The Moderating Role of Big Data Analytics Capability in the Relationship Between Supply Chain Risk Management and Organizational Performance in Nigeria's Downstream Oil and Gas Sector

Ali Shuaibu Abdulrahman[1], Norhayati Zakuan[2], Teh Zaharah Yaacob[3], Bashir Mahmood Baffa[4]

[1*]Faculty of Management, Federal University Dutse, Nigeria

[2,3,] Faculty of Management, Universiti Teknologi Malaysia, Malaysia

[4]Faculty of Management, Federal University Dutse, Nigeria

[*]Corresponding Author

DOI: https://doi.org/10.47772/IJRISS.2026.101100050

Received: 29 October 2026; Accepted: 03 November 2026; Published: 24 November 2026

ABSTRACT

The increasing volatility and data intensity of modern supply chains have made supply chain risk management increasingly dependent on big data analytics capability, shifting attention toward how analytics shapes its contribution to organizational performance. Therefore, this study evaluated the moderating role of Big Data Analytics Capability in the relationship between Supply Chain Risk Management (SCRM) and Organizational Performance (OP) in Nigeria's downstream oil and gas sector. To achieve the study's objective, a quantitative cross-sectional survey design was used. Data were gathered from key informant of major downstream oil marketing firms in Nigeria downstream oil and gas sector using a structured questionnaire adapted from established studies. Furthermore, data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Findings of the study shows that, while BDAC significantly moderates the relationship between SCRM and OP ($\beta = -0.167$, $t = 3.385$, $p = 0.001$), the effect was negative indicating that the effect of SCRM on OP declines as organizations big data analytics capability increases. Essentially, advanced analytics systems partially perform functions traditionally associated with SCRM. The findings support Information Processing Theory by demonstrating that overlapping organizational capabilities may produce reduced marginal gains beyond certain thresholds. Therefore, the study contributes to the literature by offering a nuanced understanding of the interaction between digital capabilities and risk management in an emerging economy context and provides practical insights for managers seeking to balance investments in analytics and supply chain risk management.

Keywords: Supply Chain Risk Management; Big Data Analytics Capability; Organizational Performance; Moderation Effect; Nigeria Downstream Oil and Gas Sector.

INTRODUCTION

The oil and gas sector operates in a highly volatile and disruption-prone environment where supply chain performance is heavily influenced by risk exposure, operational uncertainty, and logistical complexity. In such contexts, Supply Chain Risk Management (SCRM) has been widely recognized as a critical capability for enhancing operational stability and performance by enabling firms to identify, assess, and respond to disruptions effectively. Additionally, Shah et al. (2022), notes that oil and gas industry has increasingly become data-intensive due to current technologies. This contributes further to its complexities and the need for large scale data processing for accurate and timely identification, assessment, and treatment of supply chain risks. Moreover, Baryannis et al. (2018) emphasize that managing supply chain risks requires navigating large, multidimensional data streams. However, information technology in recent years has

experienced advancements particularly in terms of enhanced processing capabilities that enables a more precise information processing and forecasting that better facilitates assessment of supply chain risks, improve the efficiency of supply chain, and reduce response time (Seyedan & Mafkheri, 2020). This is achieved by leveraging big data analytics for information processing which has its major component as predictive analytics that can facilitate the identification of supply chain risks by analyzing large volumes of historical data and risk mapping techniques (Awwad et al. 2018). On this note, the resources, tools, techniques and processes that enable an organization to process, analyze, and visualize big data in such a way that the resulting insights make data driven planning, decision-making and implementation possible, and ultimately lead to the organization's competitive advantage, is referred to as big data analytics capability (Bahrami & Shokouhyar, 2021; Dubey et al., 2019). Research has shown that organizations that effectively harness their BDAC can better develop effective risk management tools that significantly enhance organizational performance (Park and Singh, 2022). Similarly, Singh (2020) in their research show that BDAC enhances the effectiveness of a firm's risk management infrastructure thereby improving the firm's ability to predict and mitigate future risks as well as foster supply chain resilience. Other researchers such as (Abdulameer and Ibrahim, 2024), Turi et al., 2023) and (Liu et al., 2024) have opined that big data analytics capabilities strengthens the relationship between supply chain management and sustainable performance as it essentially enhances the effects of SCRM on supply chain resilience and overall performance by providing organizations with the agility and data-driven insights needed to adapt to environmental changes. Despite these, Egwuonwu et al. (2023), notes that the adoption of BDA in developing countries like Nigeria remains uneven as much of its focus has been on early-stage adoption, with limited assessment of its post-adoption impact on firms' performance.

Therefore, while extant research has generally emphasized the enabling role of BDAC in improving performance and decision support, less attention has been given to its boundary condition role in shaping the strength of the relationship between SCRM and organizational performance outcomes. In other words, it remains unclear whether higher levels of analytics capability consistently amplify the effectiveness of risk management practices, or otherwise. It is against this background that this study examines the moderating role of Big Data Analytics Capability in the relationship between Supply Chain Risk Management and organizational performance.

LITERATURE REVIEW AND THEORETICAL BACKGROUND

Supply Chain Risk Management

The growing supply chain complexity, globalization, and dependence on interconnected physical and information networks has made supply chain disruptions increasingly frequent and inevitable (Schlegel & Trent, 2015; Blom & Niemen, 2022). The major sources of disruption in Nigeria's downstream oil and gas sector include poor supply chain information quality, inaccurate demand forecasting, inadequate storage infrastructure, third-party logistics challenges, and poor inventory visibility (John et al., 2019). These highlight the importance of Supply Chain Risk Management (SCRM), which has become a critical capability for reducing supply chain vulnerabilities and ensuring operational continuity. Therefore, SCRM has become essential for sustaining organizational performance, particularly in industries characterized by high operational uncertainty (Silva et al., 2023).

extant literature consistently conceptualizes SCRM as a systematic process of identifying, assessing, mitigating, monitoring, and controlling risks that may disrupt supply chain operations (Ho et al., 2015; Aqlan & Lam, 2016; Fan & Stevenson, 2018; Baryannis et al., 2018; Gurtu et al., 2021; Foli et al., 2022; Holgado & Niess, 2023; Ordibazar & Hussain, 2025; Al-Kharabsheh et al., 2026). Among these definitions, Fan and Stevenson (2018) provided more comprehensive conceptualizations which integrate the processes as well as the internal and external coordination mechanisms required to reduce supply chain vulnerability along with ensuring continuity and competitive advantage. More common SCRM frameworks primarily emphasize four interrelated processes including, risk identification, risk assessment, risk mitigation, and risk monitoring (Fan & Stevenson, 2018). However, recent studies argue that effective SCRM should include both proactive risk prevention and reactive risk recovery, recognizing that disruptions cannot always be avoided and organizations must possess the capability to restore operations rapidly following disruptions

(Ho et al., 2015; Norrman & Wieland, 2020; Munir et al., 2020). In recent literature, with conceptual and systematic review evidence further supports the inclusion of recovery as an integral dimension of SCRM rather than a separate post-disruption activity (Abdulrahman et al., 2025; Abdulrahman et al., 2026). Accordingly, this study operationalizes SCRM as a multidimensional second-order reflective construct comprising five first-order reflective dimensions: risk identification, risk assessment, risk mitigation, risk monitoring, and risk recovery by building on the multidimensional framework proposed by Fan and Stevenson (2018) by explicitly incorporating the recovery dimension in line with the recommendations of Ho et al. (2015) and operationalization of Munir et al (2020). It is also consistent with the SCRM measurement instrument developed and validated by Abdulrahman et al. (2026).

