

Effect of MIS-Enabled Big Data Analytics on Innovation Performance of BUA Cement

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Abstract

BUA Cement, a leading Nigerian manufacturer, faces challenges in leveraging its Management Information Systems (MIS) for advanced big data analytics, relying predominantly on descriptive data rather than predictive insights, which hampers innovation. The study aimed to examine the effect of MIS-enabled big data analytics specifically data integration and predictive insight on product and process innovation at BUA Cement. A cross-sectional survey design was employed, with data collected from 370 employees using questionnaires, and analyzed via multiple regression in SPSS v27. Findings revealed that data integration significantly influences product innovation ($\beta = 0.589$, $p < 0.001$), explaining 34.7% of its variance. Similarly, predictive insight significantly affects process innovation ($\beta = 0.712$, $p < 0.001$), accounting for 50.8% of its variance. This confirms that MIS-enabled big data analytics drives innovation performance in heavy manufacturing. It is recommended that BUA Cement upgrade its MIS for seamless cross-functional data integration and invest in predictive analytics tools for proactive process optimization. Academically, the study contributed to dynamic capabilities theory by linking data integration to sensing capabilities and predictive insight to seizing capabilities within an emerging economy context. Practically, it provided a strategic roadmap for industrial firms in Nigeria and similar economies to transition from traditional operations to data-driven innovation, thereby enhancing competitiveness, operational efficiency, and sustainability in the global market.

Keywords: MIS-enabled Big Data Analytics, Data Integration; Predictive Insight, Product Innovation, Process Innovation.

Introduction

The contemporary business landscape is increasingly shaped by data and advanced analytics. Empirical studies from high-quality journals indicate that organizations with strong data-driven capabilities tend to be more competitive, agile, and innovative (Alghamdi & Agag, 2024). Within this environment, Management Information Systems (MIS) transitioned from their traditional role as reporting mechanisms to become dynamic platforms for organizational transformation, a shift significantly amplified by their integration with big data analytics (Mikalef et al., 2020). By leveraging this integration, organizations can extract actionable insights from complex datasets, enhancing the quality of data-driven decisions, creating strategic business value, and fostering flexibility and

dynamic capabilities that support both incremental and transformative innovation (Rialti, Marzi, Caputo, & Mayah, 2020).

This transformation held particular consequence for capital-intensive sectors like cement manufacturing. The industry confronted significant challenges, including volatile energy costs and increasingly strict environmental regulations (Wang et al., 2021). At the same time, increasing demand for sustainable and specialized construction materials has made ongoing innovation in production methods and product offerings crucial for maintaining competitiveness, highlighting MIS-enabled big data analytics as a key strategic tool for driving innovation, sustainability, and long-term competitive advantage (Singh & El-Kassar, 2019).

These advanced systems provided a holistic view of operations by merging real-time data from production, supply chains, and market intelligence. Two core capabilities were fundamental to this process: data integration and predictive insight. Data integration involves consolidating fragmented information from diverse sources, such as IoT sensors and enterprise software, into a unified analytical environment. By integrating IoT-enabled sensors, cyber-physical system architectures, and big data analytics platforms, organizations gain a holistic view of operations that enables real-time monitoring, advanced analytics, and informed decision-making within smart manufacturing environments (Rosati et al., 2022). Predictive insight encompasses both the anticipation of machinery failures through predictive maintenance and the forecasting of supply chain risks or disruptions. Empirical evidence from high-quality journals highlights the pivotal role of machine learning and statistical techniques in enabling proactive maintenance and forward-looking risk management (Hector & Panjanathan, 2024). Collectively, these functions established a foundation for developing new, specialized products and for innovating manufacturing processes to enhance efficiency and environmental performance (Alghamdi & Agag, 2023).

BUA Cement, a major Nigerian producer, represented an organization operating within this complex reality. Despite investing in modernized physical and digital infrastructure, the company's approach to data was primarily descriptive, limiting its ability to generate predictive or prescriptive intelligence (Ghasemaghaei & Calic, 2020). To preserve its market leadership, a shift from conventional operations to a data-driven innovation paradigm is essential. Management Information System (MIS) enabled analytics provides a concrete pathway for this transition in the Nigerian context by transforming raw operational data into actionable information that enhances decision-making and overall firm performance in manufacturing firms (Eze et al., 2021). Implementing big data analytics in Nigerian industries enhances both financial and non-financial performance, consistent with evidence from international studies demonstrating its positive impact on firms' financial, market, operational, and broader sustainability outcomes (Raguseo & Vitari, 2018).

