

Big Data Analytics and Sustainable Supply Chain Management Practices among Manufacturing Enterprises in North-West Nigeria: A Mediating Role of Inventory Management.

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Abstract

The growing need for harmonised approaches to enhance operational efficiency, minimise costs, and optimise delivery and distribution in today's expanding, sporadic global supply chains and highly turbulent business environment has brought Big Data Analytics (BDA) to the forefront of managerial and scholarly attention. Consequently, an avalanche of literature has documented the positive influence of BDA on Sustainable Supply Chain Management Practices (SSCMP). However, despite this growing body of evidence, there remains a remarkable scarcity of studies that examine Inventory Management (IM) as a mediating mechanism between BDA and SSCMP among manufacturing enterprises. This study therefore investigated the mediating effect of IM on the relationship between BDA and SSCMP in order to extend prior findings. PLS-SEM was employed to test whether IM significantly mediates the relationship between BDA and SSCMP, using survey data obtained from 304 business owners and managers in the manufacturing sector in North-West Nigeria. The findings reveal that the effect of BDA on SSCMP is significantly mediated by IM. On the strength of this evidence, the study concludes that IM exerts a significant and positive mediating effect on the relationship between BDA and SSCMP. It therefore recommends that CEO as well as top managers of manufacturing enterprises should leverage BDA so as to analyse supply chain disruptions, identify potential risks, develop mitigation strategies, and equally deploy predictive analytics in order to optimise inventory allocation.

Keywords: *Big Data Analytics, Inventory Management, Manufacturing Enterprises, Sustainable Supply Chain Management Practices.*

1. Introduction

Harmonized approaches to optimise delivery and distribution in today's ever expanding, sporadic global supply chain, highly turbulent and unpredictable business climate have seen the emergence of big data analytics (BDA) (Huong et al., 2025). It has long been documented that BDA is an emerging supply chain (SC) game changer (Rashid et al., 2024; Waller & Fawcett, 2013), enhance efficient operations, minimize costs (Dubey et al., 2016) and optimise delivery and distribution in the present hypercompetitive business

environment (Sheffi, 2015). The concept of BDA had gained prominence in the recent decades as one of the most important issues in business analytics. The use of BDA in core business functions and operations can create benefits, such as cost savings, better decision making, and higher product and service quality (Ohakwe & Wu, 2025; Davenport, 2014). Besides, it could allow real-time process measurement and monitoring for superior quality management, logistics and order fulfillment cycles (Jum'a et al., 2023; Gupta & George, 2016).

Globally, the logistics and manufacturing sectors are under growing pressure to adopt Sustainable Supply Chain Management (SSCM) because transportation contributes roughly 14% of global greenhouse gas emissions (Ohakwe & Wu, 2025). Within this context, BDA is increasingly viewed as a strategic tool for improving both operational efficiency and environmental performance. Evidence suggests that BDA can generate 15 to 20% fuel savings through route optimisation and reduce energy costs by 30 to 40% when integrated with renewable energy systems (Ohakwe & Wu, 2025). Yet adoption remains uneven, especially in emerging economies where digital capability gaps, technological complexity, and high implementation costs continue to slow progress (Huong et al., 2025). In Nigeria, these constraints are intensified by poor infrastructure. About 68% of logistics and manufacturing firms rely on road transport, while deteriorating roads have increased transit time by 35% and vehicle maintenance costs by 25% since 2015. Electricity instability is equally severe (Efayena et al., 2026), forcing 82% of firms to depend on diesel generators for 8 to 12 hours daily.

These conditions weaken the practical gains that firms might otherwise derive from analytics-driven sustainability initiatives. Port congestion in Lagos alone is estimated to generate 450,000 tons of excess emissions annually, while the low-carbon transition remains constrained by the existence of only 14 public electric vehicle charging stations nationwide despite their significant emission-reduction potential (Ohakwe & Wu, 2025). More broadly, supply chains continue to face recurrent disruptions arising from inefficient inventory control, production failures, limited operational visibility, demand fluctuations, inadequate analytical capability, cybersecurity threats, and persistent product quality problems (Samuel, 2019). Figure 1 presents historical trends and decade-ahead projections adapted from Lagos Free Zone (2024) for Nigeria's key manufacturing sectors.