Organizational Performance

Organizational performance reflects the extent to which an organization achieves its strategic goals and objectives and remains a central outcome in management and supply chain research (Wildman et al., 2011; Sawaean & Ali, 2019; Asikhia et al., 2022). Although the concept has been viewed from multiple perspectives, extant literature frequently defines it in terms of the achievement of desired organizational outcomes (Daferighe & Edet, 2019; Ajike et al., 2021; Turi et al., 2023). These outcomes have been operationalized using various dimensions, such as customer satisfaction, employee wellbeing, market performance, operational efficiency, and financial performance (Kaur & Sharma, 2014; Abeysekara & Wang, 2019). The context of SCRM, however, operational and financial performance are the most theoretically relevant dimensions because the primary objective of SCRM is to ensure business continuity, reduce disruption-related losses, improve operational efficiency, and sustain profitability (Fan & Stevenson, 2018; Baryannis et al., 2018). This focus is particularly relevant in Nigeria's downstream oil and gas sector, where persistent logistics disruptions, infrastructure deficiencies, and supply chain inefficiencies continue to undermine firms' operational efficiency and financial viability (KPMG, 2019; Asikhia et al., 2022). Accordingly, this study operationalizes Organizational Performance as a multidimensional second-order reflective construct comprising two first-order reflective dimensions: operational performance and financial performance.

Big Data Analytics Capability

According to Akter et al (2016), Organizations today operate in an increasingly data-intensive environment characterized by large volumes of structured and unstructured data generated from a variety of sources. Additionally, the downstream oil and gas sector, has become highly data-intensive (Shah et al., 2022) thus highlighting the increasing complexity of supply chain operations and the need for accurate and timely forecasting have made traditional risk management approaches increasingly inadequate. Consequently, Big Data Analytics (BDA) has emerged as an important means of improving information processing, forecasting accuracy, risk assessment, and supply chain responsiveness (Seyedan & Mafkheri, 2020). Similarly, Turi et al. (2023) describe BDA as the process of analyzing large datasets to uncover patterns, trends, and insights that support organizational decision-making. However, beyond the availability of analytical technologies, competitive advantage depends on an organization's capability to effectively utilize them. therefore, Big Data Analytics Capability (BDAC) has been defined as an organizational capability that integrates data, technology, and human expertise to capture, process, analyse, and transform big data into actionable business insights that support superior decision-making and competitive advantage (Kiron et al., 2014; Bahrami & Shokouhyar, 2021; Dubey et al., 2019; Mikalef et al., 2020).

Despite broad agreement regarding the strategic importance of BDAC, its conceptualization and measurement varies. Studies have operationalized BDAC as both unidimensional and multidimensional constructs using reflective and formative measurement approaches. while several studies conceptualize BDAC as a single capability (e.g., Dubey et al., 2019; Wamba et al., 2019; Upadhyay & Kumar, 2020; Bahrami & Shokouhyar, 2021; Balci & Ali, 2024; Primadasa et al., 2025; Rahman et al., 2026), others argue that it comprises multiple complementary organizational capabilities (Wamba et al., 2016; Ferraris et al., 2018; Rialti et al., 2019; Bag et al., 2020; Mikalef et al., 2020; Haylemariam et al., 2025; Hussain et al., 2026; Horani et al., 2026). In line with the latter perspective, this study adopts the multidimensional formative operationalization proposed by Mikalef et al. (2020), in which BDAC comprises tangible

resources, human skills, and intangible resources. This conceptualization aligns with the view that organizational capability is created through the combined contribution of technological infrastructure, analytical talent, organizational learning, and data-driven culture rather than any single resource.

Theoretical Foundation and Hypotheses Development

Theoretically, this study is underpinned by the complementary perspectives of **Dynamic Capability Theory (DCT)** and **Information Processing Theory (IPT)**. While DCT explains how firms develop and reconfigure organizational capabilities to respond to dynamic and uncertain environments (Teece et al., 1997), IPT explains how organizations process and utilize information to reduce uncertainty and improve decision-making (Galbraith, 1974; Tushman & Nadler, 1978). Together, these theories provide the foundation for explaining the relationship between Supply Chain Risk Management (SCRM), Organizational Performance (OP), and the moderating role of Big Data Analytics Capability (BDAC). Specifically, from the perspective of DCT, SCRM represents a dynamic organizational capability that enables firms to identify, assess, mitigate, monitor, and recover from supply chain risks, thereby enhancing operational continuity and organizational performance. Complementing this view, IPT views organizations as information processing systems whose effectiveness depends on their ability to collect, process, interpret, and disseminate information under conditions of uncertainty (Galbraith, 1974; Tushman & Nadler, 1978). Therefore, Since Supply Chain Risk Management (SCRM) is inherently information-intensive, its effectiveness require strong information processing capabilities (Fan et al., 2016). IPT further purports that superior organizational performance is achieved when an organization's information processing capability matches its information processing requirements (Srinivasan & Swink, 2015). From this perspective, BDAC complements SCRM by enabling firms to transform large volumes of supply chain data into timely and actionable intelligence, thereby improving risk management decisions and operational outcomes.

Supply Chain Risk Management, Big Data Analytics Capability and Organizational Performance

Supply Chain Risk Management (SCRM) seeks to reduce supply chain vulnerability through systematic processes of risk identification, assessment, mitigation, monitoring, and recovery, thereby enhancing business continuity and profitability (Fan & Stevenson, 2018; Baryannis et al., 2018). In other words, effective SCRM enables organizations to anticipate potential disruptions, improve forecasting accuracy, enhance operational flexibility, minimize disruption-related losses, and maintain continuity of supply chain operations (Fan et al., 2016; Jüttner & Maklan, 2011; Wieland & Wallenburg, 2012; Munir et al., 2020). Previous empirical studies report that organizations implementing effective SCRM practices achieve superior organizational performance across different industrial contexts (Bhatti & Bhatti, 2019 and Munir et al., 2020). Similarly, Asikhia et al. (2023) found that SCRM significantly enhances business performance among oil and gas marketing companies in Nigeria.

Furthermore, while literature indicates that effective SCRM contributes to improved organizational performance, its effectiveness largely depends on an organization's ability to acquire, process, interpret, and utilize risk-related information in a timely manner. Empirical studies show that BDAC strengthens risk management infrastructure, improve operational continuity, and enhance organizational agility during supply chain disruptions (Singh, 2020; Jerome et al., 2024; Park & Singh, 2022). Similarly, BDAC has been shown to strengthen the relationship between customer knowledge management and organizational performance (Turi et al., 2023), while BDAC-enabled agility enhances the relationship between supply chain integration and supply chain resilience (Liu et al., 2024). Furthermore, digital technologies such as BDA strengthen the relationship between supply chain resilience and operational performance (Alkhatib & Almomani, 2023). Abdulameer and Ibrahim (2024) likewise proposed that BDAC strengthens the relationship between supply chain management practices and sustainable performance and recommended empirical validation within data-intensive industries such as oil and gas. In light of these theoretical and empirical arguments, this study proposes that organizations SCRM practices improves their performance and also organizations possessing strong Big Data Analytics Capability are better able to leverage Supply Chain Risk Management practices to improve operational and financial performance. Accordingly, the following hypotheses were proposed:

H_1: Supply Chain Risk Management positively influences Organizational Performance.

H_2: Big Data Analytics Capability significantly moderates the impact of Supply Chain Risk Management on Organizational Performance.

