ratio). In the second stage, the structural model was evaluated for path coefficients, significance levels (via bootstrapping with 5,000 replications), variance explained (R^2), and predictive relevance (Q^2). Synergistic effects (H5) were tested through hierarchical model comparison.

IV. RESULTS

➤ *Sample Characteristics*

Table 1 presents the demographic profile of the 487 responding organisations, demonstrating broad diversity across industries, revenue levels, geographic scope, and international experience.

Table 1 Sample Demographics (N = 487)

Characteristic	Category	Frequency	Percentage
Industry Sector	Manufacturing	178	36.5%
	Retail/Consumer Goods	98	20.1%
	Technology/Electronics	87	17.9%
	Pharmaceuticals/Healthcare	68	14.0%
	Logistics/Transportation	56	11.5%
Annual Revenue (USD)	\$50M–\$500M	142	29.2%
	\$500M–\$1B	115	23.6%
	\$1B–\$5B	127	26.1%
	>\$5B	103	21.1%
Geographic Scope	3–5 countries	134	27.5%
	6–10 countries	176	36.1%
	11–20 countries	109	22.4%
	>20 countries	68	14.0%
Years of Int'l Operations	<10 years	67	13.8%
	10–20 years	158	32.4%
	21–30 years	143	29.4%
	>30 years	119	24.4%

- Note. Percentages may not sum to exactly 100% due to rounding.

➤ *Measurement Model Assessment*

Table 2 Measurement Model Results Reliability and Convergent Validity

Construct	Items	Loading Range	Cronbach's α	CR	AVE
Risk Identification	5	0.819–0.845	0.887	0.917	0.689
Risk Assessment	5	0.812–0.856	0.891	0.920	0.697
Risk Mitigation	6	0.823–0.852	0.912	0.934	0.705
Risk Monitoring	4	0.812–0.834	0.847	0.892	0.674
Disruption Mitigation Effectiveness	6	0.812–0.841	0.905	0.927	0.681

Note. CR = composite reliability; AVE = average variance extracted. All indicator loadings > 0.708, all CR > 0.70, all AVE > 0.50 convergent validity confirmed (Hair et al., 2018).

All indicator loadings exceeded 0.708, Cronbach's α ranged from 0.847 to 0.912, composite reliability (CR) ranged from 0.892 to 0.934 all above the 0.70 threshold and average variance extracted (AVE) ranged from 0.674 to 0.705, all exceeding the 0.50 convergent validity

criterion (Hair et al., 2018). Table 3 reports discriminant validity assessment; all Fornell–Larcker diagonal values ($\sqrt{\text{AVE}}$) exceed the corresponding inter-construct correlations, and all HTMT ratios are below 0.85, confirming discriminant validity (Henseler et al., 2015).

Table 3 Discriminant Validity Fornell–Larcker Criterion and HTMT Ratios

Construct	RI	RA	RM	RMo	DME
Panel A: Fornell–Larcker Criterion (diagonal = $\sqrt{\text{AVE}}$)					
Risk Identification (RI)	0.830				
Risk Assessment (RA)	0.682	0.835			
Risk Mitigation (RM)	0.647	0.701	0.840		
Risk Monitoring (RMo)	0.624	0.658	0.687	0.821	
Disruption Mitigation Effectiveness (DME)	0.587	0.621	0.668	0.614	0.825
Panel B: HTMT Ratio (all values < 0.85 discriminant validity confirmed)					
Risk Assessment (vs RI)	0.769				
Risk Mitigation (vs RI)	0.712	0.778			
Risk Monitoring (vs RI)	0.714	0.741	0.774		
DME (vs RI)	0.651	0.685	0.735	0.697	

Note. Diagonal elements (Panel A) denote $\sqrt{\text{AVE}}$. HTMT = heterotrait–monotrait ratio; threshold < 0.85 (Henseler et al., 2015).