Although the value of big data in manufacturing was widely acknowledged in global literature, a scarcity of empirical research existed concerning its application within

emerging economies, specifically Nigeria's industrial sector. Few studies have quantitatively examined how digital analytics capabilities translate into tangible innovation outcomes in Nigeria's heavy industry. Despite an expanding body of research on digital technologies, Industry 4.0, and analytics adoption in manufacturing and heavy engineering, firm-level evidence from major Nigerian players, such as BUA Cement, remains limited (Raj et al., 2020). This gap in understanding impeded the creation of context-specific digital strategies and undermined the rationale for investment in industrial digitalization.

Therefore, this study investigated the relationship between MIS-enabled big data analytics and innovation performance at BUA Cement. It paid specific attention to the roles of data integration and predictive insight in driving product and process innovation. By generating evidence-based insights, the research aimed to provide guidance for industry leaders in Nigeria and add unique knowledge to the discourse on digital transformation in African manufacturing. Ultimately, it underscored that in a modern economy where data is a vital resource, the capability to analyze and act upon it strategically is what distinguishes future industry leaders.

Statement of the Problem

In today's highly competitive manufacturing environment, integrating Management Information Systems (MIS) with big data analytics is increasingly critical for driving innovation, improving resource efficiency, and enabling rapid adaptation to market and regulatory changes. Research indicates that such analytics can deliver real-time operational insights, facilitate predictive maintenance, and enhance decisions across product lifecycles, supporting both economic and environmental objectives (Dubey et al., 2019). The global manufacturing industry has realized substantial benefits from deploying big data analytics and artificial intelligence, including notable reductions in energy consumption and accelerated commercialization of new products (Dubey et al., 2020).

Conversely, Nigeria's cement industry has been slower to embrace these data-centric approaches. Despite its market dominance and considerable infrastructure investments, BUA Cement has yet to fully capitalize on the potential of MIS-enabled big data. The company's operational information remains fragmented across different functions like production and sales, with minimal analytical processing. Relying primarily on historical, backward-looking reporting rather than predictive, real-time intelligence constrains a manufacturer's capacity to optimize operations and respond rapidly to evolving market conditions, including the growing emphasis on sustainable, low-carbon cement. Studies on green and low-CO₂ cements highlight both their technical readiness and strategic significance, emphasizing how market and policy pressures are driving demand for eco-efficient cement alternatives (Althoey et al., 2023).

This implementation gap is further exacerbated by a lack of empirical research focused on Sub-Saharan Africa's heavy industry. While global studies consistently demonstrate a positive relationship between big data analytics and innovation (Niebel et al., 2018), there remains limited evidence from the Nigerian context. Furthermore, existing theoretical

frameworks often treat big data analytics as a single, undifferentiated construct, overlooking the distinct contributions of its core components data integration and predictive insight which are essential for driving targeted product and process innovations (Capurro et al., 2021).

Failure to address these intertwined gaps carries considerable consequences. For BUA Cement, the lack of a sophisticated data and analytics strategy threatens to stifle product differentiation, perpetuate operational inefficiencies, and impede compliance with national environmental commitments. On a macro level, the slow adoption of digital innovation within Nigeria's manufacturing base risks eroding its international competitiveness and stalling the achievement of key industrial policy aims. Consequently, investigating the impact of MIS-enabled big data on innovation at BUA Cement is not merely an academic exercise but a strategic imperative for the nation's sustainable industrial progression.

Objective of the Study

The main objective of the study was to investigate the effect of MIS-enabled big data analytics on innovation performance of BUA Cement. The specific objectives include:

- i. To examine the influence of data integration as a key dimension of MIS-enabled big data analytics on product innovation at BUA Cement.
- ii. To assess the effect of predictive insight as a 15core dimension of MIS-enabled big data analytics on process innovation at BUA Cement.

Literature Review

Conceptual Framework

Data Integration

Globally, integrated Management Information Systems (MIS) provide a unified platform for consolidating data across organizational functions. This enhances operational transparency and supports agile decision-making (Mokogwu et al., 2024). In Sub-Saharan Africa, data integration continues to be constrained by fragmented ICT infrastructure, limited interoperability between legacy and modern systems, and weak data governance frameworks (Mugauri et al., 2025; Kamuhanda et al., 2026). Although cloud computing and mobile-based data collection have gained traction in sectors such as financial services and agriculture, the absence of standardized data protocols and adequately trained personnel continues to weaken system coherence (Nyarko et al., 2026). Consequently, effective MIS deployment in SSA often requires context-adapted, modular architectures rather than wholesale adoption of global enterprise solutions (Hamdat et al., 2024).

Predictive Insight

Predictive analytics, which is powered by machine learning and big data, has become central to strategic MIS in advanced economies. It enables proactive risk management and demand forecasting (Aljohani, 2023). In Sub-Saharan Africa, adoption remains limited but

is growing, especially in sectors such as agribusiness and fintech. Predictive models are being piloted for applications such as crop yield estimation and credit scoring (Hossain, 2025). However, barriers remain, including sparse historical data, algorithmic bias, and a shortage of data science expertise, all of which reduce model accuracy and scalability (Mugauri et al., 2025; Kamuhanda et al., 2026). Successful implementations often combine AI-based predictive analytics with human expertise and contextual knowledge (Erica et al., 2024).

