



Development and Pilot Validation of a Measurement Instrument for Supply Chain Risk Management, Supply Chain Resilience, Big Data Analytics Capability, and Organisational Performance in Nigeria's Downstream Oil Sector

^{1*}Ali Shuaibu Abdulrahman, ²Norhayati Zakuan, ³Teh Zaharah Yaacob, ⁴Umar Gunu, ⁵Ridwan Shuaibu Abdulrahman, and ⁶Suleiman Ibrahim Kasim.

^{1*}Faculty of Management, Federal University Dutse, Nigeria and Faculty of Management, Universiti Teknologi Malaysia, Malaysia,

^{2,3}Faculty of Management, Universiti Teknologi Malaysia, Malaysia,

⁴Faculty of Management, University of Ilorin, Nigeria,

⁵Department of Quantity Surveying, Ahmadu Bello University, Zaria, and

⁶Faculty of Management, Federal University Dutse, Nigeria.

^{1*}Corresponding Authors Email: alishuaibu@graduate.utm.my

Abstract

The downstream oil and gas sector in Nigeria is highly susceptible to operational disruptions, yet there is a paucity of reliable instruments to measure supply chain risk management (SCRM), supply chain resilience (SCR), big data analytics capability (BDAC), and organizational performance in such contexts. This pilot study aimed to develop and validate a measurement instrument tailored to this high-risk, resource-constrained environment. Items were adapted from established scales in the literature and refined through expert review for content validity and contextual relevance. The instrument was administered to 40 heads of operational units across storage, distribution, and retail outlets. Reliability of reflective constructs was assessed using Cronbach's alpha and Corrected Item Total Correlation (CITC), while formative constructs were evaluated for multicollinearity using Variance Inflation Factor (VIF) and tolerance statistics. Results indicated satisfactory internal consistency across all reflective constructs (Cronbach's α ranging from 0.710 to 0.884) and no multicollinearity issues among formative indicators (VIF = 1.013–2.144). Two items were flagged for low CITC but retained for theoretical completeness. The findings demonstrate that the instrument is reliable, contextually appropriate, and suitable for full-scale validation. This study provides a methodological foundation for future empirical research in disruption-prone sectors and contributes a tool for assessing SCRM, SCR, BDAC, and organizational performance in Nigeria's downstream oil and gas industry.

Keywords: Supply Chain Risk Management, Supply Chain Resilience, Big Data Analytics Capability, Organizational Performance



Introduction

The oil and gas sector remains central to the global energy landscape and is particularly critical to Nigeria, where it accounts for approximately 95 percent of national export earnings (Ekpo, 2022). The downstream segment, however, has experienced escalating operational disruptions, especially in logistics and supply chain activities (Ekram et al., 2023). These disruptions are driven by persistent fuel shortages, weak information systems, inaccurate demand forecasts, inadequate infrastructure, and heavy reliance on third-party logistics providers (John et al., 2019). Between 2017 and 2021, Nigeria recorded more than 7,000 pipeline breakages and vandalism incidents, resulting in losses estimated at ₦4.325 trillion (Nnodim, 2023). Macroeconomic pressures including inflation, foreign exchange volatility, and recurrent labour strikes further compound these challenges, alongside sector-specific risks such as smuggling, adulteration, and hoarding (Asikhia et al., 2022). These conditions reflect a highly disruption-prone environment in which traditional supply chain strategies such as lean and agile approaches provide only partial solutions, as they do not adequately address large-scale, systemic, and externally induced risks (Ahmed & Rashdi, 2020; Huma & Siddiqui, 2019). Supply Chain Risk Management (SCRM) offers a more holistic framework by integrating risk identification, mitigation, resilience, and recovery processes. However, extant literature reveals important conceptual gaps. Many studies emphasize proactive risk management activities while neglecting recovery mechanisms that are essential for building resilience in volatile contexts (Ho et al., 2015; Norman & Wieland, 2020; Paul et al., 2021). Additionally, the enabling role of Big Data Analytics Capability (BDAC) in strengthening SCRM processes and facilitating timely decision-making remains underexplored, particularly in high-risk settings such as Nigeria's downstream oil industry (Singh, 2020; Liu et al., 2024).