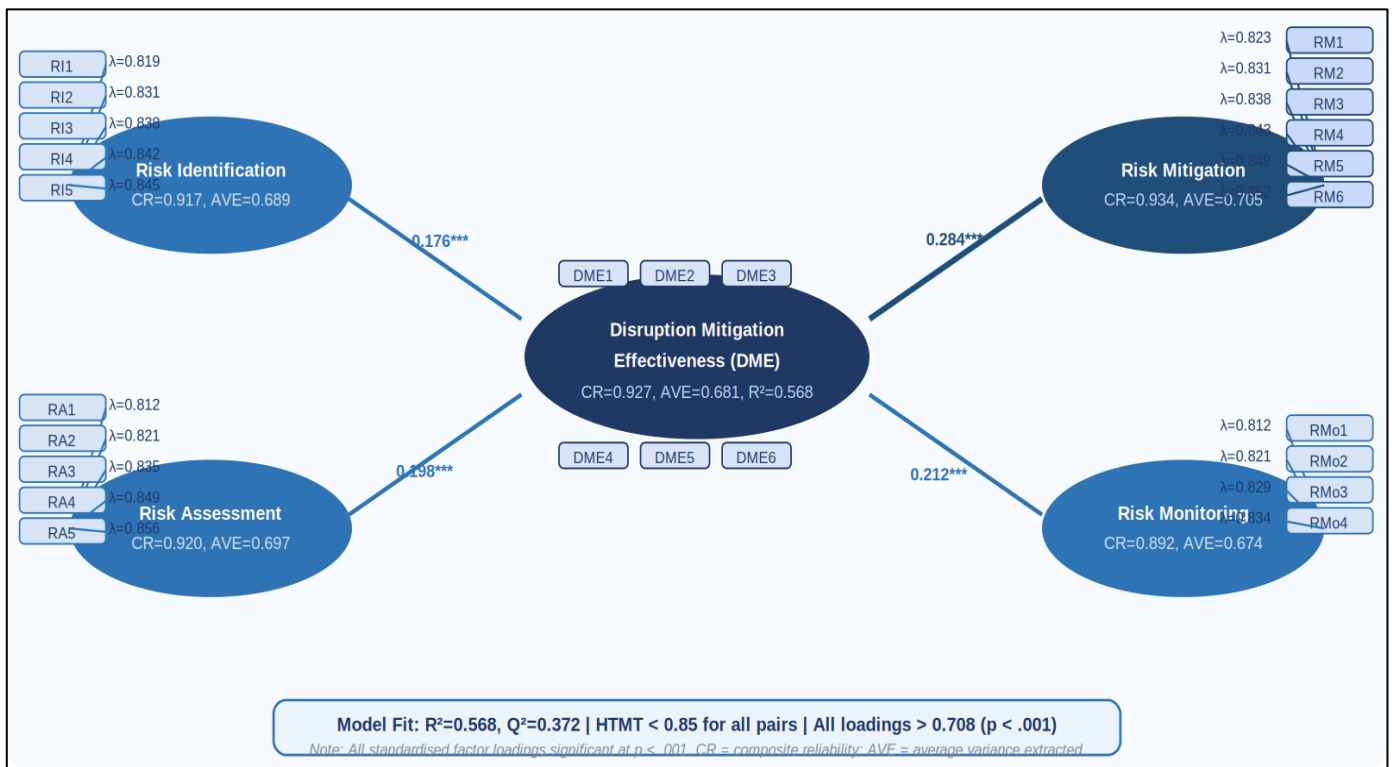


Fig 2 PLS-SEM measurement model with standardised factor loadings (λ), construct reliability, and validity statistics. All loadings significant at $p < .001$. Arrow thickness to DME reflects path coefficient magnitude. CR = composite reliability; AVE = average variance extracted; R^2 = variance explained in DME.

➤ **Structural Model and Hypothesis Testing**

Table 4 presents the structural model results for H1–H4. The model explains a substantial proportion of variance in disruption mitigation effectiveness ($R^2 = 0.568$), indicating strong explanatory power (Hair et al., 2018). The predictive relevance statistic $Q^2 = 0.372$ confirms the model's predictive validity.

• **H1–H4 Supported:**

All four SCRMs demonstrate significant positive effects on disruption mitigation effectiveness. Risk mitigation exhibits the strongest direct effect ($\beta = 0.284$, $p < .001$; $f^2 = 0.098$, medium effect size), followed by risk monitoring ($\beta = 0.212$, $p < .001$), risk assessment ($\beta = 0.198$, $p < .001$), and risk identification ($\beta = 0.176$, $p < .001$). All remaining practices exhibit small-to-medium effect sizes (Cohen, 1988).

