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FOURTH INDUSTRIAL REVOLUTION (4IR) AND THE PERFORMANCE OF BUA FOODS, LAGOS

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ABSTRACT: The Fourth Industrial Revolution (4IR), characterised by the integration of advanced digital technologies such as Artificial Intelligence (AI) and the Internet of Things (IoT), has transformed business operations and organisational performance across industries. This study examined the effect of the Fourth Industrial Revolution on the performance of BUA Foods, with specific emphasis on the influence of AI and IoT on organisational performance. A survey research design was adopted for the study. The population comprised 768 employees of BUA Foods; 264 respondents were calculated using Yamane's (1967) formula, raised to 291 after a ten per cent allowance, of which 276 were usable and utilised for data collection through structured questionnaires. Data collected were analysed using correlation and regression techniques to establish the nature and extent of the relationship between 4IR technologies and organisational performance. The findings revealed that both Artificial Intelligence and the Internet of Things have a significant and positive effect on the performance of BUA Foods. However, the study found that IoT shows an influence on organisational performance compared with AI, suggesting that IoT applications contribute to performance outcomes. The study concludes that the adoption of Fourth Industrial Revolution technologies improves organisational performance within BUA Foods. Based on these findings, it is recommended that BUA Foods should intensify investment in IoT infrastructure while simultaneously strengthening its AI capabilities through continuous technological upgrades, employee training, and strategic integration of digital innovations to sustain competitive advantage and improve overall organisational performance.

Keywords: Fourth Industrial Revolution (4IR), Artificial Intelligence (AI), Internet of Things (IoT), Performance (PFM)

INTRODUCTION

The Fourth Industrial Revolution (4IR) represents a paradigm shift in industrial development characterised by the integration of advanced digital technologies such as artificial intelligence, Internet of Things (IoT), big data analytics, robotics, cloud computing, and cyber-physical systems. According to Schwab (2016), 4IR is fundamentally transforming how organisations produce, distribute, and consume goods and services by creating intelligent and interconnected systems. In the manufacturing and food processing sector, these technologies are increasingly being deployed to improve production efficiency, improve product quality, and optimise supply chain operations. More recent studies affirm that 4IR technologies are redefining competitiveness by enabling real-

time data-driven decision-making and automation across industrial processes (Mhlanga, 2023; World Economic Forum, 2024).

In the context of the food manufacturing industry, firms are under increasing pressure to improve productivity, reduce waste, ensure food safety, and meet rising consumer demand. BUA Foods Plc, Lagos, as one of Nigeria's leading food manufacturing companies, operates in a highly competitive environment where efficiency and innovation are critical to sustaining market leadership. The adoption of 4IR technologies such as automated milling systems, predictive maintenance, and digital supply chain tracking has become essential for improving operational performance and cost efficiency. Empirical evidence suggests that firms adopting advanced digital technologies experience significant improvements in production output, quality control, and responsiveness to market dynamics (Deloitte, 2023; World Bank, 2023).

Despite these advancements, many manufacturing firms in developing economies, including Nigeria, still face challenges in fully integrating 4IR technologies due to infrastructural limitations, high implementation costs, and skills gaps. BUA Foods offers a relevant context for examining this issue empirically. The company has been expanding its production infrastructure through partnerships with international equipment manufacturers, including a 2024 agreement with IMAS of Türkiye to build four wheat and flour milling factories with a combined capacity of 3,200 tonnes per day, and a subsequent agreement with FAVA of Italy to add nine automated long-cut pasta lines capable of 6,000 kg/hr, alongside a grain-storage expansion with Cukurova Silo of Türkiye (NGX Corporate Disclosures, 2024). At its Port Harcourt integrated rice mill, project engineers have highlighted that the plant's automation allows production to be monitored remotely from anywhere in the world, reflecting an early adoption of connected, IIoT-style monitoring systems (CNBC Africa, 2019). More recently, the company has continued this trajectory with a near-complete integrated sugar complex in Lafiagi, Kwara State, and a 2025 agreement for a 32-tonnes-per-hour automated rice processing line (Billionaires Africa, 2025). While these initiatives point to a growing, if uneven, adoption of automated and digitally monitored production systems, the extent to which they have translated into measurable gains in profitability, operational efficiency, and productivity remains unexamined in the literature. This creates a research gap regarding how 4IR adoption impacts key performance indicators within the Nigerian food manufacturing sector. Therefore, this study seeks to examine the relationship between Fourth Industrial Revolution technologies and the performance of BUA Foods, Lagos, with a view to providing empirical evidence that can guide strategic decision-making and industrial policy.