Therefore, these gaps indicate that extant SCRM and BDAC literature remains conceptually and operationally incomplete in capturing the full spectrum of supply chain risk dynamics in volatile environments. In particular, the limited integration of reactive dimensions such as risk recovery, alongside the underrepresentation of enabling capabilities like BDAC, raises concerns about the adequacy of existing constructs and their measurement approaches when applied in disruption-intensive contexts. This suggests a broader methodological limitation in the availability of validated, context-sensitive instruments capable of reliably operationalizing SCRM, SCR, BDAC, and organisational performance in environments such as



Nigeria's downstream oil and gas sector. Accordingly, this study responds to this methodological gap through the development and preliminary validation of a measurement instrument for these constructs.

Problem Statement

Despite extensive research on supply chain risk management (SCRM), supply chain resilience (SCR), big data analytics capability (BDAC), and organizational performance, a key methodological gap persists in the availability of validated measurement instruments suitable for highly volatile and disruption-prone environments such as Nigeria's downstream oil and gas sector. Existing measurement scales are largely developed in stable or manufacturing-oriented contexts, limiting their contextual relevance and precision when applied to environments characterised by frequent operational disruptions, infrastructural constraints, and high uncertainty (Munir et al., 2020; Chin and Min, 2021; Mikalef et al 2020). In addition, prior work highlights conceptual incompleteness in SCRM measurement, particularly the limited operationalisation of a fully holistic risk management process (e.g, El baz and Ruel 2021; chin and min, 2021; Duong and Ha, 2021; Muka & Wahyuni, 2023) Most studies fail to integrate all phases of SCRM, with the reactive dimension, especially risk recovery, often omitted despite its theoretical importance for post-disruption restoration and continuity (Ho et al., 2015; Norman & Wieland, 2020; Abdulrahman et al., 2025). This dual limitation of contextual mismatch and incomplete construct operationalisation underscores the absence of a context-sensitive and conceptually comprehensive instrument capable of reliably measuring SCRM, SCR, BDAC, and organisational performance in disruption-intensive supply chains. Accordingly, this study adopts a pilot instrument development approach to address this gap through the adaptation, expert validation, and preliminary reliability testing of established measurement scales for application in Nigeria's downstream oil and gas sector.

Conceptualization and Operationalization of Constructs

This study followed a systematic instrument development procedure to construct and validate measures for Supply Chain Risk Management (SCRM), Supply Chain Resilience (SCR), Big Data Analytics Capability (BDAC), and Organizational Performance within Nigeria's downstream oil and gas sector. Guided by established scale development protocols, items were sourced from validated instruments in prior research, adapted for contextual relevance, and refined through expert review to ensure face and content validity. Adaptations were deliberately



minimal limited to improving clarity, aligning phrasing with a seven-point Likert scale, and ensuring applicability to the operational realities of downstream oil marketing firms.

Organizational Performance

Organizational performance is defined as the extent to which an organization achieves its objectives (Kaur & Sharma, 2014). In this study, this construct is conceptualized as a second-order reflective construct with two dimensions (first-order reflective constructs) comprising operational performance and financial performance. These two dimensions are a reflection of SCRM's objective to enhance resilience, ensure continuity, and drive profitability (Fan & Stevenson, 2018; Baryanis et al., 2019; Tang, 2006).

Operational performance as defined by Kareem and Kummitha (2020) is the effective transformation of capabilities into competitive advantage. In this study, this construct represents the first order reflective construct comprising seven-item adapted from past studies capturing key efficiency-related aspects such as productivity, quality, delivery reliability, flexibility, lead time reduction, and cost optimisation.