Innovation Performance

Innovation performance in Sub-Saharan Africa is increasingly influenced by digital capabilities, external collaboration, and organizational learning. Empirical studies indicate that firms using digital tools such as enterprise systems and Internet of Things (IoT) sensors achieve higher innovation output, particularly when combined with employee training and leadership support (Otioma, 2022; Gaglio, Kraemer-Mbula, & Lorenz, 2022). External knowledge sources, including customers, suppliers, industry associations, and consultants, play a crucial role in stimulating innovation, especially among small and medium enterprises (SMEs) with limited R&D capacity (Medase & Abdul-Basit, 2020; Adomako, 2020).

The relationship between innovation and firm performance is strongly mediated by institutional support. Access to finance, the quality of infrastructure, and regulatory protection influence how effectively innovation translates into productivity gains (Egbeleo & Sodokin, 2025; Asunka, Li, & Anaba, 2020; Abdullahi & Mohammed, 2025). Research also shows that process innovation, which enhances operational efficiency, generally produces stronger performance outcomes than product innovation in manufacturing firms under resource constraints (Edeh, Obodoechi, & Ramos-Hidalgo, 2020; Williams et al., 2025).

Product Innovation

Global manufacturers invest heavily in research and development for sustainable and smart products, such as low-carbon cement and self-healing concrete. However, innovation in SSA is constrained by underfunded ecosystems and weak industry-academia linkages (Williams et al., 2025). Despite these limitations, localized product innovations are emerging, including the use of bamboo composites, laterite, and recycled plastics in construction materials. These frugal innovations reflect engineering adapted to local contexts and circular economy principles (Chen et al., 2021; Bredenoord, 2024). Scalability of these innovations remains limited without supportive policy frameworks and access to adequate testing facilities (Stephen & Aigbavboa, 2025).

Process Innovation

Process innovation is the dominant form of innovation in SSA's manufacturing sector and is closely linked to productivity improvements. Firms increasingly adopt digital tools such as automated quality control, predictive maintenance, and digital workflow systems to

improve operational efficiency (Edeh, Obodoechi, & Ramos-Hidalgo, 2020). For example, Nigerian cement producers have incorporated sensor-based monitoring to optimize kiln operations, reducing energy consumption and downtime (Chen et al., 2021; Abdullahi & Mohammed, 2025).

Process innovation in SSA often combines formal digital systems with tacit knowledge from experienced technicians and local engineers. Collaborations with technical universities and vocational institutes further enhance adaptive capacity (Stephen & Aigbavboa, 2025). These learning partnerships are essential for contextualizing imported technologies and supporting incremental innovation in environments with limited formal R&D infrastructure (Otioma, 2022).

Theoretical Framework

This study is anchored in Dynamic Capabilities Theory (DCT), a foundational strategic management perspective developed by Teece, Pisano, and Shuen (1997) and later expanded by Teece (2007). DCT argues that sustainable competitive advantage in rapidly changing environments depends not merely on a firm's existing resources, but on its ability to integrate, build, and reconfigure competencies in response to technological and market shifts. Central to this theory are the higher-order routines of sensing opportunities, seizing them through strategic decisions, and transforming organizational resources to align with evolving conditions.

Despite its widespread influence, DCT has been criticized for being conceptually abstract, with challenges surrounding the empirical measurement of constructs such as "sensing," "seizing," and "reconfiguring" (Schäfer et al., 2020). These critiques are particularly relevant in emerging economies like Nigeria, where firms often operate under resource constraints, infrastructure gaps, and institutional volatility. Nonetheless, the theory's emphasis on adaptability, learning, and strategic renewal makes it highly suitable for examining digital transformation processes (Warner & Wäger, 2019).

In this study, MIS-enabled data integration is conceptualized as a sensing capability, allowing BUA Cement to detect operational anomalies, market shifts, and emerging opportunities through consolidated and real-time information flows. Predictive insight is positioned as a seizing capability, enabling the firm to act proactively by using forecasting models, scenario analysis, and predictive maintenance to capitalize on anticipated trends. These MIS capabilities form the micro foundations of dynamic capabilities, driving both product and process innovation, which in turn influence overall organizational performance.