Conceptual Model

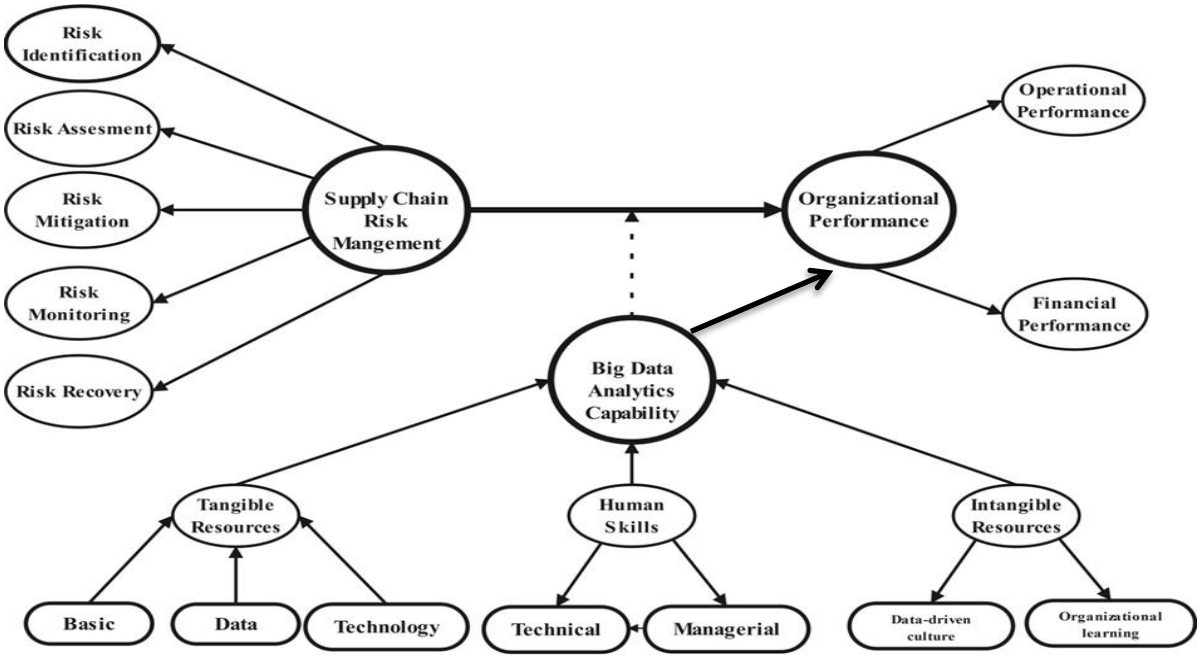


Figure 1 Research Model

Figure 1 presents the conceptual model examined in this study, extracted from the broader doctoral research framework. Drawing on Dynamic Capability Theory (DCT) and Information Processing Theory (IPT), the model proposes that Supply Chain Risk Management (SCRM) positively influences Organizational Performance (OP), while Big Data Analytics Capability (BDAC) strengthens this relationship by enhancing the firm's information processing capability. Accordingly, BDAC is conceptualized as a moderating variable that amplifies the effectiveness of SCRM in improving organizational performance. The model provides the theoretical basis for the hypotheses developed and empirically tested in this study.

Research Design

This study examines the moderating role of Big Data Analytics Capability (BDAC) in the relationship between Supply Chain Risk Management (SCRM) and Organizational Performance (OP) in Nigeria's downstream oil and gas sector. It represents an empirical component of an ongoing PhD research that investigates a broader conceptual framework involving additional constructs. Accordingly, this article reports only the relationships relevant to the study objectives. Predictive measures relating to the broader structural model are not interpreted as evidence of the specific moderation effect, as Organizational Performance is explained by multiple constructs within the full PhD framework. Consequently, the explanatory power of the full model cannot be attributed specifically to the SCRM × BDAC interaction, and additional model specifications or robustness analyses were not undertaken independently of the broader PhD model.

Furthermore, the study utilized a quantitative cross-sectional survey design, targeting major downstream oil marketing firms operating across Nigeria's storage, distribution, and retail segments. These firms operate within a highly volatile environment where effective supply chain risk management and data-driven decision-making are essential for sustaining organizational performance. The minimum sample size was determined using Daniel Soper's (2024) a priori SEM sample size calculator, assuming a moderate effect

size of 0.30, statistical power of 0.80, and a significance level of 0.05, yielding a recommended minimum sample of 237 respondents.

The study covered 25 major downstream oil marketing firms, with data collected from heads of operational units, including station managers, depot managers, and fleet/transport heads, who served as key informants for their respective organizations. Although respondents were drawn from different operational units, the questionnaire assessed organisational-level SCRM practices, supply chain resilience, BDAC, and operational and financial performance through individual managerial assessments. Accordingly, individual managers constituted the units of observation, while the firms provided the organizational context for assessing these constructs. A total of 237 responses were obtained and allocated across the 25 firms based on the number of downstream operational units, with a minimum of one respondent per firm to ensure representation; strict proportional allocation was not applied. While some firms had multiple informants, allowing broader organisational perspectives (Van Bruggen et al., 2002), responses were retained at the individual level rather than aggregated into firm-level scores, as aggregation requires a theoretically justified composition model and empirical support (Chan, 1998). Organizational identifiers were not retained to preserve firm confidentiality; consequently, within-firm response dependence could not be empirically assessed or accounted for, and is acknowledged as a limitation.

Furthermore, Data were collected using a structured questionnaire comprising measurement items adapted from established studies and contextualized to the Nigerian downstream oil and gas sector while preserving their theoretical meaning. Responses were measured on a seven-point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree), which is considered appropriate for moderation analysis because of its ability to capture greater response variability (Memon et al., 2019). Prior to the main survey, the instrument underwent expert review to establish face and content validity and was subsequently pilot-tested. Reliability assessment using Cronbach's alpha showed satisfactory internal consistency for all reflective lower-order constructs, with coefficients ranging from 0.710 to 0.884. For the formative dimensions of BDAC, multicollinearity was assessed using the Variance Inflation Factor (VIF), with values ranging from 1.013 to 2.144, well below the recommended threshold of 3.3 (Hair et al., 2017). Finally, the hypothesized relationships were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), which is appropriate for estimating moderation effects involving multidimensional constructs.

Table 1: Summary of Research Methodology

Item	Description
Research Design	Quantitative, Cross-Sectional
Population	Downstream Oil Marketing Firms in Nigeria
Sampling	Purposive (key informant) sampling
Instrument	Structured Questionnaire
Scale	7-point Likert
Sample size	237 (Daniel Soper’s, 2024 A-priori Sample size determination for SEM)
Analysis Technique	PLS-SEM

RESULT AND ANALYSIS

To safeguard against non-response cases, an additional 10% buffer was applied to the recommended 237 sample resulting in 260 questionnaires being administered. Of these, 245 were retrieved, representing a response rate of 94.2%. Following data screening and the exclusion of incomplete responses, 237 cases were retained for analysis, consistent with the recommended minimum sample size. Descriptive statistics of the sample respondents as depicted in table 2 showed a predominant male respondents (84.8%), a strong educational background with 68.8% holding at least a first degree while 31.2% possess postgraduate qualifications, and a large portion of the job roles being station managers (90.7%), then depot managers (4.2%) and fleet or transport managers (5.1%). Additionally, experience levels were more than 5 years (77.6%) and 47.7% over 10 years of experience. This suggests a good reliability and informed nature of the responses.

Table 2 : Descriptive Statistics of Respondents

Variable	Category	Frequency	Percent (%)
Gender	Female	36	15.2
	Male	201	84.8
Educational Qualification	Secondary School Certificate	7	3.0
	National Diploma (ND)/NCE	25	10.5
	Higher National Diploma (HND)	42	17.7
	First Degree	89	37.6
	Master's Degree	66	27.8
	Doctor of Philosophy (PhD)	8	3.4
Job Role	Station Manager	215	90.7
	Depot Manager	10	4.2
	Fleet Officer / Transport Manager	12	5.1
Years of Experience	1 – 5 years	53	22.4
	6 – 10 years	73	30.8
	11 – 15 years	40	16.9
	16 – 20 years	29	12.2
	21 – 25 years	26	11.0
	26 years and above	16	6.8

Outlier Detection

Potential multivariate outliers were identified using Mahalanobis distance at $p < 0.001$. Although some cases were flagged, methodological recommendations in SEM and PLS-SEM literature (Hair, et al., 2017 and Kline, 2015) notes that Mahalanobis distance should treated as a diagnostic criterion rather than an automatic deletion rule. In order to justify the decision to retain the flagged cases, response validity was further assessed using within-respondent standard deviation (SD) and variance across all items, since low SD is an indicators of careless responding or straight-lining (Meade & Craig, 2012). This assessment demonstrated a sufficient variability as the SD values of the flagged case ranged from 0.99 to 1.69 and variance 0.97 to 2.86, giving that the threshold on a 7 point scale was above 0.3 for SD and 0.10 for variance to show variability.