Table 1: Measurement Items for Operational Performance (Kareem & Kumitha, 2020)

No.	Original Items	Modified items
1	Our company's effectiveness in fulfilling requirements	Our organization effectively fulfills its requirements
2	Our company's effectiveness in responding to changes in market demand	Our organization responds promptly to changes in market demand
3	Our company's effectiveness in on-time delivery	We deliver our products on time
4	Our company's effectiveness in delivering reliable quality products	We deliver products with reliable quality
5	Reduction in lead time to fulfill customers' orders	We are able to reduce lead times to meet customer demands
6	Reduction in overhead cost	Our organization has reduced overheads costs effectively
7	Reduction in inventory cost	Our organization has effectively reduced inventory cost



Financial performance is conceptualized as the organizations effectiveness in generating revenue, profits, maximizing asset utilization, and achieving competitive growth. In this study, it operationalized as a first order reflective construct assessed using items adapted from Abuzaid (2018) and Taha et al. (2024) capturing financial indicators, including return on assets, net profit ratio, and revenue growth. While those from Taha, assess relative competitive performance, such as profitability and sales growth compared to key competitors. Combining absolute and relative indicators reflects the multidimensional nature of financial performance commonly adopted in organisational and supply chain management research.

Table 2: Measurement Items for Financial Performance

No.	Original Items	Modified items	Source
1	The rate of return on assets has increased	Our returns we generate from our assets have increased	(AbuZaid, 2018)
2	Net profit ratio has increased	Our net profit ratio has increased	(AbuZaid, 2018)
3	Revenue growth rate is high	Our revenue growth rate is high	(AbuZaid, 2018)
4	The average profitability of our company is better than that of key competitors	Our company's profitability is competitive within the downstream oil and gas sector	(Taha, 2024)
5	The sales growth of our company is better than that of key competitors	Our company's sales growth is competitive within the downstream oil and gas sector	(Taha, 2024)

Big Data Analytics Capability (BDAC)

Big Data Analytics Capability (BDAC) is defined as the firm's ability to effectively deploy technology and talent to capture, store, and analyze data, towards the generation of insight was in this study, it is operationalized as a third-order formative construct, comprising tangible resources, human skills, and intangible resources (Mikalef, 2020). This higher-order formative specification reflects the multidimensional and cumulative nature of BDAC, where each component uniquely contributes to the firm's overall analytical capability.

According to Mikalef (2020), Tangible resources refer to the physical and technological infrastructure supporting BDAC, including data access, data integration, funding, and technology adoption. Human skills encompass managerial and technical competencies while Managerial skills capture the ability of IT/data managers to understand business needs, coordinate analytics activities, and engage cross-functionally with other managers, suppliers, and customers. Technical skills



capture the capabilities of IT/data staff to execute analytics tasks effectively. Intangible resources include a data-driven culture and organizational learning. Data-driven culture reflects the degree to which decisions are informed by data rather than intuition, while organizational learning captures the acquisition and application of new knowledge to support analytics initiatives. These items were retained from the original scale with minimal modification for clarity and contextual alignment.

Table 3: Measurement Items for Big Data Tangible Resources (Mikalef, 2020)

No.	Construct	Original Items	Modified items
1	Data	We have access to very large, unstructured, or fast-moving data for analysis	
2		We integrate data from multiple internal sources into a data warehouse or mart for easy access	
3		We integrate external data with internal to facilitate high-value analysis of our business environment	
4	Basic resources	Our 'big data analytics' projects are adequately funded	Our data-driven IT projects are adequately funded
5		Our 'big data analytics' projects are given enough time to achieve their objectives	Our data-driven IT projects are given enough time to achieve their objectives
6	Technology	We have explored or adopted parallel computing approaches	
7		We have explored or adopted different data visualization tools	
8		We have explored or adopted new forms of databases	