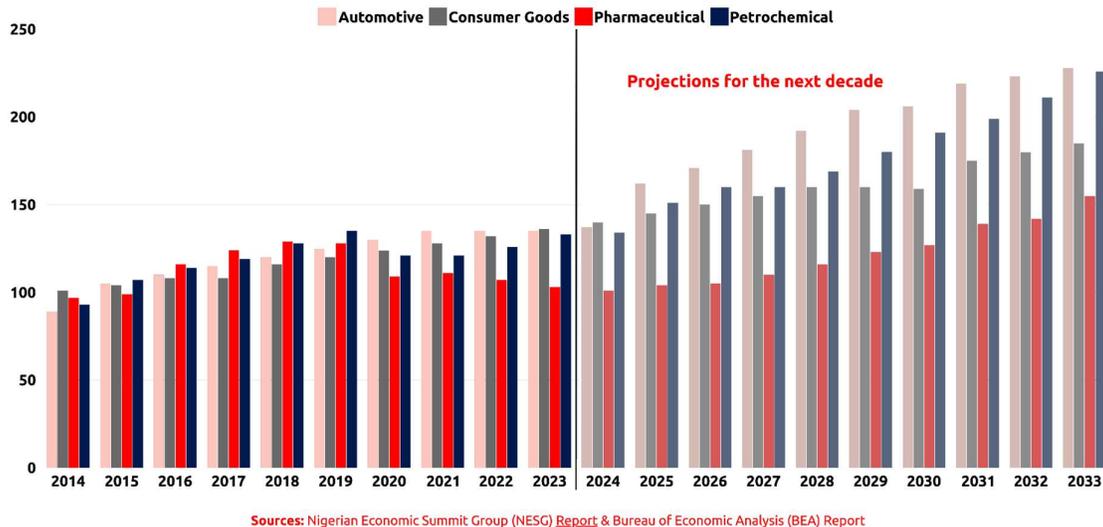


Figure 1. Historical and Projected Growth in Key Manufacturing Sectors in Nigeria

Figure 1 presents historical trends and decade-ahead projections for Nigeria's automotive, consumer goods, pharmaceutical, and petrochemical manufacturing sectors (Lagos Free Zone, 2024); it highlights expected expansion despite recent fluctuations. Although prior studies have shown that BDA can strengthen forecasting, risk evaluation, responsiveness, and recovery capacity in dynamic business environments (Tipu & Fantasy, 2023; Zhang, 2023; Muhammad et al., 2020), the pathway through which

these improvements produce Sustainable Supply Chain Management Practices (SSCMP) remains insufficiently clarified. This concern is consistent with recent studies showing that sustainability outcomes are often nonlinear and mediated by deeper structural conditions rather than driven by simple direct effects alone (Efayena et al., 2026; Irikefe et al., 2025).

Against this background, the present study argues that Inventory Management (IM) may represent a crucial explanatory mechanism in the relationship between BDA and SSCMP. While existing literature generally supports a positive association between BDA and sustainable supply chain outcomes, relatively few studies have examined whether better inventory processes help translate analytical capability into sustainability performance (Huong et al., 2025). This omission limits theoretical clarity and practical insight, particularly in emerging economy settings such as Nigeria where resource constraints and operational disruptions are pronounced (Irikefe et al., 2025). Accordingly, this study is guided by the following research questions regarding Nigerian logistics and manufacturing firms:

- (i) *How does BDA affect SSCMP?*
- (ii) *How does BDA influence IM?*
- (iii) *How does IM affect SSCMP?*
- (iv) *To what extent does IM mediate the relationship between BDA and SSCMP?*

This study contribute to the SSCMP literature in many ways. First, the study provides insights into the relationship between primary variables and extends inventory management theory by exploring the mediating role of inventory management on BDA and sustainable supply chain management practices. The findings of this study is aimed at assisting the management of manufacturing firms to improve their supply chain efficiency, reduce environmental footprint and gain a competitive advantage in the market. Besides, the study is expected to contribute to environmental sustainability and provide insights for policymakers and practitioners to develop strategies that promote sustainable economic growth and development.