Common Method Bias Assessment

Common method bias (CMB) may arise when data for both predictor and criterion variables are collected from a single source using the same measurement instrument. Therefore, this study utilized both statistical and procedural approaches to evaluate and mitigate the risk of CMB as recommended by Podsakoff et al. (2003). Firstly, Harman's single-factor test was conducted through exploratory factor analysis in SPSS. The results showed that the first unrotated factor accounted for 34.001% of the total variance, which is below the commonly accepted threshold of 50%, suggesting that a single factor did not account for the majority of the variance. Secondly, Kock's full collinearity VIF test was assessed, with values ranging from 1.102 to 6.372. Although most constructs recorded VIF values below the recommended threshold of 3.3, Risk Assessment (6.372), Risk Identification (4.257), and Risk Mitigation (4.567) exceeded this threshold, indicating elevated full collinearity for these constructs and the possibility of common method bias. However, elevated full collinearity does not independently establish the presence of CMB. Thirdly, during the design and administration of the questionnaire, procedural methods such as respondent anonymity and confidentiality were assured during data collection to reduce evaluation apprehension. In addition, measurement items were extracted from previously validated scales, thereby minimizing item ambiguity and construct contamination. Also, clarity and content validity were established through expert review and pilot study. Nevertheless, the possibility of common method bias cannot be entirely ruled out and should be considered when interpreting the study findings.

Evaluation of Reflective Constructs Measurement Models

The evaluation of the measurement model was conducted in two phases. An initial assessment was performed to examine the unrefined measurement properties of the reflective constructs and to identify any indicators requiring purification. Then, a refined assessment was performed succeeding indicator removal and model re-estimation to confirm the stability and adequacy of the measurement models. Initial assessment of the measurement model utilizing indicator loadings, internal consistency (Cronbach's alpha), convergent validity (using Average Variance extracted), and discriminant validity (Fornell & Larcker criterion and Heterotrait-Monotrait ratio) showed that several construct met the recommended threshold. However, indicators with low factor loadings or weak contribution to construct reliability were removed to improve the psychometric quality of the model. Hence, the modified measurement model forms the basis for the results reported in table 2.

Table 3 Refined Assessment of Reflective Constructs

SN	Lower Order Constructs (LOCs)	Cronbach's alpha	rho_a	rho_c	AVE
1	Risk identification	0.869	0.874	0.911	0.718
2	Risk Assessment	0.873	0.874	0.907	0.662
3	Risk Mitigation	0.858	0.936	0.895	0.683
4	Risk Monitoring	0.855	0.975	0.883	0.604
5	Risk Recovery	0.864	0.875	0.902	0.651
6	Operational Performance	0.882	0.898	0.911	0.635
7	Financial Performance	0.836	0.887	0.889	0.668
8	Big Data_Managerial skills	0.774	0.815	0.867	0.685
9	Big Data_Technical Skills	0.83	0.879	0.92	0.852
10	Big Data_Data Driven Culture	0.813	0.818	0.888	0.726
11	Big Data _Organizational Learning	0.851	0.852	0.931	0.871

As presented in Table 3, the measurement model of all reflective constructs in this study demonstrates substantial internal consistency reliability, and convergent validity. Specifically, Cronbach's alpha, rho_a, rho_c (composite reliability) values ranges between 0.774 to 0.882 exceeding recommended thresholds or 0.7. Convergent validity is also satisfactory as AVE values range from 0.604 to 0.852, confirming adequate shared variance among retained indicators.

Table 4 : Discriminant Validity Using the HTMT Criterion

	BDH_ MGRL	BDH_ TCNL	BDI_ DDC	BDI_ OL	FIN	OPR	RAS	RID	RMI	RMO
BDH_ MGRL										
BDH_ TCNL	0.324									
BDI_DDC	0.815	0.425								
BDI_OL	0.552	0.559	0.595							
FIN	0.706	0.452	0.751	0.542						
OPR	0.703	0.567	0.688	0.691	0.828					
RAS	0.748	0.472	0.837	0.615	0.722	0.86				
RID	0.761	0.315	0.78	0.554	0.66	0.779	0.924			
RMI	0.644	0.204	0.772	0.44	0.5	0.673	0.848	0.824		
RMO	0.283	0.192	0.401	0.406	0.297	0.526	0.599	0.55	0.826	
RRE	0.568	0.227	0.708	0.475	0.469	0.703	0.746	0.81	0.87	0.74

Table 4 presents the assessment of discriminant validity using the HTMT criterion following indicator refinement. The majority of construct pairs exhibit HTMT values below the recommended threshold of 0.85, indicating satisfactory discriminant validity. The HTMT value between risk assessment (RAS) and risk identification (RID) remains above the threshold of 0.9 (0.924), reflecting the strong conceptual proximity of these lower-order constructs within the supply chain risk management (SCRM) higher-order construct. Although the HTMT value between Risk Assessment (RAS) and Risk Identification (RID) was 0.924, the bias-corrected bootstrapped confidence interval ranged from 0.871 to 0.968 and did not include 1.00, indicating that the two dimensions are statistically distinguishable. Given their distinct theoretical roles within SCRM, RAS and RID were therefore retained as separate dimensions. A marginally elevated value is also observed between risk recovery (RRE) and risk mitigation (RMI) (0.870), which similarly reflects functional interdependence within the SCRM domain. These overlaps are theoretically expected in hierarchical component models and do not undermine the discriminant validity of constructs across distinct higher-order domains.

Table 5. Discriminant Validity Using the Fornell–Larcker Criterion

	BDH_MGRL	BDH_TCNL	BDI_DDC	BDI_OL	FIN	OPR	RAS	RID	RMI	RMO	RRE
BDH_MGRL	0.828										
BDH_TCNL	0.28	0.923									
BDI_DDC	0.666	0.368	0.852								
BDI_OL	0.449	0.479	0.501	0.933							
FIN	0.598	0.379	0.645	0.452	0.817						
OPR	0.607	0.503	0.609	0.598	0.738	0.797					
RAS	0.629	0.408	0.72	0.534	0.651	0.765	0.814				
RID	0.636	0.272	0.671	0.479	0.592	0.692	0.813	0.847			
RMI	0.583	0.155	0.704	0.403	0.532	0.649	0.777	0.749	0.826		
RMO	0.307	0.121	0.424	0.352	0.231	0.495	0.58	0.554	0.703	0.777	
RRE	0.478	0.199	0.605	0.411	0.421	0.617	0.658	0.704	0.75	0.691	0.807

Table 5 presents the assessment of discriminant validity using the Fornell–Larcker criterion. For all constructs, the square root of the AVE (diagonal elements) exceeds the correlations with other constructs, confirming adequate discriminant validity across the measurement model. Although correlations remain relatively high among conceptually related dimensions within the same higher-order construct, the dominance of the diagonal values confirms that each construct captures a distinct latent concept. These results corroborate the HTMT findings and provide robust evidence of discriminant validity for the reflective measurement models.

Evaluation of Formative Measurement Models Using a Sequential Disjoint Approach

The BDAC constructs construct was estimated using a sequential disjoint three-stage approach, in which the reflective and formative lower-order constructs were first validated independently, then their latent variable scores were generated, and subsequently used to form the higher-order formative construct. This sequential disjoint approach is said to minimize estimation bias, avoids multicollinearity inflation which often appears in the case of a repeated indicators approach.

Firstly, in stage one, collinearity among the formative indicators was assessed using variance inflation factors (VIF), as reported in Table 6. VIF values below 3.3 indicate no critical multicollinearity concerns, while values below 5.0 are also considered acceptable for formative measurement models. The next step is to evaluate the statistical significance and relevance of the first-order formative indicator weights. BDT2_data was not statistically significant ($p = 0.257$), suggesting a weaker relative contribution. Similarly,

BDT4_basic was not statistically significant (p = 0.136). Within the Technology dimension, BDT6_tech (p = 0.203) and BDT8_tech (p = 0.076) did not reach the conventional significance threshold. However, in formative measurement models, non-significant weights do not automatically justify indicator deletion, particularly when theoretical relevance is strong and multicollinearity is absent. To further evaluate the practical relevance of these indicators, the outer loadings and their statistical significance are then examined as recommended by Hair et al., (2021). Outer loadings reflect the absolute contribution of each indicator to its respective formative construct, with higher and statistically significant loadings confirming that the indicators meaningfully represent the construct. All indicators demonstrated high loadings, and all p-values were 0.000, indicating that every indicator contributes significantly in absolute terms. Notably, several indicators that had non-significant weights (specifically BDT2_data, BDT4_basic, BDT6_tech, and BDT8_tech) show strong and significant loadings. This confirms that while their relative contribution (weight) to the formative construct is weaker, their absolute contribution is substantial and statistically meaningful. Consequently, these indicators were retained to preserve the content validity and theoretical completeness of the construct.