The main objective of the study is to examine the effect of Fourth Industrial Revolution on the performance of BUA Foods, Lagos. The specific objectives are to:

i. examine the relationship between Artificial Intelligence and the performance of BUA Foods, Lagos.

ii. investigate the relationship between the Internet of Things and the performance of BUA Foods, Lagos.

The study tested the following null hypotheses:

Ho_1: Artificial Intelligence has no significant effect on the performance of BUA Foods, Lagos.

Ho_2: Internet of Things has no significant effect on the performance of BUA Foods, Lagos.

LITERATURE REVIEW

Fourth Industrial Revolution

The concept of the Fourth Industrial Revolution (4IR) has been defined by several scholars and institutions from different perspectives. The Fourth Industrial Revolution (4IR) is commonly understood as a phase of industrial transformation involving the convergence of digital, physical and, in some accounts, biological technologies. Schwab (2023) emphasises the broad transformative implications of this convergence for industries and society. De Oliveira et al. (2022), by contrast, focus on the industrial application of digital technologies, cyber-physical systems, automation and smart manufacturing. These perspectives share an emphasis on technological integration, but differ in scope: Schwab's account is broader, while the Industry 4.0 perspective is more directly concerned with production systems and industrial processes.

For this study, 4IR is understood as the integration of advanced digital technologies into organisational processes to support connectivity, automation, information processing and operational coordination. This conceptualisation is appropriate because the study focuses on AI and IoT as technology-related variables and examines their relationship with organisational performance.

Artificial Intelligence

Artificial Intelligence (AI) refers broadly to machine-based systems that use data and computational processes to generate predictions, recommendations, content or decisions. The OECD (2024) emphasises the ability of AI systems to infer from inputs and produce outputs that influence physical or virtual environments. Maslej et al. (2024) similarly focus on computational systems that perform functions such as pattern recognition, data processing and adaptive learning.

While these definitions differ in emphasis, they converge on the use of computational systems to perform tasks that support or approximate aspects of human reasoning and decision-making. For the present study, AI is understood as the use of intelligent computational systems to process information, identify patterns and support organisational decisions and activities. This definition aligns with the study's focus on AI as a 4IR technology associated with organisational performance.

Internet of Things

The Internet of Things (IoT) refers to a network of physical objects equipped with sensors, software and communication capabilities that enable data collection and exchange. Mansour et al. (2023) emphasise the architecture and integration of connected devices, while Choudhary (2024) highlights the capacity of smart devices to sense their environment and communicate within

connected systems. Elksasy (2023) also stresses the sensing, processing and communication capabilities of connected physical objects.

These perspectives share the view that IoT connects physical objects and digital systems to facilitate data exchange and monitoring. They differ mainly in their emphasis on system architecture, contextual services and the intelligent capabilities of connected objects. This study adopts a functional understanding of IoT as the use of connected devices and sensor-enabled systems to collect, transmit and support the use of operational data. This definition is relevant to the study because IoT is examined as a technology-related variable associated with organisational performance.

Performance

Organisational performance concerns the extent to which an organisation achieves its objectives through the effective and efficient use of resources. Zhang et al. (2023) emphasise organisational outcomes and the coordination of resources, while Castelo and Gomes (2023) focus on measurable outcomes arising from organisational activities and management practices. Mukaro et al. (2023) similarly associate performance with value creation and productivity.

These definitions converge on the achievement of organisational objectives but differ in their emphasis on resource coordination, measurable outcomes and value creation. For this study, organisational performance is understood as the extent to which an organisation achieves desired operational and organisational outcomes.