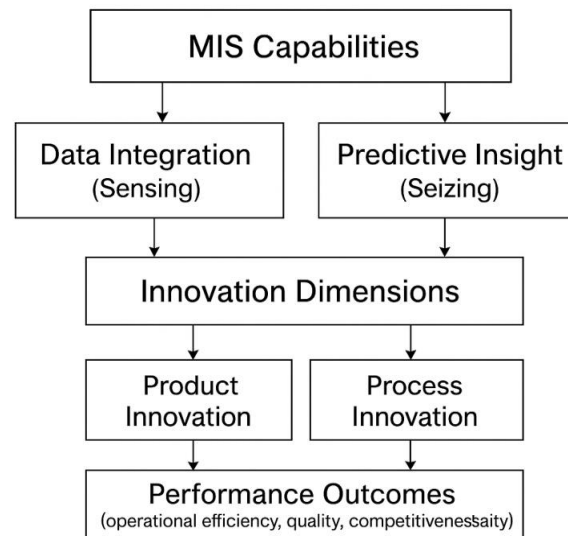


Figure 1

Conceptual Model Linking MIS Capabilities, Innovation, and Performance

Dynamic Capabilities Theory in an Emerging Market Context

This study advances Dynamic Capabilities Theory (DCT) by situating its application within an emerging African context marked by infrastructural limitations, institutional instability, and technological deficiencies. Although DCT has largely been conceptualized and validated in developed economies, this research illustrates how firms operating in resource-constrained environments utilize digital systems particularly MIS-based analytics as alternative mechanisms for building capabilities that are otherwise weak or insufficient. By highlighting how MIS-enabled sensing and seizing capabilities function within BUA Cement despite these contextual challenges, the study broadens the scope of DCT. It offers insight into how capabilities are developed, how digital adaptation occurs, and how innovation emerges in settings where organizations must rely on technology to navigate and compensate for structural constraints.

Empirical Review

Lozada et al., (2019) examined the relationship between big data analytics capabilities and co-innovation. The study adopted a quantitative empirical research design and focused on Colombian firms as the study population. A sample of 112 firms was used, while primary data were collected through a survey instrument administered to the selected firms. The data were analyzed using structural equation modelling through the partial least squares method. The findings revealed that big data analytics capabilities had a positive relationship with co-innovation, particularly in improving product and service co-creation processes and strengthening collaboration networks with both internal and external stakeholders. However, the study was limited to Colombian firms, thereby creating a contextual gap, as its findings may not fully explain how big data analytics capabilities

influenced innovation outcomes in other economies, sectors, or developing-country business environments.

Dubey et al., (2021) investigated the role of alliance management capability, big data analytics capability, and information visibility in enhancing new-product development capability. The study was guided by the dynamic capabilities view and adopted a quantitative survey research design. The population consisted of organizational respondents involved in new-product development-related activities, while 219 usable responses formed the sample size. Data were collected through a pre-tested questionnaire, and the hypotheses were analyzed using variance-based structural equation modelling, specifically PLS-SEM. The findings showed that alliance management capability positively influenced big data analytics capability and that both capabilities contributed to new-product development under the moderating influence of information visibility. The study's gap was that it concentrated on new-product development capability without sufficiently examining how big data analytics could directly improve broader organizational performance or innovation sustainability across different institutional contexts.

Gao and Sarwar (2022) explored how firms created business value and dynamic capabilities by leveraging big data analytics management capability. The objective of the study was to examine the relationship between big data analytics management capability and innovation performance through dynamic capabilities. The study adopted a quantitative empirical design and used firms as the study population. A sample of 149 firms was used, while primary data were collected through firm-level responses. The data were analyzed using partial least squares structural equation modelling. The findings indicated that big data analytics management capability significantly enhanced innovation performance through dynamic capabilities. The study also found that strategic alignment and social capital strengthened the relationship between big data analytics management capability and dynamic capabilities. Nevertheless, the study left a gap because it focused mainly on firm-level innovation performance and did not deeply address how industry type, organizational size, or country-specific digital infrastructure could influence the effectiveness of big data analytics management capability.

Azhar et al., (2025) examined the role of predictive and prescriptive big data analytics in improving small and medium-sized enterprise performance through product and process innovation. The study was anchored on the resource-based view theory and adopted a quantitative research design. The population comprised executives and managerial-level professionals working in Chinese small and medium-sized enterprises. A sample of 312 respondents was used, and primary data were collected through a structured survey questionnaire. The data were analyzed using structural equation modelling with AMOS software. The findings revealed that predictive and prescriptive big data analytics had a significant positive effect on technological innovation, including product and process innovation. The study further showed that technological innovation mediated the relationship between big data analytics and SME performance. However, the study created

a geographical and contextual gap because it was conducted among Chinese SMEs, making it necessary for future studies to examine whether similar relationships existed among SMEs in other developing economies with different technological and institutional conditions.