Table 4 Structural Model Results Hypothesis Testing

Hyp.	Path	β	SE	t-value	p-value	Decision	f ²	Effect Size
H1	RI → DME	0.176	0.048	3.667***	< .001	Supported	0.042	Small
H2	RA → DME	0.198	0.051	3.882***	< .001	Supported	0.051	Small–Medium
H3	RM → DME	0.284	0.053	5.358***	< .001	Supported	0.098	Medium ★
H4	RMo → DME	0.212	0.049	4.327***	< .001	Supported	0.058	Small–Medium
Overall	All → DME					R ² =0.568		Q ² =0.372

Note. ***p < .001. β = standardised path coefficient; SE = standard error; f² = effect size (Cohen, 1988): small \geq 0.02, medium \geq 0.15, large \geq 0.35. ★ = strongest direct effect. R² = 0.568 indicates substantial explanatory power; Q² = 0.372 confirms predictive relevance (Hair et al., 2018).

➤ *Integrated Model Analysis (H5)*

Table 5 presents the hierarchical model comparison testing H5. The integrated model incorporating all four SCRM practices (Model 5: R² = 0.568) demonstrates substantially superior explanatory power relative to the best individual practice model (Model 3, Risk Mitigation

only: R² = 0.447). The Δ R² of 0.121 (12.1 percentage points) is statistically significant (p < .001), confirming that integrated SCRM practices generate synergistic effects beyond those achievable by any single practice providing full support for H5.

Table 5 Hierarchical Model Comparison Individual vs. Integrated SCRM Practices

Model	Practices Included	R ²	Adj. R ²	Δ R ²	Q ²
Model 1	Risk Identification only	0.345	0.343		0.228
Model 2	Risk Assessment only	0.386	0.385		0.257
Model 3	Risk Mitigation only	0.447	0.446		0.299
Model 4	Risk Monitoring only	0.377	0.375		0.251
Model 5 (Integrated)	All four SCRM practices	0.568	0.564	+0.121***	0.372

Note. *** Δ R² significantly higher than best individual model (Model 3), p < .001 H5 supported. Synergistic effects confirmed.

➤ *Control Variables and Importance–Performance Map Analysis*

Table 6 presents control variable effects and IPMA results. Organisational size and geographic scope exert small but significant positive effects on disruption mitigation effectiveness (β = 0.089, p = .009 and β = 0.112, p = .003, respectively), while industry sector differences are not significant, indicating cross-sector generalisability. IPMA results identify risk mitigation practices as simultaneously the most important (β = 0.284) and the lowest-performing (performance score = 58.2) practice, designating it the highest-priority area for improvement investment.

Table 6 Control Variables and Importance–Performance Map Analysis (IPMA)

Analysis	Variable / Practice	β / Importance	p / Performance	Interpretation
Control Variables				
	Organisational Size	0.089	.009**	Small positive effect on DME
	Geographic Scope	0.112	.003**	Small positive effect on DME
	Industry Sector		n.s.	No significant inter-industry differences
Importance–Performance Map Analysis (IPMA)				
	Risk Identification	0.176	64.3	Moderate importance and performance
	Risk Assessment	0.198	67.8	Moderate importance, relatively high performance
	Risk Mitigation	0.284	58.2	HIGH importance, MODERATE performance greatest development opportunity
	Risk Monitoring	0.212	61.5	Moderate importance and performance
Note. **p < .01; n.s. = not significant. IPMA performance scores on 0–100 scale. β = importance weight (path coefficient from structural model).				

➤ Mediation Analysis

Table 7 presents mediation analysis results. Risk assessment partially mediates the risk identification–disruption mitigation effectiveness relationship (VAF = 43.4%); risk monitoring partially mediates the same pathway (VAF = 42.9%). Risk mitigation partially mediates the risk assessment–disruption mitigation

effectiveness relationship (VAF = 50.1%), the strongest mediation effect. All indirect effects are statistically significant (p < .001) and bootstrap 95% confidence intervals exclude zero, confirming mediation (Preacher & Hayes, 2008). The persistence of significant direct effects in all paths confirms partial, rather than full, mediation.