Empirical Review

Kamble et al. (2023) conducted a study titled "Industry 4.0 and Smart Manufacturing Performance in Indian Manufacturing Firms." The study was carried out in India and adopted a quantitative survey research design. The population comprised registered manufacturing firms in major industrial clusters across India, particularly automotive and engineering sectors. A sample of 312 manufacturing firms was selected using stratified random sampling. Data were collected using structured questionnaires administered to operations and production managers. The study used Structural Equation Modelling (SEM) with AMOS for data analysis to test the relationship between 4IR technologies (IoT, AI, CPS, and big data analytics) and manufacturing performance. Findings revealed that 4IR technologies significantly improve operational efficiency, productivity, and supply chain responsiveness. However, the study is limited by its reliance on self-reported data and cross-sectional design, which restricts causal interpretation. The research gap identified is the need for longitudinal and developing-economy comparative studies on 4IR and manufacturing performance.

Mittal et al. (2024) examined digital Transformation and Industry 4.0 Adoption: Effects on Manufacturing Firm Performance in European Industries. The study was carried out across Germany and selected European countries using a quantitative survey research design. The population included medium and large-scale manufacturing firms engaged in advanced manufacturing and industrial production. A sample of 287 firms was selected using purposive and

stratified sampling techniques. Data were collected from senior managers using structured questionnaires. The study used Partial Least Squares Structural Equation Modelling (PLS-SEM) via SmartPLS for data analysis. Findings revealed that 4IR technologies such as AI-driven automation, digital twins, and smart factory systems significantly improve innovation performance, production efficiency, and competitive advantage. However, the study is limited by its focus on advanced economies with strong infrastructure, which may not reflect conditions in developing countries. The identified research gap is the need for context-specific studies in developing economies to examine infrastructural and institutional constraints affecting 4IR–performance relationships.

Obi (2024) examined the effect of the management of artificial intelligence (AI) on the performance of manufacturing firms in Enugu State, Nigeria, with specific objectives to assess the effect of infrastructural development and workforce skills on firm performance. A descriptive research design was adopted. Primary data were collected using a structured questionnaire administered to staff of selected manufacturing firms in Enugu State. Data were analysed using simple percentages, mean and standard deviation, and a one-sample t-test to test the stated hypotheses. The study found that infrastructural development had a statistically significant effect on the performance of manufacturing firms ($t = 12.308$, $p = 0.000$), and that workforce skills also had a significant effect on firm performance ($p = 0.000 < 0.05$). The study concluded that the management of AI significantly affects the performance of manufacturing firms in Enugu State and recommended that government and stakeholders prioritise infrastructural investment to support AI implementation. The study focused narrowly on infrastructural development and workforce skills as proxies for AI management, and it was restricted to manufacturing firms in Enugu State, a single sub-national context. It did not disaggregate specific 4IR technologies (e.g., IoT, automation, big data) or examine sector-specific dynamics such as those in large-scale food manufacturing, leaving room for studies that examine broader 4IR technology adoption and its effect on performance in other Nigerian manufacturing sub-sectors, such as food production.

Amaugo (2024) analysed the impact of AI adoption on business process automation and competitiveness in the Nigerian manufacturing industry, using Dangote Cement Plc and Nigerian Breweries Plc as case studies, with a focus on operational efficiency, productivity, and competitive advantage. The study employed structured questionnaires administered to a sample of 301 respondents drawn from the two case-study firms. Data were analysed using regression analysis to test the relationships between AI adoption and the identified performance outcomes. The results showed a strong, statistically significant positive relationship between AI adoption and improved operational efficiency, with AI adoption found to reduce human error and optimise production processes, thereby improving productivity and competitiveness in the sampled firms. The study was restricted to two large, already technologically advanced firms (Dangote Cement and Nigerian Breweries) in the cement and brewing sub-sectors, which may not be representative of the wider Nigerian food and FMCG manufacturing sector. It also concentrated on AI specifically rather than the broader range of 4IR technologies, and did not examine profitability as a distinct performance indicator alongside efficiency and productivity.

Ndubisi (2025) examined the impact of Artificial Intelligence on sustainability and operational efficiency of SMEs in South-East, Nigeria. Specifically, it determined the effect of machine

learning on operational efficiency of SMEs. A descriptive research design was adopted. The population of the study comprised 27,546 SMEs registered and certified under the Corporate Affairs Commission (CAC). A sample size of 379 was arrived at by utilising Krejcie and Morgan's 1970 sample size determination formula. A structured questionnaire was the major instrument used for data collection. The instrument was validated and tested for reliability. A reliability coefficient of 0.86 was obtained which was considered reliable. Data analysis was executed using inferential statistics consisting of simple regression analysis. Result indicated that machine learning had a significant positive effect on operational efficiency of SMEs in South-East, Nigeria. The study aggregates SMEs across sectors without disaggregating manufacturing, service, or trade businesses, thereby obscuring sector-specific insights. Manufacturing, which relies heavily on machinery, logistics, and production optimisation, may experience AI differently from service-based SMEs. There is a lack of sector-focused evidence on how AI improves operational efficiency in BUA manufacturing.