**Table 4: Measurement Items for Big Data Human Skills (Mikalef, 2020)**

No.	Construct	Items	Modified
1	Managerial	Our 'big data analytics' managers are able to understand the business need of (and collaborate with) other functional managers, suppliers, and customers to determine opportunities that big data might bring to our business	Our IT/ data managers are able to understand the business need of (and collaborate with) other functional managers, suppliers, and customers to determine opportunities that big data might bring to our business
2		Our 'big data analytics' managers are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers	Our IT/ data managers are able to coordinate big data-related activities in ways that support other functional managers, suppliers, and customers
3		Our 'big data analytics' managers are able to understand and evaluate the output extracted from big data	Our IT/ data managers are able to understand and evaluate the output extracted from big data
4	Technical skills	Our 'big data analytics' staff has the right skills to accomplish their jobs successfully	Our IT/ data staff has the right skills to accomplish their jobs successfully
5		Our 'big data analytics' staff is well trained	Our IT/ data staff are well trained

Table 5: Measurement Items for Big Data Intangible Resources (Mikalef, 2020)

No.	Construct	Items
1	Data-driven culture	We base our decisions on data rather than on instinct
2		We are willing to override our own intuition when data contradict our viewpoints
3		We continuously coach our employees to make decisions based on data
4	Organizational learning	We are able to acquire new and relevant knowledge
5		We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge

Supply Chain Resilience

Supply Chain Resilience (SCR) is viewed as the ability of a supply chain to absorb the shock of a disruptive event, respond to the disruption, and recover quickly to its original state or achieve a more optimal operational state, as originally noted by Ponomarov and Holcomb (2009), Yu et al. (2019), Sheffi and Rice (2005), and Ali et al. (2017). In this study, it is operationalized as a **three-dimensional construct**, encompassing **absorptive**, **response**, and **recovery capabilities**, adapted from Zhao et al. (2023). This multidimensional specification reflects the theoretical and



empirical understanding that resilient supply chains require a combination of **pre-disruption preparedness, effective response during disruptions, and rapid post-disruption recovery**. **Absorptive capability** captures a firm's preparedness to absorb disruptions without significant performance degradation. This includes maintaining redundant resources, ensuring high data visibility across the supply chain, and sustaining situational awareness and crisis prediction. **Response capability** reflects the ability to make timely and effective decisions when disruptions occur. Key aspects include rapid decision-making, quick response to disruptions, and maintaining supply chain connectivity and collaboration under stress. **Recovery capability** measures the effectiveness with which a firm returns to normal operations following disruption. It includes restructuring resources, deploying continuity plans, and extracting lessons from disruptions to improve future operations. Each dimension was measured using reflective items adapted from Zhao et al. (2023).

Table 6: Measurement Items for Supply Chain Resilience (Zhao et al., 2023)

No.	Construct	Items
1	Absorptive capability	We can have redundant resources in place prior to the onset of disruption
2		We can achieve a high level of data visibility
3		We are able to maintain a high level of situational awareness and crisis prediction
4	Response capability	We are able to make the right management decision at the time of disruption
5		We are able to provide quick response to supply chain disruption
6		We are always able to maintain supply chain connectivity and collaboration at the time of disruptions
7	Recovery capability	We are able to speedily and efficiently return to normal operations after being disrupted
8		We are able to restructure resources and deploy new supply chain continuity business plans after being disrupted
9		We are able to extract useful knowledge from disruptions and achieve better supply chain operations after being disrupted.

Supply Chain Risk Management (SCRM)

Supply Chain Risk Management (SCRM) is An inter-Organizational collaborative endeavor utilizing both quantitative and qualitative risk management methodologies, involving the identification, evaluation, mitigation, monitoring, and recovery or risks that could adversely impact any part of a supply chain (adapted from Ho et al., 2015). This construct is operationalized as a second-order reflective construct comprising five



dimensions: risk identification, risk assessment, risk mitigation, risk monitoring, and risk recovery. This higher-order specification reflects the multidimensional nature of SCRM, capturing the full spectrum of practices that firms employ to anticipate, manage, and recover from supply chain disruptions.