Adeyoyin et al., (2022) proposed a conceptual framework for predictive analytics and data-driven process improvement. The objective of the paper was to explain how predictive analytics could support organizational process improvement through descriptive, diagnostic, predictive, and prescriptive analytical dimensions. The study did not adopt a conventional empirical survey or experimental design; rather, it used a conceptual and literature-based approach. The population, sample size, and primary data collection method were not specified because the paper relied mainly on existing literature and cross-sectoral applications. The analysis was carried out through literature synthesis and conceptual integration. The study found that predictive analytics could improve early detection of process deviations, enhance resource allocation, support evidence-based decision-making, and strengthen operational efficiency. The major gap was that the framework was not empirically tested, making it necessary for future studies to validate the model using real organizational data and measurable performance indicators.

Capurro et al., (2021) analyzed the role of big data analytics in supporting firms' innovation processes from a dynamic capability's perspective. The study adopted an interpretive qualitative research design. The population consisted of big data analytics experts in digitally related firms, while data were collected through interviews. The exact sample size was not clearly stated in the available study summary. The data were analyzed using interpretive analysis of interview evidence and relevant literature. The findings showed that firms used big data analytics to obtain richer and deeper insights at the intersection of digital and physical environments. The study also revealed that firms could use counterintuitive innovation strategies to develop products, services, or solutions that might initially differ from established customer needs. The gap in the study was that it relied on qualitative evidence from experts in digitally related sectors, which limited the generalizability of the findings to non-digital sectors or firms with lower levels of technological maturity.

Ciampi et al., (2021) investigated the impact of big data analytics capabilities on business model innovation and the mediating role of entrepreneurial orientation. The study was grounded in the dynamic capabilities view and adopted a quantitative research design. The population comprised firms in the United Kingdom, while a sample of 253 firms was used. Primary data were collected through survey responses from the selected firms. The data were analyzed using partial least squares structural equation modelling and fuzzy-set qualitative comparative analysis. The findings showed that big data analytics capabilities had both direct and indirect positive effects on business model innovation, with entrepreneurial orientation serving as a mediating variable. The study contributed to innovation management literature by showing that big data analytics capabilities influenced firms' strategic logic and value creation. However, the study was limited to UK

firms, thereby leaving a gap for studies in developing economies and sectors where digital capability, entrepreneurial orientation, and business model innovation may operate differently.

Zhang and Yuan (2023) examined how and when big data analytics capability boosted innovation performance. The study specifically tested the mediating roles of strategic flexibility and strategic innovation, as well as the moderating role of environmental uncertainty. The research adopted a quantitative survey design and focused on Chinese managers and employees engaged in big data analytics. A sample of 421 respondents was used, and primary data were collected through a structured survey. The data were analyzed using statistical modelling techniques suitable for mediation and moderation analysis. The findings revealed that big data analytics capability had a positive effect on innovation performance. The study also showed that strategic flexibility and strategic innovation serially mediated the relationship, while environmental uncertainty strengthened the effect of big data analytics capability on innovation performance. The gap was that the study focused on Chinese respondents working in big data-related fields, which limited its applicability to other national contexts and to organizations with weaker analytics infrastructure.

Ghasemaghahi and Calic (2020) assessed the impact of big data characteristics on firm innovation performance. The objective of the study was to examine how big data volume, variety, and velocity influenced innovation efficacy and innovation efficiency, and how these innovation outcomes affected firm performance. The study adopted a quantitative empirical research design. The population consisted of managers in firms using big data, while a sample of 239 managers was used. Primary data were collected from the managers through a survey method, and the proposed model was tested empirically. The findings showed that data variety and data velocity positively improved innovation performance, while data volume had no significant effect. The study further found that data velocity played a stronger role in enhancing innovation performance than other big data characteristics. The gap in the study was that it focused mainly on the characteristics of big data rather than the organizational capabilities, human skills, and managerial practices needed to convert big data into sustainable innovation performance.

Mikalef et al., (2019) examined the relationship between big data analytics capability and innovation capability, with attention to the mediating role of dynamic capabilities and the moderating effect of the environment. The study drew from the resource-based view and dynamic capabilities view and adopted a quantitative research design. The population consisted of chief information officers and IT managers working in Greek firms. A sample of 175 respondents was used, and primary data were collected through a survey. The data were analyzed using partial least squares structural equation modelling. The findings confirmed that big data analytics capability indirectly influenced incremental and radical innovation capabilities through dynamic capabilities. The study also found that environmental heterogeneity and environmental dynamism strengthened some of these

relationships. However, the study was limited to Greek firms and IT-related managerial respondents, thereby leaving a gap for broader studies involving other industries, developing economies, and different categories of organizational employees.

Methodology

The study employed a cross-sectional survey research design to investigate the effect of MIS-Enabled Big Data Analytics (ME-BDA) on Innovation Performance (IP) at BUA Cement. This design was deemed appropriate because it facilitated the collection of data from respondents at a single point in time, allowing for a clear assessment of the relationships between the independent variable (MIS-enabled big data analytics with dimensions of Data Integration (DI) and Predictive Insight (PI)) and the dependent variable (IP comprising Product Innovation (PDI) and Process Innovation (PCI)). The design also eliminated the need for repeated observations, making it suitable for organizational settings where longitudinal access is limited.