The analysis proceeds to Stage 2, where the latent variable scores generated from these first-order constructs are used to build the second-order formative construct. As with stage one, all VIFs, weights, weights p values, outer loadings, and outer loadings p values all met the thresholds as presented in table 5. Specifically, within the Tangible Dimension, the VIF values ranged from 1.179 for BDT_BASIC to 1.599 for BDT_DATA. In the Human Skills Dimension, BDH_MGRL and BDH_TCNL both recorded VIFs of 1.085, while in the Intangible Dimension, BDI_DDC and BDI_OL both had VIFs of 1.336. These results confirm that each second-order indicator contributes unique information to the higher-order construct without redundancy. As for their weights, all three first-order constructs of the Tangible Dimension (BDT_BASIC, BDT_DATA, and BDT_TECH) had significant weights with p-values below 0.01. Additionally, In the Human Skills dimension, the weights and their P values along with Indicator Loadings and P values for both BDH_MGRL and BDH_TCNL were significant.

Having established the significance and relevance of these indicators, the analysis proceeds to Stage 3, and evaluates the third-order formative construct of BDAC. This step is crucial as it validates the aggregation of lower-level constructs into a coherent higher-order formative construct that accurately represents the overall capability (BDAC). The VIF values, the weights, loadings and their respective P values for the second-order latent variable scores (Tangible, Human Skills, Intangible) forming the third-order construct, Big Data Analytics Capability (BDAC) were all significant and within the thresholds recommended by Hair et al., 2021. This suggests that multicollinearity is not a concern at the third-order level.

Table 6 Assessment of Formative Measurement model usingVIFs, Formative Indicator Weights and loadings

Construct	Item	VIF	Weights(O)	Weight P values	Loadings (O)	Loadings P values
Stage One						
Data	BDT1_data	2.307	0.519	0.004	0.916	0.000
	BDT2_data	2.737	0.219	0.257	0.869	0.000
	BDT3_data	1.906	0.393	0.005	0.85	0.000
Basic	BDT4_basic	2.206	0.317	0.136	0.866	0.000
	BDT5_basic	2.206	0.742	0.000	0.977	0.000
Technolog y	BDT6_tech	1.943	0.234	0.203	0.805	0.000
	BDT7_tech	2.248	0.619	0.000	0.954	0.000
	BDT8_tech	2.085	0.265	0.076	0.834	0.000
Stage Two						
Big Data Tangible	BDT_BASIC	1.179	0.444	0.000	0.709	0.000
	BDT_DATA	1.599	0.413	0.001	0.830	0.000
	BDT_TECH	1.435	0.442	0.000	0.774	0.000
Big Data	BDH_MGRL	1.085	0.865	0.000	0.953	0.000

Human Skills	BDH_TCNL	1.085	0.316	0.000	0.558	0.000
Big Data Intangible	BDI_DDC	1.336	0.749	0.000	0.943	0.000
	BDI_OL	1.336	0.386	0.000	0.761	0.000
Stage Three						
BDAC	BDT (Tangible)	1.388	0.316	0.000	0.89	0.000
	BDH(Human Skills)	2.339	0.375	0.000	0.90	0.000
	BDI (Intangible)	2.155	0.485	0.000	0.729	0.000

Structural Model Evaluation: Moderation Analysis

Having validated the measurement model, the structural model was assessed to examine the hypothesized relationships among constructs in the proposed research model. The structural model was evaluated to examine the moderation effect of BDAC as well as the direct effect of Big Data Analytics Capability (BDAC) on organizational performance as presented in table 6.

Table 7 Structural Model Path Coefficients, T-Statistics, and P-Values for Direct Effect and interaction effect

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P value
SCRM -> OP	0.159	0.16	0.052	3.052	0.002
BDAC -> OP	0.428	0.426	0.064	6.672	0.000
BDAC x SCRM -> OP	-0.167	-0.166	0.049	3.385	0.001

The direct effect of Supply Chain Risk Management on Organizational Performance is positive and statistically significant ($\beta = 0.159$, $p = 0.002$), and therefore H1 is supported. Additionally, the interaction term between Big Data Analytics Capability and Supply Chain Risk Management on Organizational Performance, as shown in Table 7, shows a statistically significant and negative effect ($\beta = -0.167$, $t = 3.385$, $p = 0.001$), indicating that Big Data Analytics Capability significantly moderates the relationship between Supply Chain Risk Management and Organizational Performance, thereby supporting the hypothesised moderation effect (H2). However, a negative β coefficient is counterintuitive and denotes that the presence of BDAC diminishes the effect of SCRM on OP which contrasts with the expected amplifying role of BDAC proposed in Section 2.6, where higher levels of BDAC were expected to strengthen the positive effect of SCRM on OP. Additionally; a Post-hoc Probing of Moderation Effects using Simple Slope Analysis further confirms this result. Specifically, the simple slope analysis clarifies how the effect of SCRM on OP varies across different levels of BDAC. Figure 2 show that at low levels of BDAC, the positive effect of SCRM on OP is stronger, whereas at high levels of BDAC, the slope becomes flatter and even slightly reverse, demonstrating a negative moderation effect. This change in slope direction highlights that while SCRM improves organizational performance, the marginal benefit decreases as BDAC increases, suggesting that firms with very high analytics capability gain relatively less incremental performance from additional SCRM efforts. This result may suggest a diminishing marginal return effect, whereby the additional contribution of SCRM practices becomes less pronounced in firms with stronger analytics capability. Organizations with advanced BDAC may already possess systems for data visibility, predictive analysis, forecasting, and decision support that enable faster interpretation of operational signals and more informed responses. Consequently, some performance-enhancing functions of SCRM may overlap with or be partially substituted by BDAC, reducing the incremental performance gains from additional SCRM

practices. The implication is not that SCRM becomes less valuable in highly digitalized firms, but rather that its relative contribution may decrease when analytics systems perform overlapping functions.

To further assess the magnitude of the moderation effect, the effect size (f^2) of the SCRM × BDAC interaction was examined. The interaction term produced an f^2 of 0.044, indicating a small effect according to the recommended thresholds. R^2 for Organizational Performance is not reported separately for the moderation analysis because OP is simultaneously explained by multiple relationships within the broader structural model, including SCRM and Supply Chain Resilience. Therefore, the R^2 value for OP reflects the combined explanatory contribution of the broader model and cannot be attributed specifically to the SCRM × BDAC interaction.