Risk identification focuses on the proactive recognition of potential supply chain threats. It captures awareness, early detection, observation fields, and early-warning indicators. Risk assessment measures the systematic evaluation of identified risks, including sources, probability, potential impact, classification, and urgency. Risk mitigation assesses strategies implemented to reduce the likelihood or impact of supply chain disruptions covering strategic planning, supplier collaboration, redundancy, and contingency measures. Risk monitoring evaluates the continuous surveillance of supply chain risks capturing information gathering, assessment criteria, cataloging of risk factors, severity tracking, regulatory monitoring, and early-warning alerts. Risk recovery reflects the organization's capability to restore operations following disruptions. Items include activating task forces, implementing contingency plans, leveraging backup suppliers, utilizing inventory reserves, collaborating with distribution partners, and employing alternative transport modes. Including recovery explicitly addresses a frequent critique in SCRM research that many frameworks neglect post-disruption restoration, which is particularly critical in high-risk environments such as the Nigerian downstream oil sector.

Table 7: Measurement Items for Supply Chain Risk Identification

No.	Original Items	Modified Items	Source
1	We are comprehensively informed about basically possible risks in our supply chain	-	Kern et al (2012); Elbaz and Reul (2021)
2	We are constantly searching for short-term risks in our supply chain	We actively identify short-term risks that could impact our supply chain	
3	In the course of risk analysis for all suppliers and SC partners, we select relevant observation field for supply risks	We select relevant observation fields for identifying supply risks among our supply chain partners.	
4	In the course of our risk analysis for all SC partners, we define early warning indicators	We define early warning indicators to help identify emerging risks among our <u>supply chain</u>	

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**Table 8: Measurement Items for Supply Chain Risk Assessment**

No.	Original Items	Modified Items	source
1	In the course of our risk analysis, we look for possible sources of supply chain risks	We look for possible sources of supply chain risks	Kern et al (2012); Elbaz and Reul (2021)
2	In the course of our risk analysis, we evaluate the probability of supply chain risks	We evaluate the probability of supply chain risks	
3	In the course of our risk analysis, we analyze the possible impact of supply chain risks	We analyze the possible impact of supply chain risks	
4	In the course of our risk analysis, we classify and prioritize our supply chain risks	We classify and prioritize our supply chain risks	
5	In the course of our risk analysis, we evaluate the urgency of our supply chain risks	We evaluate the urgency of our supply chain risks	

Table 9: Measurement Items for Supply Chain Risk Mitigation

No.	Original Items	Modified Items	Source
1	In the course of our risk analysis, we demonstrate possible reaction strategies	We demonstrate possible reaction strategies	Kern et al (2012); Elbaz and Reul (2021)
2	In the course of our risk analysis, we evaluate the effectiveness of possible reaction strategies	We evaluate the effectiveness of possible reaction strategies	
3	Supply chain risk management is an important activity in our organization	Supply chain risk management is an important activity in our organization	
4	We collaborate with suppliers and customers to ensure supply chain continuity during disruption		Juttner (2003);
5	We maintain alternative suppliers and safety stock to minimize the impact of supply chain disruptions		Roshani et al. (2024).
6	We have established contingency plans (e.g., inventory sharing, emergency resource deployment, or ad hoc rerouting) that we activate immediately after a supply chain disruption to minimize its impact.		

**Table 10: Measurement Items for Supply Chain Risk Monitoring**

No.	Original items	Modified(derived) items	Source
1	Gathering and processing supplier and customer information	We systematically gather and process information on suppliers, customers and external trends to continuously identify potential risks	Klassen & Vereecke (2012)
2	Setting assessment criteria	We establish specific criteria to assess supplier and customer performance for risk management purposes	
3	Evaluating product related factors	We regularly evaluate factors related to our products	
4	Cataloging risk factors	Through Our data management system, we maintains a catalog of identified supply chain risk factors	Tummala and Schoenherr (2011)
5	Tracking severity and probability of risk	Our organization tracks the severity and probability of supply chain risks in real time	
6	Monitoring regulatory policies	Our data management system includes updates on government regulations, tariffs, and customs policies related to supply chain risk	
7	Generating risk alerts	Our system generates early-warning alerts based on identified supply chain risk triggers for timely corrective actions	