The study population consisted of all BUA Cement employees who interact with, or are influenced by, the organization's Management Information Systems and innovation-related processes. This included personnel across production, information technology, research and development, operations, and strategic planning units. Official company records indicated that the total population was 1,342 employees.

The unit of analysis was the individual employee, as employees' engagement with MIS tools, analytical platforms, and innovation activities directly shapes organizational innovation outcomes. Analyzing responses at the individual level therefore provided an accurate and context-rich understanding of how MIS-enabled big data analytics influences innovation performance within BUA Cement.

The sample size was determined using Taro Yamane's (1967) formula for finite populations:

$$n = \frac{N}{1 + N(e)^2}$$

Where:

- n = required sample size
- N = population size (1,342)
- e = margin of error (0.05, corresponding to a 95% confidence level)

Substituting the values:

$$n = \frac{1342}{1 + 1342(0.05)^2} = \frac{1342}{1 + 3.355} = \frac{1342}{4.355} = 308.2$$

Thus, an initial sample size of 308 respondents was obtained. To address the possibility of non-responses, incomplete questionnaires, and data attrition, a 20% contingency was added, yielding a final sample size of 370 respondents.

Given operational considerations and the need to target staff directly involved with MIS and innovation activities, the study adopted a mixed sampling strategy combining convenience sampling and purposive sampling. Convenience sampling enabled access to readily available employees within administrative and plant units, while purposive sampling

ensured the inclusion of participants from departments with significant involvement in MIS-enabled big data analytics, such as production control, quality assurance, and digital transformation. This approach enhanced both the relevance and rigor of the data collected. Primary data were gathered using a structured questionnaire comprising closed-ended items measured on a 5-point Likert scale. The instrument captured all key constructs: MIS-enabled big data analytics (DI and PI) as the independent variable, and Innovation performance (IP) (Product Innovation (PDI) and Process Innovation (PCI)) as the dependent variable. The questionnaire was pretested to ensure clarity and face validity.

To test reliability, Cronbach's Alpha coefficients were computed for each construct using SPSS version 27. The results demonstrated strong internal consistency: data integration ($\alpha = 0.861$), predictive insight ($\alpha = 0.884$), product innovation ($\alpha = 0.842$), and process innovation ($\alpha = 0.857$) all above the recommended 0.70 threshold. Content validity was established through expert review by three specialists in information systems and manufacturing innovation, who evaluated the instrument for theoretical adequacy and domain coverage.

Data were analyzed using multiple regression analysis in SPSS version 27 to test the hypothesized relationships between the dimensions of MIS-enabled big data analytics and innovation performance. This analytical technique was appropriate as it enabled the quantification of the predictive effects of data integration and predictive insight on product and process innovation, while controlling for inter-variable influences. The results provided robust empirical evidence to support the proposed conceptual framework.

The study involved both dependent and independent variables. The dependent variable, Innovation Performance, was measured through its dimensions: Product Innovation and Process Innovation. The independent variable, MIS-Enabled Big Data Analytics, was operationalized using two key indicators: Data Integration and Predictive Insight.

Theoretical Model

$$Y = \alpha + \beta_i X_i + \epsilon \dots\dots\dots 1$$

Where: Y =dependent variable (that is Product innovation and Process Innovation)

α =intercept,

β_i = The parameter of the predictor variables

X represents the predictor variable (Data Integration and Predictive Insight)

ϵ denotes the stochastic error component.

Empirical frameworks are formulated as:

$$PDI = \beta_0 + \beta_1 DI + \epsilon_i$$

$$PCI = \beta_0 + \beta_1 PI + \epsilon_i$$

Where:

DI= Data Integration

PI= Predictive Insight

PDI= Product innovation

PCI= Process Innovation

Ethical standards were strictly observed throughout the study. Informed consent was obtained from all respondents, who were assured that participation was voluntary and that they could withdraw at any time without consequences. Respondents were also informed about the purpose of the study, and anonymity and confidentiality were fully guaranteed. No personal identifiers were collected, and the data were used exclusively for academic research purposes. Approval to conduct the study was granted by the appropriate organizational authorities at BUA Cement.

Results and Discussion

Test of Hypotheses

Test of Hypothesis one

Data integration, as a dimension of MIS-enabled big data analytics, has no significant influence on product innovation at BUA Cement.