Müller et al. (2024) examined Internet of Things and Industry 4.0 Integration: Implications for Manufacturing Firm Performance in European Industries. The study adopted a quantitative survey research design. The population consisted of manufacturing firms in Germany and selected European Union countries operating advanced production systems. A sample of 276 firms was selected using purposive and stratified sampling techniques. Data were collected from senior managers and engineers using structured questionnaires. The relationships were tested using structural equation modelling in AMOS. The findings indicated that IoT adoption significantly improves innovation capability, operational efficiency, and competitive advantage, particularly when integrated with other Industry 4.0 technologies such as AI and cloud computing. However, the study is limited by its focus on highly developed economies with advanced infrastructure, limiting applicability to developing countries. The key research gap identified is the need for context-sensitive studies in developing economies to examine infrastructural and institutional constraints affecting IoT performance relationships.

Technology Acceptance Model

The Technology Acceptance Model (TAM), developed by Davis (1989), explains technology adoption behaviour through two core determinants: perceived usefulness (the degree to which a user believes that using a technology will improve job or organisational performance) and perceived ease of use (the degree to which a technology is believed to be free of effort). In the context of the Fourth Industrial Revolution (4IR), TAM is highly relevant because advanced technologies such as the Internet of Things (IoT), artificial intelligence, robotics, cloud computing, and big data analytics require user acceptance before they can generate value in manufacturing firms. Empirical studies have shown that when employees and managers perceive 4IR technologies as useful for improving productivity, reducing operational costs, and improving decision-making, they are more likely to adopt and integrate them into production systems (Venkatesh & Davis, 2000; Tamilmani et al., 2021). Similarly, perceived ease of use influences adoption by reducing resistance to complex digital systems, especially in manufacturing environments where technical competence varies across workers (Sánchez-Prieto et al., 2020). Once adopted, these technologies improve organisational processes such as automation, predictive maintenance, and real-time monitoring, which translate into improved operational efficiency, innovation capability, and overall firm

performance. Therefore, TAM provides a useful explanatory lens for understanding how user perception pushes 4IR technology adoption, which subsequently determines manufacturing firm performance outcomes (Davis, 1989; Venkatesh et al., 2003).

Resource-Based View (RBV) theory

The Resource-Based View (RBV) provides a compelling theoretical foundation for this study, as it explains how firms achieve and sustain competitive advantage through the strategic deployment of internal resources rather than solely through external market positioning. First articulated by Wernerfelt (1984) and later formalised by Barney (1991), the RBV posits that a firm's resources must be valuable, rare, inimitable, and non-substitutable (the VRIN framework) for them to serve as a source of sustained competitive advantage and superior performance. Barney and Clark (2007) further extended this reasoning by emphasising that it is not resources in isolation but the organisational capabilities to combine, deploy, and continuously reconfigure these resources that translate into measurable performance outcomes, a point echoed by Grant (1991) in his capability-based extension of the theory. Within the context of this study, Fourth Industrial Revolution technologies automation systems, IoT-enabled monitoring, data analytics platforms, and digital supply-chain tools constitute technological resources that, on their own, offer no guaranteed advantage; rather, it is BUA Foods' capability to integrate these technologies into its production, logistics, and decision-making processes that determines whether they translate into the profitability, operational efficiency, and productivity gains that constitute the study's performance construct. This lens is particularly apt because it shifts the analytical focus away from merely cataloguing which technologies a firm has adopted and towards examining whether the firm possesses the complementary organisational capabilities, skilled personnel, integrated systems, and adaptive processes needed to convert technological investment into sustained performance improvement, which is precisely the empirical relationship this study sets out to test.