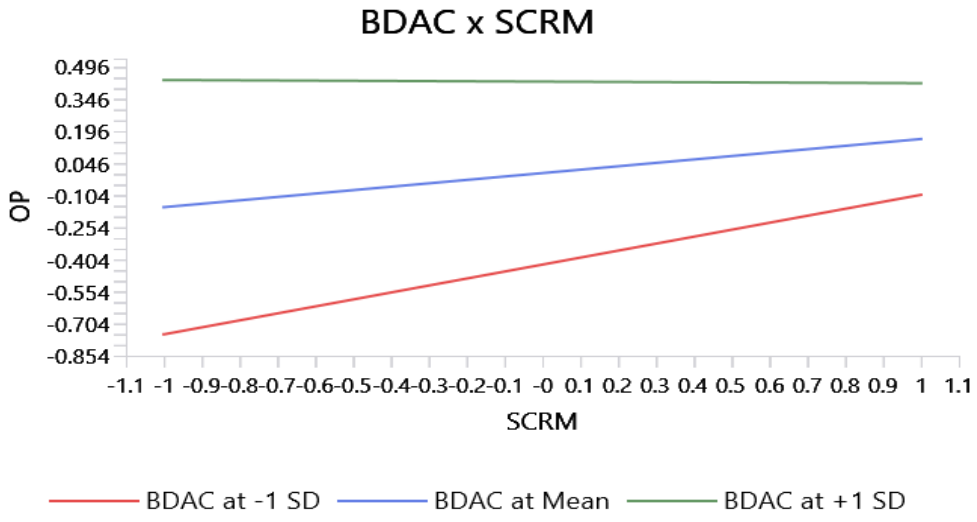


Figure 2 Moderating Effect of BDAC on SCRM-OP

DISCUSSION OF FINDINGS

The study sought to examine the moderating role of Big Data Analytics Capability on the relationship between supply chain risk management and firms' performance in Nigeria's oil and gas downstream sector. The results presented in Table 6, supported by Figure 2 (the simple slope analysis), reveal that BDAC significantly moderates the relationship between SCRM and OP ($\beta = -0.167$, $t = 3.385$, $p = 0.001$). However, a negative moderation effect was found, suggesting that while SCRM maintains a positive direct influence on organizational performance, the strength of this effect declines as BDAC increases. This implies a diminishing marginal return effect in which the additional contribution of SCRM practices to organizational performance becomes less pronounced in firms with stronger analytics capability. In other words, organizations with advanced BDAC may already possess highly developed systems for data visibility, predictive analysis, forecasting, and decision support, such that some of the benefits typically derived from SCRM practices may already be embedded within the firm's analytical infrastructure. Consequently, incremental investments in traditional SCRM activities may produce smaller gains in performance compared to firms with lower analytics maturity. Furthermore, the result does not imply that SCRM becomes less valuable in highly digitalized firms; instead, its relative contribution may decrease when analytics systems perform overlapping functions. For instance, supply chain risk monitoring activities such as tracking and assessing supplier/customer performance, identifying external trends, and generating early-warning alerts may be substantially strengthened through advanced analytics platforms. Similarly, risk assessment processes involving probability estimation, impact evaluation, prioritization, and urgency assessment may be supported by data-driven tools. Consequently, some performance benefits associated with SCRM may already be partly realised through analytics-enabled processes in firms with stronger BDAC, potentially reducing the incremental contribution of additional SCRM practices. This functional overlap offers a plausible explanation for the observed negative moderation, rather than evidence that BDAC directly replaces SCRM.

Theoretically, this finding can be explained through Information Processing Theory, which posits that organizational effectiveness depends on the alignment between information-processing requirements and information-processing capacity (Galbraith, 1974; Tushman & Nadler, 1978). SCRM generates and utilises information through activities such as risk identification, assessment, monitoring, and response, while BDAC enhances the organization's capacity to process large volumes of information, identify patterns, and support timely decisions. Consequently, firms with stronger BDAC may already possess enhanced information-processing capacity for managing supply chain risks, reducing the additional performance contribution associated with SCRM. From a Dynamic Capabilities Theory perspective, BDAC may also strengthen firms' ability to sense emerging risks and seize opportunities through timely, data-informed decisions. Where these analytics-enabled capabilities perform functions that overlap with SCRM activities, the incremental performance contribution of SCRM may become less pronounced as BDAC increases. These theoretical perspectives therefore provide a plausible explanation for the negative interaction observed in this study, without implying that BDAC makes SCRM unnecessary. Empirically, this finding extends studies such as Jerome et al. (2024), Singh (2020), and Liu et al. (2024), which establish that the effectiveness of SCRM is contingent on firms' digital capabilities. While prior studies largely emphasize the enabling and strengthening role of analytics, the present study reveals that in Nigeria's downstream oil and gas sector, BDAC may also reduce the incremental performance gains derived from SCRM, indicating a more nuanced and context-sensitive moderating role.

CONCLUSION

This study evaluated the moderating role of Big Data Analytics Capability (BDAC) in the relationship between Supply Chain Risk Management (SCRM) and Organizational Performance (OP) among major downstream oil and gas marketers in Nigeria. The findings show that SCRM positively influences OP, while BDAC significantly and negatively moderates this relationship. The moderating effect finding is counterintuitive such that higher BDAC is associated with a weaker incremental contribution of SCRM to performance, potentially reflecting functional overlap and diminishing marginal returns between the two capabilities. The study therefore extends understanding of BDAC as a boundary condition of the SCRM–performance relationship by demonstrating that its role may be more nuanced than the predominantly enabling effect reported in prior research. These findings also provide context-specific evidence from Nigeria's downstream oil and gas sector and suggest that firms should align analytics and risk management capabilities to ensure complementary rather than overlapping investments.

Contribution to knowledge

This study makes theoretical contributions to the supply chain management and risk literature by integrating Big Data Analytics Capability (BDAC) into SCRM-Performance Model as a moderator. The study advances theoretical knowledge on the boundary condition of BDAC influence on SCRM influences organizational performance thereby by showing that technology-driven information processing capabilities can influence how risk management translates into performance. The study also contributes to the empirical literature by situating these relationships in the Nigerian downstream oil and gas sector, a context underrepresented in prior studies, thereby extending the generalizability of SCRM, BDAC, OP frameworks beyond developed-country contexts. From a practical standpoint, the study offers actionable insights for managers and practitioners in high-risk, complex supply chains. The moderating insights related to Big Data Analytics Capability (BDAC) shows that while BDAC may shape the extent to which SCRM translates into organizational performance, the negative moderation effect suggests that managers need to carefully balance data-driven interventions with operational realities to avoid potential complexities and overlaps or diminishing returns.

LIMITATIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

First, the cross-sectional design limits the ability to make definitive causal inferences. Although Structural Equation Modelling (SEM) was employed to test hypothesized relationships, the data capture a single point in time and therefore reflect associations rather than dynamic causal processes. Future research employing

longitudinal or experimental designs could provide stronger evidence of temporal and causal relationships between SCRM, BDAC, and organizational performance.

Second, the scope of the study is context-specific, focusing exclusively on major downstream oil and gas marketers in Nigeria. While this provides insights into a high-risk, complex sector, the generalizability of the findings to other industries, geographic regions, or upstream and midstream operations may be limited. Future studies could apply the framework across these contexts to assess its wider applicability.

Third, the study relies on self-reported data from organizational representatives. Although respondents were knowledgeable heads of operational units, responses may be susceptible to social desirability bias and perceptual differences. Furthermore, despite procedural and statistical assessments, the possibility of common method bias cannot be entirely ruled out. Future studies could incorporate objective measures and data from multiple sources. Additionally, the 237 individual responses were analysed without aggregation into firm-level scores, and organizational identifiers were not retained to preserve confidentiality. Consequently, potential within-firm response dependence could not be empirically assessed. Future research could retain appropriate organizational identifiers to assess response dependence and determine whether aggregation or multilevel analysis is warranted.

Finally, only selected relationships were reported, since the article is from a broader PhD research framework. Therefore, independent robustness checks and alternative model specifications were not undertaken, and the full-model explanatory power cannot be attributed specifically to the examined SCRM-BDAC interaction. Moreover, the proposed functional overlap between SCRM and BDAC remains a theoretical explanation rather than a directly tested mechanism. Future research could examine alternative model specifications and investigate this potential overlap more directly.

ACKNOWLEDGMENT

The first author gratefully acknowledges the sponsorship support received from the Petroleum Technology Development Fund (PTDF), Nigeria, under the Overseas Scholarship Scheme (OSS) for Ph.D. studies.