2. Literature Review

Big data analytics is a new concept that is gaining an increased recognition in the operations research and production management literature. In contemporary times, it has evolved into a widely deployed and comprehensively studied discipline. BDA is often proclaimed by many scholars as characterized by 5Vs: volume, variety, velocity, veracity, and value (Keskar et al., 2020; Wamba et al., 2015; Assunção et al., 2015; Emani et al., 2015). Volume refers to the magnitude of data, which has exponentially increased, posing a challenge to the capacity of existing storage devices (Chen & Zhang, 2014). Velocity is the rate at which the data is being collected (Assunção et al., 2015). Variety refers to the fact that data can be generated from heterogeneous sources, for example sensors, Internet of things (IoT), mobile devices, online social networks, etc., in structured, semi-structured, and unstructured formats (Tan et al., 2015). Veracity is often defined as the quality or trustworthiness of the collected data while value of a dataset can be determined by estimating the insights that can be generated from the dataset post-analytics (Keskar et al., 2020; Gandomi & Haider, 2015).

SSCMP encompasses all integrated activities that bring product to market and create satisfied customers. Strengthening management of supply chain enhances both customer satisfaction and profitability (David et al., 2014), creates price advantages that help attract and retain customers (Fantazy & Tipu, 2023) and leads to increased market share which in turn brings with it competitive advantages such as lower warehousing and transportation costs, reduced inventory levels, less waste, and lower transaction costs (James, 1995). Its cardinal objective is to create the most value for the entire supply chain network, including the end-customer, reduce working capital, accelerate cash-to-cash cycles and increase inventory turns (Tipu & Fantazy, 2023; Zigiariis, 2000). IM refers to the systematic process of planning, organizing, and controlling the flow of goods, products, or materials from the point of origin to the point of consumption. IM, a critical element of the supply chain, is the tracking of inventory from manufacturers

to a point of sale (Keely et al., 2001). It involves managing the inventory levels, storage, and movement of goods to meet customer demand while minimising costs and maximizing efficiency.

There have been several studies (Zhang, 2023; Mohammad et al., 2022; Randy et al., 2023; Al-Khatib, 2022; Shabbar et al., 2021; Muhammad et al., 2020; Cheng & Lu, 2018) on the effect of BDA on SSCM. There is an overwhelming consensus in the literature that BDA is fundamental for the sustainability of supply chain management practices of any business (Rashid et al., 2024; Tipu & Fantasy, 2023). However, there is actually limited empirical evidence on inventory management (IM) as mediator in the relationship in emerging economy such as Nigeria; an important drawback of the BDA-SSCMP literature. The research implication is that the accurate nature and mechanism through which variables relate may be difficult to understand, estimates of the relationship between independent and dependent variables may be biased, model may be mis-specified and drawing clear-cut conclusion might be complicated. Besides, in the context of BDA and SSCMP, omitting inventory management may result in reduced predictive power and lack of explanatory power, which can limit the usefulness of the model and the theory. This study, therefore, aims to contribute to filling this knowledge gap.

Mediating effect of inventory management on the SSCMP effect of BDA is hinged on dynamic capabilities theory (DCT) instead of resource-based view (RBV). RBV fails to provide explanation of how and in what context the resources can provide competitive advantage to a firm in dynamic and unpredictable environments (Eisenhardt & Martin, 2000), scholars have argued that the DCT, provides explanation for the organization's competitive advantage in changing environments (Singh et al. 2013; Sirmon et al. 2010; Eisenhardt & Martin, 2000; Teece et al. 1997). DCT can help explain organizations' process of utilising resources and focusing on learning and changing functionality and associating it with organisational performance (Gupta et al., 2019). The conceptual framework of the study is depicted in Figure 2.