Table 7 Mediation Analysis Results

Mediation Path	Direct Effect (c')	Indirect Effect (a×b)	Total Effect (c)	VAF	Mediation Type
RI → Risk Assessment → DME	0.176***	0.135***	0.311***	43.4%	Partial
RI → Risk Monitoring → DME	0.176***	0.132***	0.308***	42.9%	Partial
RA → Risk Mitigation → DME	0.198***	0.199***	0.397***	50.1%	Partial
Note. ***p < .001. VAF = variance accounted for. Bootstrap 95% CIs exclude zero for all indirect effects (5,000 replications). Partial mediation: direct effect remains significant after inclusion of mediator.					

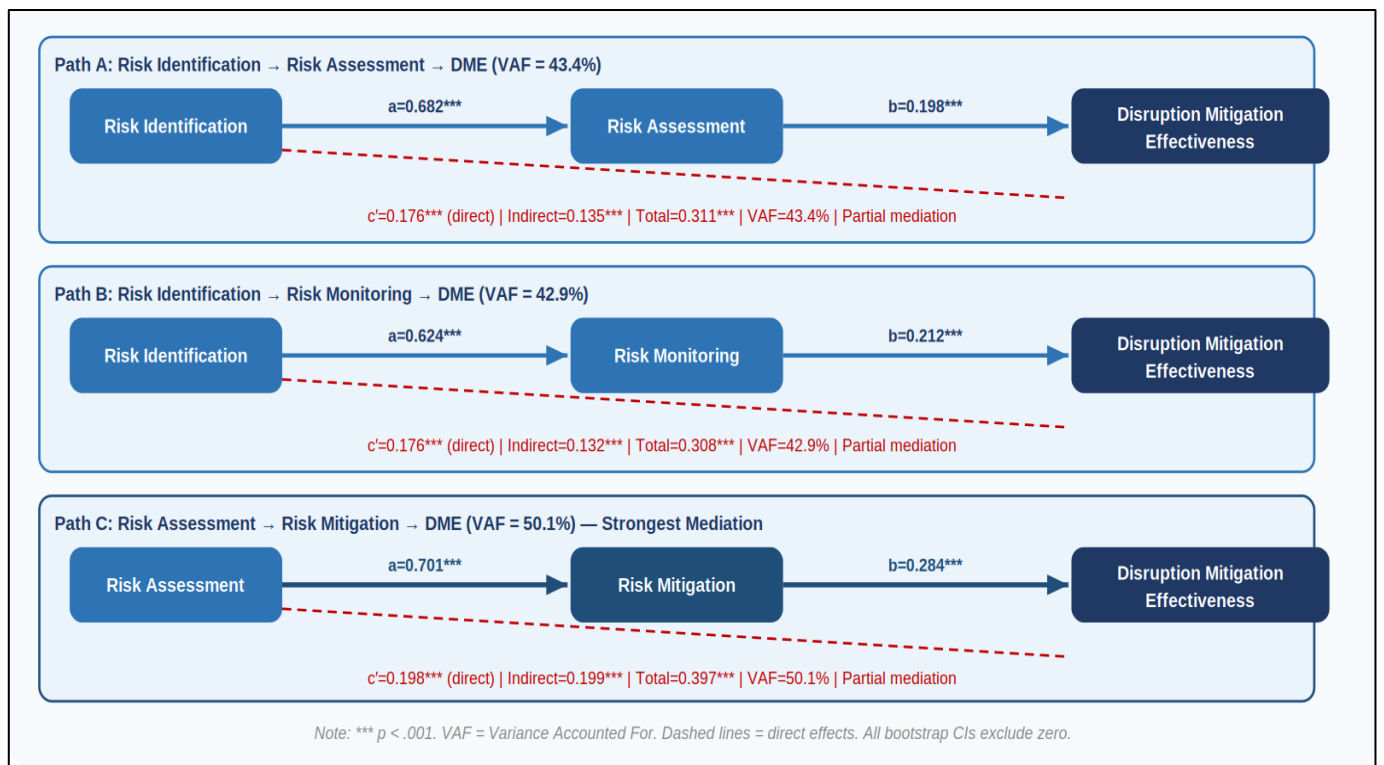


Fig 3 Mediation analysis diagrams for all three significant indirect pathways. Solid arrows = direct effects (c'); dashed arrows = indirect effects (a × b). VAF = variance accounted for. All indirect effects significant at p < .001 with bootstrap 95% CIs excluding zero.