Model 1

$$PDI_i = \beta_0 + \beta_1 DTI_i + \epsilon_i$$

Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.589 ^a	.347	.346	.43022
a. Predictors: (Constant), DTI				
source Spss version 27				

The regression model, with Digital Technology Integration (DTI) as the sole predictor, explains approximately 34.7% of the variance in the dependent variable, as indicated by an R Square value of .347. The Adjusted R Square of .346 suggests that the model maintains its explanatory power even after accounting for the number of predictors, reflecting minimal over fitting. The correlation coefficient (R) of .589 indicates a moderate positive linear relationship between DTI and the outcome variable. Additionally, the standard error of the estimate (.43022) provides a measure of the average distance that the observed values fall from the regression line, suggesting a reasonable level of precision in predictions. Overall, DTI demonstrates a statistically meaningful and moderate influence on the dependent variable in this model.

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	41.051	1	41.051	221.793	.000 ^b
	Residual	77.182	417	.185		
	Total	118.234	418			
a. Dependent Variable: PDI						
b. Predictors: (Constant), DTI						

Source SPSS Version 27

The ANOVA results for the regression model indicate that the predictor Digital Technology Integration (DTI) significantly explains variation in the dependent variable, Perceived Digital Impact (PDI). The regression sum of squares (41.051) reflects the variability accounted for by DTI, while the residual sum of squares (77.182) represents unexplained variability. With 1 and 417 degrees of freedom for regression and residual, respectively, the model yields an F-statistic of 221.793, which is highly significant ($p < .001$). This confirms that the overall regression model is statistically significant and that DTI contributes meaningfully to predicting PDI. The total sum of squares (118.234) further contextualizes the proportion of explained variance, aligning with the earlier reported R^2 of approximately .347.

Coefficients ^a						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.090	.149		14.006	.000
	DTI	.561	.038	.589	14.893	.000

a. Dependent Variable: PDI

Source SPSS Version 27

The coefficients table shows that both the constant and Digital Technology Integration (DTI) are statistically significant predictors of Perceived Digital Impact (PDI). The unstandardized coefficient (B) for DTI is .561, meaning that a one-unit increase in DTI is associated with a 0.561-unit increase in PDI, holding other factors constant. This effect is highly significant ($t = 14.893$, $p < .001$). The standardized coefficient (Beta = .589) indicates a moderate to strong positive relationship between DTI and PDI, consistent with the model's R value of .589. The constant term (2.090) is also statistically significant ($t = 14.006$, $p < .001$), representing the baseline level of PDI when DTI is zero. These results confirm that DTI exerts a substantial and statistically reliable positive influence on PDI.

Test of Hypothesis two

Predictive insight, as a dimension of MIS-enabled big data analytics, has no significant effect on process innovation at BUA Cement.

Model 2

$$PDI_i = \beta_0 + \beta_1 PTI_i + \epsilon_i$$

Model Summary					
Model	R	R Square	Adjusted R Square	R	Std. Error of the Estimate
1	.712 ^a	.508	.506		.36555

a. Predictors: (Constant), PTI

Source SPSS Version 27

The model summary indicates that Process Technology Integration (PTI) has a substantial explanatory power regarding the dependent variable, with an R value of .712, reflecting a strong positive linear relationship. The R Square of .508 suggests that PTI accounts for approximately 50.8% of the variance in the dependent variable, while the Adjusted R Square of .506 confirms that this explanatory power remains robust after adjusting for the number of predictors (in this case, just one). The standard error of the estimate (.36555) is relatively low, indicating that the observed values are, on average, close to the predicted values thus demonstrating good predictive accuracy. Overall, PTI emerges as a highly influential predictor in the model.

ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	57.425	1	57.425	429.729	.000 ^b
	Residual	55.724	417	.134		
	Total	113.148	418			
a. Dependent Variable: PRI						
b. Predictors: (Constant), PTI						

Source SPSS Version 27

The ANOVA results confirm that the regression model with Process Technology Integration (PTI) as the predictor significantly explains variation in the dependent variable, Perceived Responsiveness Impact (PRI). The regression sum of squares (57.425) indicates the amount of variability in PRI accounted for by PTI, while the residual sum of squares (55.724) represents the unexplained variability. With 1 degree of freedom for regression and 417 for residual, the model yields a high F-statistic of 429.729, which is statistically significant at $p < .001$. This demonstrates that PTI is a powerful and significant predictor of PRI. The total sum of squares (113.148) further supports that over half of the total variance in PRI is explained by the model, consistent with the R^2 value of approximately .508 reported earlier.

Coefficients ^a						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.495	.122		12.219	.000
	PTI	.629	.030	.712	20.730	.000
a. Dependent Variable: PRI						

Source SPSS Version 27

The coefficients table reveals that both the constant and the predictor Process Technology Integration (PTI) are statistically significant in predicting Perceived Responsiveness Impact (PRI). The unstandardized regression coefficient (B) for PTI is .629, indicating that for every

one-unit increase in PTI, PRI increases by 0.629 units, holding all else constant. This relationship is highly significant ($t = 20.730$, $p < .001$). The standardized coefficient ($\text{Beta} = .712$) confirms a strong positive effect of PTI on PRI, aligning the earlier reported R value. The constant term (1.495) is also significant ($t = 12.219$, $p < .001$), representing the predicted value of PRI when PTI is zero. Overall, the results provide robust evidence that PTI is a major and statistically reliable predictor of PRI in this model.