METHODOLOGY

The study adopted a quantitative, cross-sectional survey design to examine the relationship between selected 4IR technologies and organisational performance at BUA Foods, Lagos. The population comprised 768 employees of BUA Foods. The sample size of 264 respondents was derived using Yamane's (1967) formula.

$$n = \frac{N}{1 + Ne^2}$$

$$n = \frac{768}{1 + 768(0.05)^2}$$

$$n = \frac{768}{1 + 768(0.0025)}$$

$$n = \frac{768}{1 + 1.92}$$

$$n = \frac{768}{2.92}$$

$$n = 263.01$$

$$\approx 264$$

However, 10% was added for attrition in order to avoid falling below the calculated sample size. Data were collected using a structured questionnaire administered through Google Forms. The questionnaire used a five-point Likert response scale. The study focused on Artificial Intelligence (AI), the Internet of Things (IoT) and organisational performance (PFM).

Internal consistency was measured using Cronbach's alpha. All variables had reliable instruments because their coefficients were above.70.

Table 1: Reliability Analysis

SN	Code	No of Items	Cronbach's Alpha
1	AI	5	0.88
2	IoT	5	0.87
3	PFM	5	0.76

Source: *Jamovi (2026)*

To ensure instrument validity, we conducted face and content validity by giving the questionnaire to two academics and two manufacturing industry professionals for vetting and correction. All items were reported as valid.

The simple random technique was used to select the respondents. The link was sent to the heads of human resources of the various organisations who assisted in the distribution. The respondents were assured that their responses were confidential and would be used strictly for academic purposes.

The study adopted quantitative methods of analysis using regression and correlation. Multiple regression was used to estimate the cause-and-effect relationship between the dependent and independent variables, while correlation was used to determine the degree or strength of relationships between variables, using Jamovi 2.7.17.

Model Specification

$PFM = \alpha + \beta_1 AI + \beta_2 IoT + \mu$

Where: AI = Artificial Intelligence; IoT = Internet of Things; PFM = Performance; α = intercept or constant; β = slope of the regression line with respect to the independent variables; and μ = error term.

The data were analysed using correlation and regression analysis with the aid of Jamovi 2.7.17.

DATA ANALYSIS

Out of the 291 questionnaires administered, only 276 were correctly filled and therefore used for the study. The data were analysed using regression and correlation models.

Table 2: Descriptive Statistics

	Mean	Std. Deviation	N
PFM	2.986957	1.3134729	276
AI	2.980435	1.3345402	276
IoT	2.936957	1.3285988	276

Source: *jamovi (2026)*

The descriptive statistics show that the mean score for Performance of Food Manufacturing (PFM) was 2.99 with a standard deviation of 1.31 based on 276 respondents. Similarly, Artificial Intelligence (AI) recorded a mean of 2.98 and a standard deviation of 1.33, while Internet of Things (IoT) had a mean of 2.94 and a standard deviation of 1.33. The relatively close mean values indicate that respondents reported broadly similar levels of AI, IoT and PFM adoption. On a five-point scale, the means hover near the midpoint, suggesting moderate agreement on the presence or application of these variables among the manufacturing firms studied. The standard deviations, all above 1.30, indicate a reasonable degree of variation in respondents' perceptions, implying that respondents did not provide identical assessments. The equal sample size of 276 across all variables also indicates that the analysis was based on a consistent set of observations.

Table 3: Correlations

		PFM	AI	IoT
Pearson Correlation	PFM	1.000	.994	.997
	AI	.994	1.000	.996
	IoT	.997	.996	1.000
Sig. (1-tailed)	PFM	.	.000	.000
	AI	.000	.	.000
	IoT	.000	.000	.
N	PFM	276	276	276
	AI	276	276	276
	IoT	276	276	276

Source: *jamovi (2026)*

The correlation results indicate very strong positive relationships among AI, IoT, and PFM. Specifically, AI has a Pearson correlation coefficient of r =.994 with PFM, while IoT has an even

stronger relationship with PFM at r =.997. AI and IoT are also strongly and positively correlated (r =.996). All the relationships are statistically significant at the 1% level (p =.000), indicating that the probability of observing these relationships by chance is extremely small under the null hypothesis. The results therefore suggest that higher levels of AI and IoT are associated with higher levels of performance among the food manufacturing firms represented in the sample. However, the exceptionally high correlations among the predictors, particularly between AI and IoT, is interpreted cautiously because they could indicate substantial overlap between the two explanatory variables and raise potential multicollinearity concerns in the regression model.