Table 11: Measurement Items for Supply Chain Risk Recovery

No.	Original items	Modified items	Source
1	Task force (recovering from operational risk)	We have a task force to manage risk events in our supply chain	Munir et al. (2020)
2	Contingency plans (recovering from operations risk)	We activate our contingency plans to mitigate the impact of risk events	Munir et al. (2020); Duhadway (2019)
3	Back up suppliers (responding to operations risk)	We promptly activates backup supply channels to restore fuel availability after a risk event	Ivanov (2023); Munir et al. (2020); Duhadway (2019)
4	Utilizing inventory and capacity reservations	We draw from strategic fuel reserves to quickly support recovery efforts after a risk event	Ivanov (2023).



5	Supply chain collaboration	We collaborates closely with distribution partners to resume fuel supply after a risk event	Rahman et al. (2021).
6	Alternative transportation modes	We employ alternative transportation options (e.g., switching from rail to road) to resume fuel delivery schedules affected by a risk	Ivanov (2023); Munir et al. (2020)

Methodology

This study forms part of an ongoing PhD research and adopted a pilot survey research design to develop and preliminarily validate a measurement instrument for assessing supply chain risk management (SCRM), supply chain resilience (SCR), big data analytics capability (BDAC), and organizational performance within Nigeria's downstream oil and gas sector. The constructs were theoretically specified as reflective and formative based on prior literature and established measurement conventions in supply chain and information systems research. The instrument development process began with an extensive review of relevant literature, through which initial measurement items were sourced from validated scales in prior empirical studies. These items were then adapted to align with the theoretical definitions of the constructs and the contextual realities of a downstream oil and gas environment in Nigeria. Item refinement was undertaken iteratively following expert review, where subject matter experts evaluated the instrument for content validity and face validity, ensuring clarity, relevance, and conceptual alignment with the intended constructs before pilot administration. The refined instrument was subsequently administered to a purposive sample of 40 heads of operational units drawn from storage, distribution, and retail outlets within the downstream supply chain, a group considered suitable for providing informed responses in a pilot-scale validation exercise. The pilot data were analysed to assess the psychometric properties of the measurement scales. For reflective constructs, internal consistency reliability was evaluated using Cronbach's alpha, while Corrected Item–Total Correlation (CITC) was used to assess the contribution and adequacy of individual items within each construct, guiding preliminary item purification decisions. For formative constructs, multicollinearity among indicators was examined using Variance Inflation Factor (VIF) and tolerance statistics to ensure that indicators were not redundant and met acceptable statistical thresholds.



Expert Review: Face and Content Validity

To ensure content validity, the instrument underwent a **systematic expert review** by professionals with academic and practical expertise in supply chain and risk management. The panel consisted of a Professor of Business Administration with supervisory experience in supply chain research, a PhD holder in Business Administration, and a PhD holder in Risk Management from three different Nigerian universities. These experts assessed the instrument for **clarity, wording precision, relevance, and alignment with the study objectives**. Their feedback prompted minor revisions to enhance readability, standardize phrasing (e.g., replacing “we” with “our company”), and improve contextual suitability for the Nigerian downstream oil and gas sector. Specific adjustments included ensuring all items were compatible with a 7-point Likert agreement scale (1 = strongly disagree to 7 = strongly agree), emphasizing measurable practices rather than binary responses, and refining terminology such as Big Data Analytics to match sector-specific understanding. Overall, the expert review **enhanced measurement precision and construct clarity** without altering the theoretical meaning of the items.

Reliability Assessment of the Measurement Instrument

The pilot study was conducted to evaluate the clarity of the survey items and the internal consistency reliability of the constructs, serving as a preliminary check on the measurement model’s suitability for full-scale analysis. The questionnaire was administered to 40 respondents drawn from operational units of oil marketers in Nigeria’s downstream oil and gas sector within the Federal Capital Territory (FCT). Respondents were selected to closely match the characteristics of the target population (given that this study forms part of an ongoing PhD research) thus, ensuring a representative basis for preliminary instrument testing.