REFERENCE

1. Abdulameer, S. S., & Ibrahim, Y. M. (2024). The moderating role of big data analytics capabilities in the relationship between supply chain management practices and sustainable performance: A conceptual framework from a metaverse perspective. In M. Al-Emran, J. H. Ali, M. Valeri, A. Alnoor, & Z. A. Hussien (Eds.), beyond reality: Navigating the power of metaverse and its applications (Vol. 1, pp. xx-xx). Proceedings of the 3rd International Multi-Disciplinary Conference
2. Abdulrahman, A. S., Zakuan, N., Yaacob, T. Z., Gunu, U., & Nowakowska, M. (2025). The role of big data analytics capability in enhancing supply chain risk management, resilience, and performance. International Journal of Academic Research in Business and Social Sciences, *15*(12), 1491–1500. https://doi.org/10.6007/IJARBSS/v15-i12/27274
3. Abdulrahman, A. S., Zakuan, N., Yaacob, T. Z., & Nowakowska, M. (2026). Supply chain recovery research: A systematic literature review of focus areas, strategies, methods and emerging sustainability insights. International Journal of Academic Research in Business and Social Sciences, 16(2), 333–354. https://doi.org/10.6007/IJARBSS/v16-i2/27577
4. Abdulrahman, A. S., Zakuan, N., Yaacob, T. Z., Gunu, U., Abdulrahman, R. S., & Kasim, S. I. (2026). *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*. *Dutse Business Review, 1*(1), 69–88
5. Abeysekara, N., Wang, H. and Kuruppuarachchi, D. (2019), "Effect of supply-chain resilience on firm performance and competitive advantage: A study of the Sri Lankan apparel industry", Business Process Management Journal, Vol. 25 No. 7, pp. 1673-1695. https://doi.org/10.1108/BPMJ-09-2018-0241

6. Ajike, E. O., Egbuta, O. U., Nwankwere, I. O., Ogundiwin, I., & Adeeoko, A. E. (2021). External business environment and entrepreneurship performance of small and medium enterprises (SMEs) in Lagos, Nigeria. Hallmark University Journal of Management & Social Sciences, 3(2), 137-151.
7. Akter, S., Fosso Wamba, S., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? International Journal of Production Economics, 182, 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018
8. Al-Kharabsheh, A., Mkheimer, I., Assaf, N., Alkhrabsheh, A., & Mohammad, A. M. (2026). The role of supply chain collaborative in enhancing sustainability through supply chain risk management. Production, 36, e20250076. https://doi.org/10.1590/0103-6513.20250076
9. Alkhatib, S. F., & Momani, R. A. (2023). Supply Chain Resilience and Operational Performance: The Role of Digital Technologies in Jordanian Manufacturing Firms. Administrative Sciences, 13(2). https://doi.org/10.3390/admsci13020040
10. Aqlan, F., & Lam, S. S. (2016). Supply chain optimization under risk and uncertainty: A case study for high-end server manufacturing. Computers and Industrial Engineering, 93, 78–87. https://doi.org/10.1016/j.cie.2015.12.025
11. Asikhia O.U., Makinde, G. O., Akinlabi, H. B. & Olawore O. P. (2022). Supply Chain Risk Management and Business Performance of Selected Oil and Gas Marketing Companies in Lagos State, Nigeria: Moderating Role of Firms' Size, Journal of Procurement & Supply Chain, Vol 6(1), 58-75
12. Awwad, M., Kulkarni, P., Bapna, R., & Marathe, A. (2018). Big data analytics in supply chain: A literature review. In Proceedings of the International Conference on Industrial Engineering and Operations Management (pp. 418–425). IEOM Society International
13. Bahrami, M. and Shokouhyar, S. (2021), "The role of big data analytics capabilities in bolstering supply chain resilience and firm performance: a dynamic capability view", Information Technology & People, Vol. 35 No. 5, pp. 1621-1651. https://doi.org/10.1108/ITP-01-2021-0048
14. Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2018). Supply chain risk management and artificial intelligence: state of the art and future research directions. In International Journal of Production Research (Vol. 57, Issue 7, pp. 2179–2202). Taylor and Francis Ltd. https://doi.org/10.1080/00207543.2018.1530476
15. Balci, G. and Ali, S.I. (2024), "The relationship between information processing capabilities, Net-Zero capability and supply chain performance", Supply Chain Management, Vol. 29 No. 2, pp. 351-370. https://doi.org/10.1108/SCM-06-2023-0320
16. Bhatti, S. H., & Bhatti, A. A. (2019). Impact of supply chain risk management on organizational performance: Moderating role of supply chain integration. University of Cambridge Conference Proceedings, 26–27 September 2019, 1–6.
17. Blom, T., & Niemann, W. (2022). Managing reputational risk during supply chain disruption recovery: A triadic logistics outsourcing perspective. Journal of Transport and Supply Chain Management, 16. https://doi.org/10.4102/jtscm.v16i0.623
18. Daferighe, E. E., & Edet, J. P. (2019). Empirical investigation of determinants of financial performance of listed oil and gas companies in Nigeria. East African Scholars Journal of Economics, Business and Management, 2(12), 718-733.
19. Dubey, R., Gunasekaran, A., & Childe, S. J. (2019). Big data analytics capability in supply chain agility: The moderating effect of organizational flexibility. Management Decision, 57(8), 2092–2112. https://doi.org/10.1108/MD-01-2018-0119
20. Egwuonwu, A., Mendy, J., Smart-Oruh, E., & Egwuonwu, A. (2023). Drivers of Big Data Analytics' Adoption and Implications of Management Decision-Making on Big Data Adoption and Firms' Financial and Nonfinancial Performance: Evidence from Nigeria's Manufacturing and Service Industries. IEEE Transactions on Engineering Management, 71, 11907–11922. https://doi.org/10.1109/TEM.2023.3321426
21. Fan, Y., & Stevenson, M. (2018). A review of supply chain risk management: definition, theory, and research agenda. In International Journal of Physical Distribution and Logistics Management (Vol. 48, Issue 3, pp. 205–230). Emerald Group Holdings Ltd. https://doi.org/10.1108/IJPDLM-01-2017-0043

22. Fan, H., Li, G., Sun, H., Cheng, T., 2016. An information processing perspective on supply chain risk management: antecedents, mechanism, and consequences. Int. J. Prod. Econ. 185, 63–75.
23. Ferraris, A., Mazzoleni, A., Devalle, A. and Couturier, J. (2019), "Big data analytics capabilities and knowledge management: impact on firm performance", Management Decision, Vol. 57 No. 8, pp. 1923-1936. https://doi.org/10.1108/MD-07-2018-0825
24. Foli, S., Durst, S., Davies, L., & Temel, S. (2022). Supply chain risk management in young and mature SMEs. Journal of Risk and Financial Management, 15(8), Article 328. https://doi.org/10.3390/jrfm15080328
25. Galbraith, J. R. (1974) Organization Design: An Information Processing View. Interfaces 4(3):28-36. http://dx.doi.org/10.1287/inte.4.3.28
26. Gurtu, Amulya, and Jestin Johny. 2021. Supply Chain Risk Management: Literature Review. Risks 9: 16. https://doi.org/10.3390/risks9010016
27. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A primer on partial least squares structural equation modeling (PLS-SEM) (2nd ed.). Thousand Oaks, CA: SAGE Publications.
28. Hair, J. F., Ringle, C. M., Danks, N. P., Hult, G. T. M., Sarstedt, M., & Ray, S. (2021). Partial least squares structural equation modeling (PLS-SEM) using R: A workbook. Springer. https://doi.org/10.1007/978-3-030-80519-7
29. Haylemariam, L. G., Umar, R. M., & Oduro, S. (2025). Modeling the role of big data analytics capabilities in impacting corporate environmental performance: A serial mediation analysis. Business Strategy and the Environment, 34, 7791–7815. https://doi.org/10.1002/bse.4373
30. Ho, W., Zheng, T., Yildiz, H., & Talluri, S. (2015). Supply chain risk management: A literature review. In International Journal of Production Research (Vol. 53, Issue 16, pp. 5031–5069). Taylor and Francis Ltd. https://doi.org/10.1080/00207543.2015.1030467
31. Holgado, M. and Niess, A. (2023), "Resilience in global supply chains: analysis of responses, recovery actions and strategic changes triggered by major disruptions", Supply Chain Management: An International Journal, Vol. 28 No. 6, pp. 1040-1059, doi: 10.1108/SCM-01-2023-0020.
32. Horani, O. M., Al-Adwan, A. S., Al-Rahmi, W. M., & Alkhalifah, A. (2026). Enabling innovation with big data analytics capabilities: The moderating role of organizational learning culture. Data Science and Management, 9, 100158. https://doi.org/10.1016/j.dsm.2025.100158
33. Hussain, H., Sheng, D. X., & Rehman, S. (2026). Impact of big data analytic capabilities on firm performance: A dynamic capability view. Journal of the Knowledge Economy. Advance online publication. https://doi.org/10.1007/s13132-026-03168-3
34. Jerome, J. J., Sonwaney, V., Bryde, D., & et al. (2024). Achieving competitive advantage through technology-driven proactive supply chain risk management: An empirical study. Annals of Operations Research, 332, 149–190. https://doi.org/10.1007/s10479-023-05604-y
35. John, N. E., Margaret, E.-W. T., Anyandike, T. O., & Ortencia, M. M. (2019). Supply chain disruption in Nigeria oil and gas sector: Some mitigation strategies. International Journal of Scientific and Research Publications, 9(2), Article p8611. https://doi.org/10.29322/IJSRP.9.02.2019.p8611
36. Jüttner, U., Maklan, S., (2011). Supply chain resilience in the global financial crisis: an empirical study. Supply Chain Management. Int. J. 16 (4), 246–259. https://doi.org/ 10.1108/13598541111139062
37. Kaur, P., & Sharma, S. K. (2014). Evaluating the relationship and influence of critical success factors of TQM on business performance: Evidence from SMEs of manufacturing sector. The IUP Journal of Operations Management, 1(4), 17-30.
38. Kiron, D.,Prentice,P.K.,Ferguson,R.B.,2014.The analytics mandate. MITS loan Man ag. Rev.55,1–25.
39. Kline, R. B. (2015). Principles and practice of structural equation modeling (4th ed.). New York, NY: The Guilford Press.
40. KPMG. (2019). Downstream oil and gas sector watch. https://assets.kpmg.com/content/dam/kpmg/ng/pdf/tax/Downstream-Oil-and-Gas-Sector-Watch.pdf
41. Liu, H., Xu, X., Cheng, T. C. E., & Yu, Y. (2024). Building resilience or maintaining robustness: Insights from relational view and information processing perspective. Transportation Research Part