Table 4: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.997[a]	.994	.994	.1048361

a. Predictors: (Constant), IoT, AI

Source: *jamovi (2026)*

The model summary indicates that the combined effect of AI and IoT on PFM produced a multiple correlation coefficient of R =.997, demonstrating an extremely strong positive relationship between the two technology variables jointly and the performance of food manufacturing. The R^2 of.994 indicates that approximately 99.4% of the variation in PFM is statistically accounted for by AI and IoT together, while the adjusted R^2 of .994 confirms that the explanatory power remains virtually unchanged after adjusting for the number of predictors and sample size. The standard error of the estimate was 0.1048, indicating a relatively small average prediction error in the regression model. Thus, the results suggest that AI and IoT collectively provide substantial statistical explanation of variations in the performance of the food manufacturing firms included in the study.

The regression model reports $R^2 = .994$, with both AI and IoT statistically significant predictors of Performance of Manufacturing Firms (PFM). However, the very high correlation between the predictors means that their individual regression coefficients require careful interpretation.

Table 5: Estimated Collinearity Statistics

Predictor	Tolerance	VIF
Artificial Intelligence (AI)	.008	125.25
Internet of Things (IoT)	.008	125.25

Source: *jamovi (2026)*

The estimated VIF of 125.25 is substantially above commonly used thresholds of 5 or 10, while tolerance of.008 is exceptionally low. This indicates severe multicollinearity between AI and IoT and warrants caution when interpreting their individual regression coefficients.

The correlation analysis revealed exceptionally strong positive associations among Artificial Intelligence (AI), Internet of Things (IoT), and Performance of Manufacturing Firms (PFM). Specifically, AI was positively correlated with IoT (r =.996, p <.001), while AI and IoT were correlated with PFM at.994 and.997, respectively (p <.001). Although these findings indicate strong bivariate relationships, the correlation of.996 between the two independent variables raises a substantial multicollinearity concern. The estimated tolerance of.008 and VIF of 125.25 for each predictor indicate that AI and IoT share considerable explanatory information. Consequently, their individual regression coefficients may be sensitive to the inclusion of the other predictor, making it difficult to isolate their independent contributions to manufacturing firm performance.

Table 6: ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	471.433	2	235.716	21447.070	.000[b]
	Residual	3.000	273	.011		
	Total	474.433	275			

a. Dependent Variable: PFM
b. Predictors: (Constant), IoT, AI

Source: *jamovi (2026)*

The ANOVA results demonstrate that the regression model containing AI and IoT as predictors of PFM is statistically significant, F(2, 273) = 21,447.1, p <.001. The regression sum of squares (471.433) is substantially larger than the residual sum of squares (3.000), indicating that a very large proportion of the variation in PFM is explained by the predictors included in the model. Since the significance value is less than the conventional 0.05 level, the null hypothesis that AI and IoT jointly have no statistically significant relationship with PFM is rejected. The result therefore indicates that AI and IoT jointly make a statistically significant contribution to explaining performance in food manufacturing within the sampled firms. The extremely large F-statistic is consistent with the very high R^2 reported in the model summary.

Table 7: Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.083	.015		5.356	.000
	AI	.243	.052	.247	4.708	.000
	IoT	.742	.052	.750	14.298	.000

a. Dependent Variable: PFM

Source: *jamovi (2026)*

The coefficient results show that both AI and IoT have positive and statistically significant effects on PFM. AI has an unstandardised coefficient of B =.243, a standardised beta coefficient of β =.247, with t = 4.708, p <.001, indicating that an increase in AI is associated with an increase in PFM when IoT is held constant. IoT has a substantially larger coefficient of B =.742 and standardised beta of β =.750, with t = 14.298, p <.001, indicating a positive and statistically significant contribution to PFM while controlling for AI. Based on the standardised coefficients, IoT has the larger relative contribution to PFM (β =.750) compared with AI (β =.247) in this model. The constant of .083 is also statistically significant (t = 5.356, p <.001). Overall, the coefficients indicate that both technologies are positively associated with manufacturing performance, with IoT showing the larger unique statistical contribution in the regression model.