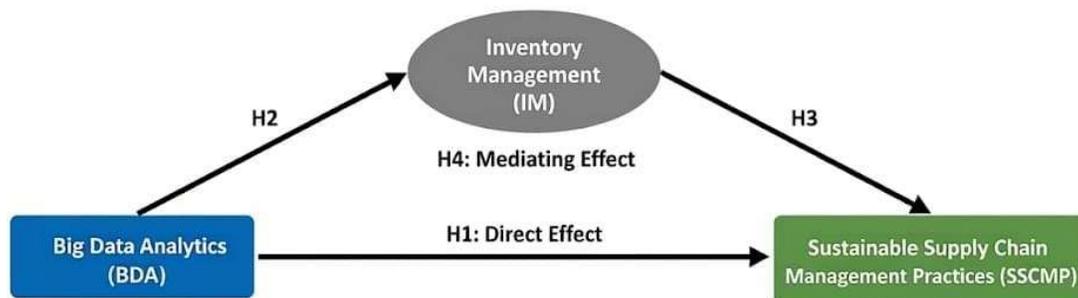


Figure 2. Conceptual Framework

3. Methodology

This study employed a cross-sectional survey research design to obtain quantitative data from different sources at one point in time. The target population for the study comprises SMEs owners in manufacturing enterprises in Kaduna, Kano and Sokoto state. The research relies on primary data collected across the study states through structured questionnaire administered to three hundred and four (304) out of three hundred and sixty-two (362) owners/managers obtained through Krejcie and Morgan (1972) model. The structured questionnaire contained closed ended questions on a five-point rating scale and was grouped into four parts. Part one includes demographic information of the respondents while part two comprises nine (9) items used to measure BDA and adapted from Wamba et al. (2015). Part three includes eleven (11) items of SSCMP adapted from Zigiariis (2000) while part four covers seven (7) items adapted from Keely et al. (2001) to measure IM.

The study sampling technique was three stages: purposive, quota and simple random sampling techniques for sample selection. Purposive sampling is used in the first stage to select manufacturing enterprises and states to be studied. Manufacturing firms with a long-term digitalization process and data-driven transformation, and three states out of the seven states in the Northwest region are selected for the study

based on homogeneity characteristics among the states. The second stage of the sampling technique involves quota sampling based on enterprises and selected states contribution to the target population. In the final stage, the sample units are drawn by simple random sampling technique. The use of this sampling technique is to give every member of the population a chance of being selected and to ensure that sample of this study is a true and fair representative of the population.

Data analysis utilized descriptive and inferential statistics. Descriptive statistics tools include frequency table, percentage, minimum, maximum, mean, standard deviation and Pearson correlation while partial least squares structural equation model (PLS-SEM) was employed as inferential statistics for testing mediation hypothesis. PLS-SEM focuses on prediction and explanation of variance and consequently incorporated via SmartPLS 3.0 software to establish mediating role of IM on the SCM effect of BDA using causal-steps procedure developed by Baron and Kenny (1986). This procedure is expressed in terms of the three regression equations shown below as: This procedure is expressed through three regression equations. First, the dependent variable is regressed on the independent variable to estimate the total effect. Second, the mediator is regressed on the independent variable. Third, the dependent variable is regressed simultaneously on both the independent variable and the mediator. Specifically:

$$\begin{aligned} Y &= cX + e_1 \\ M &= aX + e_2 \\ Y &= c'X + bM + e_3 \end{aligned}$$

where X represents BDA, M denotes IM, and Y refers to SSCMP. The coefficients a , b , c , and c' are regression estimates, while e_1 , e_2 , and e_3 are residual terms. According to Baron and Kenny (1986), mediation is established when c , a , and b are significant. Full mediation occurs when c' becomes insignificant after the inclusion of the mediator, whereas partial mediation occurs when c' remains significant but decreases in magnitude.