➤ *Multi-Group Analysis*

Table 8 presents multi-group analysis comparing manufacturing and service industry sub-samples. No statistically significant inter-group path differences were detected (all p > .05), indicating that the structural relationships between SCRM practices and disruption mitigation effectiveness are robust across industry contexts.

Table 8 Multi-Group Analysis: Manufacturing vs. Service Industries

Path	Manufacturing (n=265)	Service (n=222)	Path Difference	p-value	Interpretation
RI → DME	0.183	0.168	0.015	0.687	No sig. difference
RA → DME	0.206	0.189	0.017	0.724	No sig. difference
RM → DME	0.312	0.251	0.061	0.173	No sig. difference
RMo → DME	0.221	0.201	0.020	0.631	No sig. difference

Note. All p > .05 no significant inter-industry differences detected. Findings generalisable across manufacturing and service supply chain contexts.

➤ *Robustness Checks*

Table 9 summarises five robustness tests. Alternative CB-SEM estimation (AMOS 26.0) yields path coefficients deviating by no more than 0.03 from PLS-SEM estimates. Split-sample validation produces path correlations exceeding 0.95 across sub-samples. Alternative dependent variable specifications, outlier exclusion analyses, and the unmeasured latent common method factor test all confirm the stability and generalisability of findings.

Table 9 Robustness Checks Summary

Robustness Test	Method	Result	Interpretation
Alternative estimation	CB-SEM (AMOS 26.0)	Path coefficients differ by < 0.03	Robust to estimation method
Split-sample validation	Random split (n ₁ =244, n ₂ =243)	Path correlation > 0.95	Stable across sub-samples
Alternative DV specification	Operational vs. Financial DME	Consistent directional effects	Generalises across DME dimensions
Outlier analysis	Exclusion of 12 extreme cases	Path coefficients change < 0.04	Not driven by outliers
Common method variance	Unmeasured latent method factor	Factor loadings < 0.15	CMV not a concern

Note. All robustness tests confirm the stability and validity of findings across analytical methods and specifications.