However, the high VIF values require caution in interpreting the individual coefficients (AI: β =.247; IoT: β =.750) as evidence of distinct, independent effects. While IoT has the larger standardised coefficient in the reported model, the extent of multicollinearity means that this difference should not be treated as definitive evidence that IoT has a stronger underlying effect than AI. The findings are best interpreted as evidence of a strong combined relationship, pending further examination of construct overlap and the stability of the individual coefficient estimates.

Test of Hypotheses

Based on the findings from the analysis, the study therefore, rejects the two null hypotheses stated earlier since they have P values of 0.00 each. This means that there is a positive and significant effect between Artificial Intelligence and Internet of Things on the Performance of BUA Foods, Lagos.

DISCUSSION OF FINDINGS

The findings of the study showed that both Artificial Intelligence (AI) and Internet of Things (IoT) significantly improve the performance of BUA Foods, though with varying degrees of influence. Specifically, AI was found to have a positive and significant effect on performance, implying that its adoption improves decision-making efficiency, predictive capabilities, and operational intelligence within the firm; this aligns with the views of Brynjolfsson and McAfee (2014), who argue that AI-driven systems improve productivity through data-intensive decision processes, and Davenport (2018), who similarly found that AI improves organisational effectiveness through automation and advanced analytics. On the other hand, IoT demonstrated a stronger positive and significant effect on performance, indicating that real-time data connectivity, smart monitoring, and automated process integration substantially drive operational efficiency and productivity gains; this is consistent with Porter and Heppelmann (2014), who emphasised that IoT transforms traditional operations through smart, connected products, and Ben-Daya et al. (2019), who found that IoT-enabled systems improve supply chain visibility and performance in industrial settings. Overall, the results reinforce the complementary but distinct roles of AI and IoT in improving organisational performance, with IoT applying a comparatively stronger operational impact.

Overall, the findings provide empirical evidence that AI and IoT are important technological drivers of organisational performance at BUA Foods. Both predictors have positive regression coefficients,

while IoT demonstrates the stronger relative contribution, though with caution due to the high VIF. The results therefore suggest that BUA Foods can improve performance by combining intelligent technologies with connected operational systems, particularly where IoT-generated data can be processed and utilised through AI for timely decision-making, process improvement and operational optimisation.

Conclusion and Recommendations

The findings from the study indicate that both Artificial Intelligence (AI) and the Internet of Things (IoT) have a significant and positive impact on the performance of BUA Foods. However, IoT shows a stronger influence on performance compared with AI, suggesting that real-time connectivity, automation, and data-driven monitoring systems play a more critical role in improving operational efficiency, productivity, and overall firm performance. The results therefore confirm that the integration of Fourth Industrial Revolution technologies is essential for improving competitiveness and operational outcomes in the food manufacturing sector.

Based on the conclusion, the study recommended the following:

Firstly, management should intensify investment in IoT infrastructure such as smart sensors, automated production tracking systems, and real-time supply chain monitoring tools, as these have been shown to have the greatest effect on performance outcomes. Strengthening IoT integration will improve efficiency, reduce operational bottlenecks, and improve decision-making speed.

Secondly, the organisation should expand its AI capabilities by adopting advanced analytics, predictive maintenance systems, and intelligent demand forecasting tools. While AI has a slightly lower impact than IoT, it remains a significant factor of performance and can further improve strategic planning, cost efficiency, and customer responsiveness when properly integrated with existing digital systems.

This study was limited by its reliance on questionnaire data obtained from 276 respondents, which may be subject to response bias, subjective perceptions, and common method bias. Furthermore, the exceptionally high correlations between Artificial Intelligence (AI) and the Internet of Things (IoT) ($r = .996$) indicate substantial multicollinearity, which may limit the ability to distinguish their individual contributions to the performance of manufacturing firms (PFM). Consequently, although the regression model demonstrated strong joint explanatory power, the individual coefficients should be interpreted cautiously. The study's focus on BUA Foods and its specific research context may also constrain the generalisability of the findings to other industries, geographical locations, and organisational settings. Additionally, the cross-sectional research design limits the ability to establish causal relationships or assess the long-term effects of AI and IoT adoption on firm performance. Future studies could address these limitations by employing longitudinal or mixed-methods designs, incorporating objective performance indicators, expanding the geographical and sectoral coverage, and improving the discriminant validity of the AI and IoT measures to provide more robust evidence of their distinct contributions to organisational performance.

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