Discussion of Findings

The study found that data integration, as a dimension of MIS-enabled big data analytics, significantly influenced product innovation at BUA Cement. This aligns with prior empirical studies showing that the ability to consolidate and harmonize diverse data streams from production systems, market intelligence, customer feedback, and supply chains enhances firms' innovation capabilities (Lozada et al., 2019; Dubey et al., 2021; Ciampi et al., 2021). The findings support the Dynamic Capabilities Theory and demonstrate that integrated data allows the firm to sense shifts in market demand and seize emerging technological opportunities. Similar to observations in other emerging-market contexts (Azhar et al., 2025; Gao & Sarwar, 2022), these capabilities facilitated the timely development of new or improved products despite infrastructural constraints, skill gaps, and inconsistent data governance. The study emphasizes that managers should foster a data-driven culture, encourage cross-departmental sharing of insights, and implement evidence-based decision-making to convert integrated data into sustainable product innovation.

The study revealed that predictive insight had a substantial effect on process innovation at BUA Cement. The application of machine learning algorithms, real-time monitoring, and trend forecasting tools enabled the firm to anticipate equipment failures, optimize energy usage, and reduce production bottlenecks. These results are consistent with previous research indicating that predictive and prescriptive analytics improve technological and process innovation (Azhar et al., 2025; Adeyoyin et al., 2022; Zhang & Yuan, 2023). Predictive analytics strengthened the firm's ability to reconfigure resources and adapt operational processes to dynamic internal and external conditions. The findings highlight the importance of integrating predictive dashboards into daily planning and maintenance activities to support proactive decision-making and effective resource allocation.

The study highlighted that firms in emerging economies such as Nigeria face contextual constraints including unstable power supply, limited automation, and fragmented technological infrastructure. These factors influence the maturity and efficiency of analytics-driven innovations. This observation is supported by the literature, which indicates that big data analytics capabilities produce different outcomes depending on the contextual conditions (Ghasemaghahi & Calic, 2020; Mikalef et al., 2019; Capurro et al., 2021). Therefore, emerging-market firms benefit from a hybrid innovation approach that combines human expertise with digital tools. Strategic flexibility, careful investment prioritization, and continuous capability development are critical to ensure that managerial

and technological resources are effectively leveraged to sustain both product and process innovation.

Conclusion and Recommendation

This study examined the effect of MIS-enabled Big Data Analytics on innovation performance at BUA Cement, focusing on how data integration influences product innovation and how predictive insight enhances process innovation. The findings confirm that MIS-enabled Big Data Analytics significantly boosts innovation performance: data integration enables the firm to develop market-responsive products by synthesizing insights from diverse internal and external sources, while predictive insight drives process innovation by supporting proactive, data-driven optimization of production workflows. Together, these capabilities underscore the strategic value of big data analytics in fostering both product and process innovation within a heavy manufacturing setting in an emerging economy.

In addition to organizational implications, the findings highlight important policy implications for Nigeria's manufacturing sector. Strengthening national data infrastructure such as expanding broadband coverage, enhancing digital interoperability standards, and promoting data governance frameworks would provide a more stable foundation for advanced analytics adoption across industries. Policymakers should also incentivize manufacturers to invest in digital technologies through tax rebates, grants, or public-private partnerships focused on industrial digitalization. Establishing national centers for manufacturing analytics or innovation hubs could further support capacity building, knowledge sharing, and sector-wide digital transformation.

Based on these findings, two key recommendations are proposed:

- i. BUA Cement should upgrade its Management Information Systems to enable seamless integration of cross-functional data (e.g., from R&D, sales, production, and customer service) into a centralized analytics platform. This will support faster, evidence-based product development cycles and improve responsiveness to market needs.
- ii. The company should invest in predictive analytics tools, such as machine learning models for equipment maintenance, energy consumption forecasting, and process optimization, to systematically drive process innovation, reduce downtime, and enhance production efficiency.

The study opens opportunities for future research. Comparative studies across industries such as manufacturing, telecommunications, and banking could offer broader insights into how big data capabilities influence innovation in different operational contexts. Additionally, adopting longitudinal research designs would allow future studies to examine how MIS-enabled analytics capabilities evolve over time and how their long-term adoption impacts sustained innovation performance. Such approaches would deepen understanding of the dynamic nature of analytics-driven innovation, particularly within emerging economies.

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