Reliability Analysis of Reflective Constructs

Internal consistency reliability was assessed using Cronbach’s alpha and Corrected Item–Total Correlation (CITC) in SPSS v.25. The reflective constructs examined included subdimensions of Supply Chain Risk Management (SCRM), Supply Chain Resilience (SCR), Organizational Performance (OP), and selected dimensions of Big Data Analytics Capability (BDAC). Following established benchmarks (Nunnally, 1978; Pallant, 2020), Cronbach’s alpha values of 0.70 or higher indicate satisfactory reliability. All subdimensions exceeded this threshold, demonstrating that the items consistently measure their respective constructs. CITC



values further confirmed that individual items contributed appropriately to the internal consistency of each scale. These results support the preliminary suitability of the instrument for the subsequent full-scale study. Reliability statistics for each construct are presented in Table 3.15.

Table 12: Reliability Assessment of Reflective Constructs

Construct	First-order Dimensions	No. of Items	Cronbach's α
Supply Chain Risk Management (SCRM)	Risk Identification	4	0.849
	Risk Assessment	5	0.875
	Risk Mitigation	6	0.784
	Risk Monitoring	7	0.770
	Risk Recovery	6	0.839
Supply Chain Resilience (SCR)	Absorptive Capability	3	0.727
	Response Capability	3	0.728
	Recovery Capability	3	0.780
Organizational Performance (OP)	Operational Performance	7	0.884
	Financial Performance	5	0.755
Big Data Analytics Capability (BDAC)	Managerial Skills	3	0.710
	Technical Skills	2	0.733
	Data-driven Culture	3	0.823
	Organizational Learning	2	0.778

Item-level diagnostics were performed to further evaluate scale coherence. Corrected Item–Total Correlation (CITC) values below 0.30 (Pallant, 2020) or 0.40 (Gliem & Gliem, 2003) were considered indicative of weak item scale associations. Two items fell within this range. **Risk Monitoring (RMO5)** “Our organization tracks the severity and probability of supply chain risks in real time” exhibited a negative item-total correlation. Its removal would have increased Cronbach’s alpha from 0.770 to 0.840. Additionally, **risk Mitigation (RMI1)** “Our company demonstrates possible reaction strategies during risk analysis” also showed a negative item-total correlation (–0.069). Removing this item would have increased Cronbach’s alpha from 0.784 to 0.852. Despite these flags, both items were **retained** to preserve theoretical completeness and construct coverage, particularly as they represent important aspects of risk monitoring and mitigation in the context



of Nigerian downstream oil operations. Their performance will be further assessed in the main study using **PLS-SEM outer loadings**. Comprehensive reliability outputs, including inter-item correlations, CITC values, and “alpha if item deleted” statistics, are provided in the Appendix.

Multicollinearity Diagnostics for Formative Constructs

Formative constructs within Big Data Analytics Capability (BDAC) including Data, Basic Resources, and Technology were assessed for multicollinearity using Variance Inflation Factor (VIF) and Tolerance statistics, as recommended by Hair et al. (2017). This evaluation ensures that each indicator contributes uniquely to its construct without redundancy, a key requirement for formative measurement models.

Table 13: Multicollinearity Diagnostics for Formative Constructs

Construct	Indicator	Tolerance	VIF
Data	BDT1	0.466	2.144
	BDT2	0.665	1.503
	BDT3	0.706	1.416
Basic Resources	BDT4	0.890	1.123
	BDT5	0.890	1.123
Technology	BDT6	0.715	1.399
	BDT7	0.822	1.217
	BDT8	0.987	1.013

All VIF values were well below the recommended thresholds of 3.3 (Hair et al., 2017) and 5.0 (Diamantopoulos & Siguaw, 2006), indicating that multicollinearity is not a concern. The indicators demonstrated sufficient distinctiveness to justify their inclusion in the formative measurement model.