E: Logistics and Transportation Review, 188, Article 103609. https://doi.org/10.1016/j.tre.2024.103609

42. Meade, A. W., & Craig, S. B. (2012, April 16). Identifying Careless Responses in Survey Data. Psychological Methods. Advance online publication. doi: 10.1037/a0028085
43. Memon, M. A., Cheah, J.-H., Ramayah, T., Ting, H., Chuah, F., & Cham, T. H. (2019). Moderation analysis: Issues and guidelines. Journal of Applied Structural Equation Modeling, 3(1), i–xi. https://doi.org/10.47263/JASEM.3(1)01
44. Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. Information & Management, 57(2), 103169. https://doi.org/10.1016/j.im.2019.05.004
45. Munir, M., Sadiq Jajja, M. S., Chatha, K. A., & Farooq, S. (2020). Supply Chain Risk Management and Operational Performance: The Enabling Role of Supply Chain Integration. International Journal of Production Economics, 107667. doi:10.1016/j.ijpe.2020.107667
46. Norrman, A., & Wieland, A. (2020). The development of supply chain risk management over time: revisiting Ericsson. International Journal of Physical Distribution and Logistics Management, 50(6), 641–666. https://doi.org/10.1108/IJPDLM-07-2019-0219
47. Ordibazar, A. H., Hussain, O. K., Chakrabortty, R. K., Irannezhad, E., & Saberi, M. (2025). Artificial intelligence applications for supply chain risk management considering interconnectivity, external events exposures and transparency: A systematic literature review. Modern Supply Chain Research and Applications, 7(2), 148–179. https://doi.org/10.1108/MSCRA-10-2024-0041
48. Park, M. and Singh, N.P. (2022), "Predicting supply chain risks through big data analytics: role of risk alert tool in mitigating business disruption", Benchmarking: An International Journal, Vol. 30 No. 5, pp. 1457-1484. https://doi.org/10.1108/BIJ-03-2022-0169
49. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
50. Primadasa, R., Kusrini, E., Mansur, A., & Setiaji, H. (2025). The role of green ambidexterity innovation, agile supply chain, and big data analytics capability to enhance sustainable SCM performance in SMEs: An integration of CFA-SEM-ANN approach. Process Integration and Optimization for Sustainability, 10, 3–20. https://doi.org/10.1007/s41660-025-00560-5
51. Rahman, M. A., Saha, P., Belal, H. M., Ratul, S. H., & Graham, G. (2026). Big data analytics capability and supply chain sustainability: Analyzing the moderating role of green supply chain management practices. Benchmarking: An International Journal, 33(2), 417–443. https://doi.org/10.1108/BIJ-10-2024-0852
52. Rialti, R., Zollo, L., Ferraris, A., & Alon, I. (2019). Big data analytics capabilities and performance: Evidence from a moderated multi-mediation model. Technological Forecasting and Social Change, 149, 119781. https://doi.org/10.1016/j.techfore.2019.119781
53. Sawaean, F. A. A., & Mohd Ali, K. A. (2020). The impact of entrepreneurial leadership and learning orientation on organizational performance of SMEs: The mediating role of innovation capacity. Management Science Letters, 10(2), 369–380. https://doi.org/10.5267/j.msl.2019.8.033
54. Schlegel, G. L., & Trent, R. J. (2015). Supply chain risk management: An emerging discipline. CRC Press, Taylor & Francis Group
55. Seyedan, M., & Mafakheri, F. (2020). Predictive big data analytics for supply chain demand forecasting: Methods, applications, and research opportunities. Journal of Big Data, 7, Article 53. https://doi.org/10.1186/s40537-020-00329-2
56. Shah, V., Shah, J., Dudhat, K., Mehta, P., & Shah, M. (2022). Big data analytics in oil and gas industry. In Emerging technologies for sustainable and smart energy. https://doi.org/10.1201/b23013-3
57. Singh, N. (2020). Developing Business Risk Resilience through Risk Management Infrastructure: The Moderating Role of Big Data Analytics. Information Systems Management, 39(1), 34–52. https://doi.org/10.1080/10580530.2020.1833386
58. Silva, U.S.K.D., Paul, A., Hasan, K.W., Paul, S.K., Ali, S.M. and Chakrabortty, R.K. (2023), "Examining risks and strategies for the spice processing supply chain in the context of an emerging

economy", International Journal of Emerging Markets, Vol. 18 No. 5, pp. 1124-1146. https://doi.org/10.1108/IJOEM-07-2020-0776

59. Soper, D.S. (2024). A-priori Sample Size Calculator for Structural Equation Models [Software]. Available from https://www.danielsoper.com/statcalc
60. Srinivasan, R., & Swink, M. (2015). Leveraging supply chain integration through planning comprehensiveness: An organizational information processing theory perspective. Decision Sciences, 46(5), 823–861. https://doi.org/10.1111/deci.12166
61. Teece, D.J., Pisano, G. and Shuen, A. (1997). Dynamic Capabilities and Strategic Management. Strategic Management Journal, Vol. 18 No. 7, pp. 509-533.
62. Turi,s J.A., Khwaja, M.G., Tariq, F. and Hameed, A. (2023), "The role of big data analytics and organizational agility in improving organizational performance of business processing organizations", Business Process Management Journal, Vol. 29 No. 7, pp. 2081-2106. https://doi.org/10.1108/BPMJ-01-2023-0058
63. Tushman, M. L., & Nadler, D. A. (1978). Information processing as an integrating concept in organizational design. Academy of Management Review, 3(3), 613–624. https://doi.org/10.5465/amr.1978.4305791
64. Upadhyay, P., & Kumar, A. (2020). The intermediating role of organizational culture and internal analytical knowledge between the capability of big data analytics and a firm's performance. International Journal of Information Management, 52, 102100. https://doi.org/10.1016/j.ijinfomgt.2020.102100
65. Wamba, S. F., Dubey, R., Gunasekaran, A., & Akter, S. (2019). The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. International Journal of Production Economics, 222, 107498. https://doi.org/10.1016/j.ijpe.2019.09.019
66. Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009
67. Wieland, A., & Wallenburg, C. M. (2012). Dealing with supply chain risks: Linking risk management practices and strategies to performance. International Journal of Physical Distribution & Logistics Management, 42(10), 887–905.
68. Wildman, J. L., Bedwell, W. L., Salas, E., & Smith-Jentsch, K. A. (2011). Performance measurement at work: A multilevel perspective. In S. Zedeck (Ed.), APA handbook of industrial and organizational psychology: Vol. 1. Building and developing the organization (pp. 303–341). American Psychological Association. https://doi.org/10.1037/12169-0