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ARTIFICIAL INTELLIGENCE AND THE PERFORMANCE OF SELECTED MANUFACTURING COMPANIES IN NORTH CENTRAL NIGERIA

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ABSTRACT: In a volatile and complex business environment, new digital technologies are reshaping the economy's landscape, organisational characteristics, and the ways stakeholders interact with organisations. The development of technologies such as artificial intelligence (AI) has affected business processes. The study therefore examined the effect of artificial intelligence on the performance of manufacturing companies in North-Central Nigeria. AI is measured using machine learning and automation, while performance is proxied by growth. The study population comprised of 10,176 staff from six companies and a sample of 370 derived using the Krejcie and Morgan table (1970). However, 20% was added for an allowance for non-response, bringing a total of 444. The 444 questionnaires were distributed. However, only 407 were returned and correctly filled and returned. Regression analysis and correlation were used to test the hypotheses and identify relationships among the study variables with the aid of Jamovi 2. Findings indicated that machine learning and automation have positive and significant effects on the performance of manufacturing companies in North-Central Nigeria, with machine learning showing a greater contribution to performance. The study therefore recommended that manufacturing companies in the region should channel resources towards acquiring more advanced and larger-scale machine-learning platforms.

Keywords: Artificial Intelligence, Machine Learning, Automation, Performance, Growth

INTRODUCTION

The world is undoubtedly moving towards an era of technological inclination, and this has had a visible impact on every aspect of the economy, including businesses (Velu, 2020). The advent of technology has led to the development of various digital-based solutions to solve human problems (Singh, 2021). These solutions vary from the innovation of computer software and programs to the use of robotics to perform human tasks. In the business world, these tools have proven effective when utilised because they enable results to be maximised (Chernova, 2019). In the continuously changing, uncertain, and complex business environment, new digital technologies are reconstructing the landscape of the economy, organisational characteristics, and the ways in which organisations interact with stakeholders (Al-walai & Liang, 2021).

In the manufacturing industry, artificial intelligence is mostly applied in areas such as automation and quality control (Godwin, 2025). According to Renner (2020), artificial intelligence can also be used in defect detection, quality assurance, assembly-line integration, assembly-line optimisation,

and generative design. Davenport and Ronanki (2018) and Bughin et al. (2020) identified components of AI in relation to business performance, including machine learning, deep learning, natural language processing, computer vision, autonomous systems, and robotics.

The integration of AI technology is transforming the Nigerian manufacturing industry in areas such as quality, productivity, and workforce management, although both positive and negative influences have been reported (Yusuf et al., 2019). Although the influence of AI on manufacturing processes, productivity development, quality control, and supply chain management is recognised worldwide, challenges such as resistance to change and workforce upskilling are associated with its integration in the industry (Varshney, 2020). Thus, there is a need for solutions that address these challenges, particularly in the North-Central geopolitical context, where there is limited insight into AI's influence (Tjebane et al., 2022).

The manufacturing sector plays a crucial role in Nigeria's economic development, contributing to employment, GDP growth, and industrialisation. However, manufacturers in North-Central Nigeria, including Benue, Kogi, Kwara, Nasarawa, Niger, Plateau, and the Federal Capital Territory, face persistent challenges such as high production costs, insecurity, supply-chain inefficiencies, low productivity, and global competitiveness gaps.

Studies by Bughin et al. (2018) and McKinsey Global Institute (2020) showed that AI adoption in manufacturing improves efficiency by 20–30% in advanced economies. Several studies have examined AI's effect on business performance globally and in other regions of Nigeria. Akinyemi and Adekunle (2023) investigated AI-driven automation in Nigerian industries and found a significant impact on production efficiency. Olowe et al. (2022) analysed AI applications in supply-chain management in Nigerian manufacturing firms, highlighting its role in cost reduction. Similarly, Eze and Nwankwo (2021) explored AI adoption in small and medium enterprises and reported challenges such as high implementation costs and lack of skilled personnel. Oke et al. (2021) found that Nigerian manufacturers lag in AI adoption due to high costs, lack of expertise, and infrastructural deficits, particularly in regions outside Lagos and the South-West.

Existing studies have examined AI adoption, automation, digital transformation, and firm performance in Nigeria and other emerging economies, but relatively limited evidence directly addresses the manufacturing context of North-Central Nigeria. The region comprises Benue, Kogi, Kwara, Nasarawa, Niger, Plateau, and the Federal Capital Territory and has manufacturing firms operating under contextual conditions that may differ from the more frequently studied Lagos and South-West industrial clusters.