4. Findings and Discussion

The key components of this section include measurement and structural model evaluation, descriptive analysis, inferential statistics and discussion of findings. First, the samples' adequacy test is determined. The general criterion is that the sample is adequate if the KMO score exceeded the cutoff value of 0.5 ($KMO \geq 0.5$) and falls within the range of 0.70–1.00. For this study, the KMO value was 0.841 while Bartlett's test value was 437.24, $p < .05$ ($p\text{-value} = 000$), both confirming the adequacy of the sample and support the factorability of the correlation matrix. Similarly, a full collinearity test was performed to confirm common method bias (CMB) using variance inflation factors (VIFs). The statistical evidence validates the model CMB as the highest VIF was 2.834, suggesting that the model is free from CMB.

Table 1. KMO and Bartlett's Test

Measure	Value
Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy	0.841
Bartlett's Test of Sphericity Approx. Chi-Square	437.24
df	26
Sig.	0.000

Table 1 KMO value of 0.841 indicates adequate sampling adequacy, while Bartlett's Test of Sphericity was significant ($\chi^2 = 437.24$, $df = 26$, $p < 0.001$), confirming that the data were suitable for factor analysis.

4.1 Measurement Model Evaluation

The research instrument was subjected to reliability and validity test. Cronbach's alpha (α) and composite reliability (CR) statistics were adopted to evaluate construct-level reliability while average variance

extracted (AVE) was employed to empirically validate convergent validity of the constructs. To maintain construct internal consistency, α and CR indices have to be between 0.7 and 0.9 (Hair et al., 2016). In the context of this study, α and CR tests were above 0.7 suggesting that the measuring model showed strong internal consistency. An AVE value of 0.5 or above is considered acceptable. The AVE values for the study exceeded the threshold value of 0.50, implying that the variance in the indicators is adequately captured.

Table 2. Measurement Model Statistics

Variables/Constructs	Item	Correlation	Cronbach α	AVE	CR
BDA	BDA1	0.81	0.85	0.664	0.933
	BDA2	0.78			
	BDA3	0.88			
	BDA4	0.79			
	BDA5	0.74			
	BDA6	0.88			
	BDA7	0.85			
	BDA8	0.71			
	BDA9	0.82			
SSCMP	SSCMP1	0.76	0.81	0.567	0.901
	SSCMP2	0.78			
	SSCMP3	0.91			
	SSCMP4	0.94			
	SSCMP5	0.86			
	SSCMP6	0.78			
	SSCMP7	0.80			
	SSCMP8	0.77			
	SSCMP9	0.84			
	SSCMP10	0.84			
	SSCMP11	0.90			
IM	IM1	0.87	0.83	0.628	0.914
	IM2	0.82			
	IM3	0.83			
	IM4	0.93			
	IM5	0.83			
	IM6	0.75			
	IM7	0.76			

Table 2 indicates that the measurement model is reliable and valid. All constructs recorded Cronbach's alpha and composite reliability values above 0.70, while average variance extracted exceeded 0.50, confirming strong internal consistency and acceptable convergent validity for BDA, SSCMP, and IM.

4.2. Structural Model Evaluation

Structural model statistics in Table 3 depicts the variance inflation factors (VIFs), explanatory power (R^2) of the endogenous construct, Stone-Geisser (Q^2) values, Cohen (f^2) formula and goodness of fit (GoF). VIF and R^2 are examined to check multi-collinearity within the data while Q^2 and GoF determine the predictive relevance of the inner model and overall model fit values for each dependent variable. Statistical evidence validates the model collinearity as all the VIFs values are less than 10; therefore multi-collinearity was absent within the structural model. Dependent and mediating variables displayed a satisfactory level of R^2 with 0.513 and 0.427 for SSCMP and IM, demonstrating a moderate degree of explanatory power in term of predictive power for the research model. The Q^2 and f^2 are more than the cut-off value of 0.0,

indicating appropriate predictive relevance. Finally, the GoF was determined by $\sqrt{AVE \times R^2}$ and found to be 0.51 which implies that the overall fit of the structural model is acceptable.