Discussion

This study reported the development and pilot validation of measurement scales for Supply Chain Risk Management, Supply Chain Resilience, and Big Data Analytics Capability within the Nigerian context. The pilot findings demonstrate that the instrument exhibits acceptable to strong internal consistency across all constructs, supporting its suitability for subsequent full-scale empirical analysis. The Cronbach’s alpha values obtained exceed commonly accepted thresholds for exploratory and pilot research, indicating that the items within each construct consistently capture coherent underlying dimensions. Beyond statistical adequacy,



the results confirm the practical feasibility of administering the instrument to industry respondents. Feedback obtained during pilot administration indicated that item wording was generally clear, contextually relevant, and understandable to practitioners, reducing the likelihood of response bias or misinterpretation in the main study. This practical validation is particularly important in applied infrastructure and operations research, where measurement instruments must balance theoretical rigor with operational clarity.

Methodologically, the study contributes by demonstrating a systematic process of scale development that integrates theoretical grounding, expert validation, and preliminary psychometric testing. While many empirical studies in this domain rely on adapted instruments without rigorous pretesting (e.g. Bag et al., 2020; Upadhyay and Kumar, 2020; Duong and Ha, 2021), the present approach strengthens construct credibility prior to structural modeling. This is especially relevant for studies employing structural equation modeling, where measurement quality directly affects the stability and interpretability of causal relationships. Substantively, the instrument operationalizes multidimensional representations of SCRM, SCR, and BDAC, enabling future empirical examination of how risk management practices, resilience capabilities, and analytics competencies jointly influence organizational outcomes. Although causal relationships were not tested in this pilot phase, establishing a reliable measurement foundation enhances confidence in subsequent theory testing and model estimation. Consistent with the objectives of pilot research, the findings should be interpreted as evidence of measurement readiness rather than confirmation of substantive hypotheses. Convergent validity, discriminant validity, and structural relationships will be evaluated rigorously in the main study using a larger sample and advanced multivariate techniques.

Conclusion

This paper presented the development and pilot validation of a structured measurement instrument designed to capture Supply Chain Risk Management practices, Supply Chain Resilience capabilities, and Big Data Analytics Capability within a Nigerian operational context. Through systematic item generation, expert validation, and preliminary reliability assessment, the study established that the instrument demonstrates satisfactory internal consistency and practical usability for field deployment. Furthermore, the pilot results confirm that the refined questionnaire items reliably represent their intended constructs and are comprehensible to industry respondents. By validating the measurement foundation



prior to large-scale data collection, the study enhances the robustness of subsequent empirical modeling and reduces the risk of measurement error compromising theoretical inference. The instrument provides a methodological contribution by offering a rigorously pretested tool suitable for examining complex interrelationships among risk management, resilience, and analytics capabilities in emerging economy contexts. It also supports future application of structural equation modeling in supply chain and infrastructure research, where validated measurement models remain limited. The next phase of the research will extend validation through full-scale data collection and structural model testing.

Limitations and Future Research

Several limitations should be acknowledged. First, the pilot sample size was intentionally modest, consistent with the objectives of instrument testing rather than inferential generalization. As a result, statistical conclusions are restricted to preliminary reliability assessment and cannot support broader population inference. Second, the pilot relied on self-reported perceptions, which may be subject to response bias or common method variance. Third, the validation scope was limited to internal consistency and expert-based content and face validity. More advanced psychometric assessments, including convergent validity, discriminant validity, and measurement invariance, were not examined at this stage. Finally, the instrument was contextualized within a Nigerian operational environment, which may limit immediate generalizability to other institutional or geographic contexts without further validation.

Future research should extend this pilot work through large-scale data collection to formally assess construct validity using confirmatory factor analysis and structural equation modeling. Convergent validity, discriminant validity, composite reliability, and model fit indices will be examined to further establish the robustness of the measurement model. Structural relationships among SCRM, SCR, and BDAC will then be tested to evaluate theoretical propositions and causal pathways. Subsequent studies may also replicate and adapt the instrument across different sectors, countries, or institutional settings to assess measurement stability and cross-context applicability. Longitudinal designs could further explore the dynamic evolution of resilience and analytics capabilities over time. Collectively, these extensions will strengthen both the empirical and theoretical contributions of the measurement framework.



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