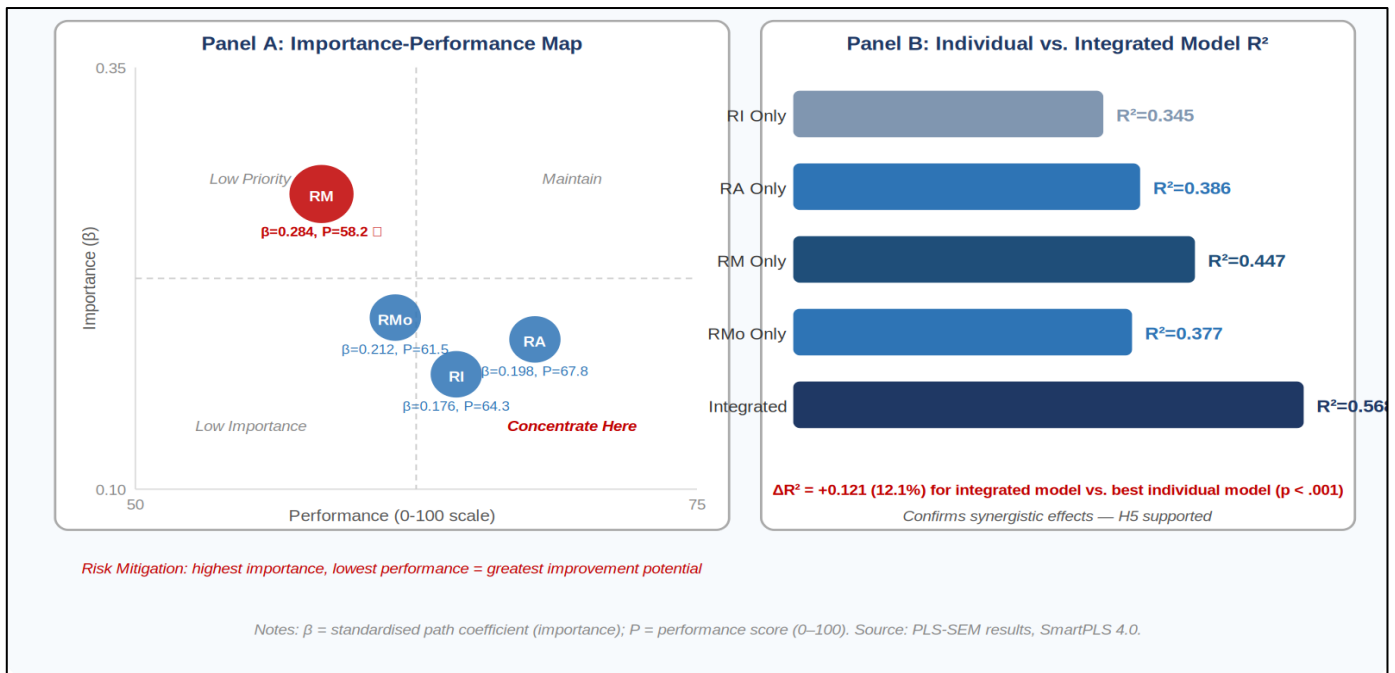


Fig 4 Panel A: Importance–Performance Map Analysis (IPMA). Risk Mitigation (RM) occupies the "Concentrate Here" quadrant highest importance ($\beta=0.284$), lowest performance score (58.2), signifying the greatest development opportunity. Panel B: R² comparison across individual and integrated SCRM practice models, demonstrating the 12.1% synergistic improvement from integrated implementation (H5 supported).

V. DISCUSSION

➤ Theoretical Implications

This study makes several significant theoretical contributions to the SCRM literature. First, it provides robust empirical confirmation of positive direct relationships between individual SCRM practices and disruption mitigation effectiveness across diverse global supply network contexts. Whilst these relationships have previously been theorised (Fan et al., 2017; Wieland & Durach, 2021), this study offers quantitative validation across a broad cross-section of organisational environments advancing beyond the predominantly conceptual and sector-specific literature (Bier et al., 2020).

Second, the application of RBV and dynamic capabilities theory provides novel theoretical insight into the mechanisms through which SCRM practices function

as organisational capabilities. The findings confirm that risk management practices constitute valuable strategic assets enabling organisations to sense, seize, and reconfigure resources in response to disruptive events (Tece, 2018; Ambulkar et al., 2016). The significant positive contribution of all four practices provides empirical support for the theoretical proposition that these capabilities collectively enhance organisational resilience through improved information processing, resource allocation, and adaptive responsiveness (Chowdhury et al., 2021).

Third, the empirically confirmed synergistic effect of integrated SCRM practices ($\Delta R^2 = 12.1\%$) constitutes a meaningful theoretical advancement by demonstrating that SCRM practices function as complementary capabilities rather than substitutes. This finding corroborates theoretical propositions regarding the inter-

connectedness of risk management processes (Wieland & Durach, 2021) and establishes empirically that organisations benefit from developing SCRM as a holistic capability system rather than investing in isolated practices.

Fourth, mediation analysis provides new theoretical insight into the mechanisms through which risk identification ultimately contributes to disruption mitigation. Partial mediation effects suggest that risk identification improves mitigation outcomes both directly and indirectly through superior assessment and monitoring capabilities consistent with information processing theory (Bode et al., 2011). The RA → RM → DME pathway (VAF = 50.1%) is particularly noteworthy, demonstrating that effective assessment translates into more impactful mitigation strategies.

➤ *Practical Implications*

The findings carry several actionable implications for supply chain practitioners. Organisations should invest in developing holistic SCRM capabilities encompassing all four practices, as the synergistic R² improvement of 12.1% demonstrates that integrated approaches yield substantially superior disruption mitigation outcomes relative to single-practice investments. While resource constraints may necessitate prioritisation, the complementary nature of SCRM practices means that investments across the full capability portfolio deliver the greatest returns.