Table 3. Structural Model Statistics

Variables	VIF	R ²	Q ²	f ²	GoF
BDA	1.873	-	-	-	-
SSCMP	2.834	0.513	0.317	0.0023	0.583
IM	1.657	0.427	0.236	0.0031	0.462

4.3. Descriptive Analysis

The total validly observed sample comprises three hundred and four (304) SMEs owners in manufacturing enterprises in Kaduna, Kano and Sokoto state. The minimum observation ranges from 9 to 19 score while maximum observation ranges between 23 to 57. All variables standard deviation indicates low variability to the variables mean. For instance, BDA had a mean of 21.451 with a standard deviation of 3.657; SSCMP recorded a mean of 34.534 with a standard deviation of 7.684 while IM mean was 15.74 with a standard deviation of 1.418, suggesting that all variables means are good representation of sample data. Among these variables, BDA (21.451) and IM (15.74) recorded fairly higher scores than the average score while SSCMP (34.534) had score moderately related to the average score on five point rating scale with respect to each variable number of items in the questionnaire. The correlation matrix provided that each variable is perfectly correlated with itself along diagonal of the table and imperfectly correlated to other variables. All imperfect correlations were positive and significant at 0.05 levels. The results in Table 4 clearly suggest that BDA can enhance sustainable supply chain management practices by optimizing inventory management.

Table 4. Descriptive Statistics and Correlation

Variable	Obs	Mean	Std. Dev	Min	Max	BDA	SSCMP	IM
BDA	304	21.451	3.657	12	38	1.000		
SSCMP	304	34.534	7.684	19	57	0.7021*	1.0000	
IM	304	15.742	1.418	9	23	0.6209*	0.5251*	1.000

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

4.4. Test of Hypotheses

PLS-SEM was employed to assess the mediating effect of IM on the relationship between BDA and SSCMP. The statistics presented include path coefficients, significance values, variance accounted for, and conclusion. Bootstrapping with 5,000 resamples at a 95% confidence level was used to determine the significance of the path coefficients. The findings show that H1, H2, and H3 were positive and significant at $p < 0.05$, indicating that the hypotheses were supported. In addition, the indirect path, H4 (BDA → IM → SSCMP), was also positive and significant. Given that both the direct and indirect effects were significant, the study concludes that IM partially mediates the relationship between BDA and SSCMP. The VAF value of 0.927 further suggests that a large proportion of the effect of BDA on SSCMP is explained through IM. These results are presented in Table 5.

Table 5. PLS-SEM Statistics

Hyp	Path	Path Coefficient	Sig	Supported	VAF	Conclusion
H ₁	BDA → SSCMP	0.062	0.027	Yes	0.073	-
H ₂	BDA → IM	0.463	0.000	Yes	0.267	-
H ₃	IM → SSCMP	0.514	0.000	Yes	0.473	-
H ₄	BDA → IM → SSCMP	0.572	0.000	Yes	0.187	Partial Mediation

4.5. Discussion

The findings of the current study sharpen an issue that recent scholarship has often implied but not fully settled; BDA does not automatically translate into SSCMP. Rather, its effect becomes practically meaningful when it is channelled through IM. Empirically, the current study's model appears credible. The sample was adequate, the measures satisfied reliability and convergent validity thresholds, multicollinearity was not problematic, and the structural model showed moderate explanatory power for both SSCMP and IM. More importantly, the path results indicate that BDA exerts only a weak direct effect on SSCMP, whereas its effect on IM is substantial, and IM, in turn, has a strong positive effect on SSCMP. The mediation result therefore suggests that what matters is not merely the possession of analytics capability, but the operational mechanism through which that capability is converted into disciplined inventory decisions and, from there, into sustainable supply chain outcomes.