IPMA results provide targeted resource allocation guidance. Risk mitigation practices present the highest development potential high strategic importance combined with moderate current performance levels warranting priority investment. Specifically, organisations should focus on: (1) supplier diversification strategies to reduce single-source dependency; (2) flexible production and logistics systems enabling rapid network reconfiguration; (3) strategic inventory buffering to absorb demand and supply shocks; (4) comprehensive business continuity planning covering diverse disruption scenarios; and (5) collaborative risk management with key supply chain partners.

For risk identification, organisations should establish regular supplier risk assessment programmes, intelligence-driven market scanning, cross-functional risk identification teams, technology-enabled monitoring (IoT, AI, and blockchain), and inter-organisational information sharing alliances. Risk assessment capabilities should be developed through systematic frameworks incorporating quantitative risk modelling, scenario analysis, network interdependency mapping, simulation tools, and integration of external data sources. Risk monitoring capabilities should be enhanced through real-time dashboards, periodic review processes, KPI-based performance measurement, organisational learning mechanisms, and technology platforms providing end-to-end supply chain visibility.

The finding that organisational size and geographic scope exert small but significant positive effects on disruption mitigation effectiveness indicates that larger, globally diversified organisations derive some structural advantage. However, the modest effect sizes suggest that smaller organisations can achieve effective disruption mitigation through targeted SCRM capability investments, without requiring the scale advantages of larger counterparts.

➤ *Limitations and Future Research Directions*

This study has several limitations that circumscribe interpretation and indicate promising future research directions. First, the cross-sectional design constrains causal inference; future longitudinal studies should trace how SCRM capability investments evolve and their lagged effects on disruption outcomes over time. Second, self-reported perceptual measures may not fully capture objective organisational SCRM capability levels; future research would benefit from objective performance metrics, such as actual recovery durations, financial loss quantification, and operational continuity measures.

Third, the sample is concentrated in larger organisations with substantial international operations; future research should extend SCRM investigations to small and medium-sized enterprises (SMEs), which face distinct resource constraints and risk profiles. Fourth, this study examines four core SCRM practices; future research should explore additional practices including risk communication, collaborative risk governance, and the application of digital technologies (AI, blockchain, IoT, digital twins) as SCRM enhancers.

Fifth, configuration theory and qualitative comparative analysis (QCA) could productively be applied to investigate whether alternative combinations of SCRM practices yield equifinal disruption mitigation outcomes. Sixth, cost-benefit analysis of SCRM practice investments remains an important gap warranting empirical attention. Finally, future research should investigate moderating factors including environmental dynamism, supply chain complexity, organisational culture, leadership commitment, and disruption type that condition the effectiveness of SCRM practices.

VI. CONCLUSION

This study examines the relationships between SCRM practices and disruption mitigation effectiveness in global supply networks. Based on data from 487 organisations, all four SCRM practices risk identification, risk assessment, risk mitigation, and risk monitoring demonstrate significant positive effects on disruption mitigation effectiveness, with risk mitigation exhibiting the strongest direct influence ($\beta = 0.284, p < .001$).

The findings carry substantial theoretical and practical value. Theoretically, this study provides empirical validation of SCRM capability frameworks, advances understanding of risk management practices as dynamic capabilities, and demonstrates the synergistic

benefits of integrated SCRM implementation. Practically, the findings offer specific, prioritised guidance on resource allocation, with risk mitigation practices representing the most critical investment opportunity.

The integrated SCRM model's explanatory superiority ($R^2 = 0.568$, representing a 12.1 percentage-point improvement over the best single-practice model) underscores the importance of holistic approaches to supply chain risk management. Organisations seeking to build genuine resilience should develop balanced capabilities across identification, assessment, mitigation, and monitoring, rather than concentrating resources in any single practice domain.

As global supply chains face compounding disruption threats from pandemics, geopolitical volatility, climate change, and technological disruption, the imperative to build robust risk management capabilities has never been more pressing. The evidence-based framework offered by this study provides actionable guidance for organisations seeking to navigate turbulent global environments and build supply chains that are not merely efficient, but genuinely resilient.

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