The pattern is persuasive because it aligns with a growing stream of recent studies that treat analytics as an enabling capability rather than a self-executing resource. Studies have shown that BDA improves forecasting, responsiveness, resilience, visibility, innovation, and knowledge development; yet these gains usually become visible when embedded in specific organisational processes (Muhammad et al., 2020; Shabbar et al., 2021; Mohammad et al., 2022; Al-Khatib, 2022; Randy et al., 2023; Fantazy & Tipu, 2023; Tipu & Fantazy, 2023; Jum'a et al., 2023; Zhang, 2023; Rashid et al., 2024). In that sense, the present study makes a sharper contribution than much of the existing literature because it shows that IM is not a peripheral operational variable; it is the transmission belt through which analytical capability acquires sustainability relevance. Such conclusion is especially compelling in the Nigerian manufacturing context, where infrastructural deficiencies, logistics bottlenecks, energy instability, and rising sustainability pressures make operational discipline more consequential than abstract digital adoption alone (Lagos Free Zone, 2024; Ohakwe & Wu, 2025; Efayena et al., 2026). The study therefore strengthens the dynamic capabilities argument that value arises not from resources in isolation, but from how firms reconfigure them into usable organisational routines.

Nonetheless, the study's claims should not be overstated. Its focus on manufacturing enterprises in Kaduna, Kano, and Sokoto narrows contextual breadth; the cross-sectional design limits causal confidence; and the sample of 304 owner-managers, while analytically adequate, does not settle questions of sector-wide generalisability. Future research should test the study's framework as depicted in Figure 2 across industries and regions, employ longitudinal or mixed-method designs, and examine whether factors such as digital capability maturity, firm size, supply chain visibility, innovation climate, and institutional infrastructure intensify or weaken the mediating role of IM. These extensions would not merely replicate the present findings; they would clarify when, how, and for whom BDA genuinely advances sustainable supply chain practice.

5. Conclusion and Recommendations

This study examined whether IM mediates the relationship between BDA and SSCMP among manufacturing enterprises in North-West Nigeria; specifically, Kaduna, Kano, and Sokoto states. Using a cross-sectional survey design, data from 304 respondents were analysed with PLS-SEM to test the hypothesised relationships. The evidence shows that the contribution of BDA to SSCMP is not primarily direct; rather, its effect is mechanized via IM, which emerged as the decisive pathway through which analytical capability is converted into operational as well as sustainability gains. The study therefore came to the conclusion that BDA becomes strategically valuable to SSCMP only when it is embedded in efficient inventory processes that reduce waste, minimise cost, and improve supply chain performance. In theoretical terms, this finding supports the DCT, which holds that resources yield results only when translated into workable organisational capabilities.

Recommendations follow that:

- (i) Manufacturing firms should not treat BDA as an end in itself; its deployment must be tied to clearly defined SSCMP objectives such as waste reduction, cost efficiency, cleaner operations, and better resource utilisation.
- (ii) Top managers should invest in BDA tools that improve demand forecasting, anomaly detection, and stock planning, since the evidence indicates that BDA becomes valuable when it strengthens IM decisions.
- (iii) Firms should optimise IM through digital inventory systems that monitor demand patterns, lead times, and stock levels in real time so as to reduce stock-outs, overstocking, waste, and storage costs.
- (iv) Since IM is the principal pathway through which BDA improves SSCMP, enterprises should adopt an integrated supply chain strategy that deliberately aligns analytics capability, inventory control, and sustainability performance within one managerial framework.

Declarations

Funding

This research received no external funding.

Conflict of Interest

The authors declare no conflict of interest.

Ethical Approval and Informed Consent

Informed consent was obtained from all subjects involved in the study.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon request.

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