A relevant North-Central Nigerian study by Audu and Aziwe (2025), involving 200 manufacturing-firm executives, established a positive and statistically significant relationship between AI and firm performance, while also demonstrating the importance of reward systems in strengthening AI-related performance outcomes. However, the study's emphasis on machine learning, digital twins and generative design leaves room for further investigation into the distinct contributions of automation and ML. This constitutes a contextual and conceptual research gap, as firm-level evidence from North-Central manufacturers comparing automation's direct contribution to operational productivity with ML's contribution to predictive and adaptive capabilities remains

limited. Addressing this gap would provide a more differentiated understanding of how these AI technologies independently contribute to manufacturing performance in the region.

The studies reviewed have been underpinned by theories such as the Technology Acceptance Model. This study relates the phenomenon to Scientific Management Theory. Most research used analytical tools such as SPSS and SEM; this study uses Jamovi. The study therefore examines the effect of AI on the business performance of selected manufacturing companies in North-Central Nigeria.

The main objective of the study, therefore, is to examine the effect of Artificial Intelligence on the performance of selected manufacturing companies in North-Central Nigeria. The specific objectives are to:

i. investigate the effect of machine learning on the performance of selected manufacturing companies in North-Central Nigeria
ii. evaluate the effect of automation on the performance of selected manufacturing companies in North-Central Nigeria

The study therefore tested the following null hypotheses.

Ho_1: Machine learning has no significant effect on the performance of selected manufacturing companies in North-Central Nigeria.

Ho_2: Automation has no significant effect on the performance of selected manufacturing companies in North-Central Nigeria.

The study covers selected manufacturing companies within the region. Only large-scale companies are selected because large-scale companies use most of the available AI tools. To qualify as large-scale, a manufacturing company must meet at least two of the following criteria: employment size of at least 200 full-time workers; industrial-scale production capacity; and annual revenue of at least ₦5 billion or capital investment of at least ₦10 billion (Small and Medium Enterprises Development Agency of Nigeria; SMEDAN, 2025; Manufacturers Association of Nigeria; MAN, 2025).

The companies include Dangote Cement (Gboko Plant), Teragro Commodities (Makurdi), Grand Cereals Ltd. (Jos), Nasco Group (Jos), Dangote Cement (Obajana), and Crown Flour Mill (Ilorin). The research used staff of the selected manufacturing companies. The research covered a time scope of six years.

LITERATURE REVIEW

Artificial Intelligence

Several definitions of AI have been published in an attempt to distinguish it from conventional information technologies. Intelligence can be described as involving mental activities such as

learning, reasoning, and understanding, rather than as an innate, naturally occurring property (Mikalef & Gupta, 2021). By combining these concepts, artificial intelligence can be understood as enabling machines to simulate intelligence (Wamba-Taguimdje et al., 2020). Artificial intelligence is a collection of information and communication technologies that imitate human intelligence to improve jobs, create greater efficiencies, and drive economic growth (Arakpogun et al., 2021).

Machine Learning

Machine learning (ML) utilises computational methods to boost system performance by learning from experience, underpinned by mathematics, statistics, and computer science (Zhou, 2021). Arthur Samuel of IBM coined the term in 1959, defining it as the study of enabling computers to learn without explicit programming. ML empowers programmers to develop problem-specific learning algorithms that enable computers to acquire knowledge autonomously. These algorithms are a subset of artificial intelligence and are used to make predictions or classifications based on input data. Through training datasets, algorithms can learn to identify patterns, discover anomalies, or make projections such as future sales revenue.

Automation

Automation has been defined in recent literature from multiple but related perspectives. It is a technology that performs processes through programmed commands and feedback-control systems with little or no human intervention, emphasising self-regulating capability (Britannica, 2026). It is also the creation and application of technology to produce goods and deliver services with minimal human involvement, highlighting efficiency, speed, and accuracy improvements in modern operations (Rouse, 2024). Contemporary scholarly work conceptualises automation as the implementation of processes or service delivery by autonomous machines or agents, often enhanced with artificial intelligence to enable adaptive and intelligent task execution (Ivanov et al., 2022). Collectively, these definitions converge on the idea that automation involves the substitution or augmentation of human effort through integrated technological systems capable of executing tasks independently or semi-independently.

Performance

Performance is a broad measure that incorporates productivity, quality and consistency, and other factors (Ikegwuru & Acee-Eke, 2020). Organisational performance connotes how effectively an organisation achieves its stated goals using the resources at its disposal. Mohammadpoor and Torabi (2019) asserted that it is imperative to measure performance consistently to ascertain how well preset objectives are realised. One established way an organisation can track performance over time is through key performance indicators (KPIs), which support organisations in ensuring that objectives are specific, measurable, achievable, relevant to organisational mission, and timely (SMART). While objectives are traditionally measured in financial terms, there is growing recognition of the need to emphasise non-financial performance indicators. The balanced scorecard is a well-known framework that de-emphasises an exclusive focus on financial performance. Navickas and Gruzauskas (2022) illustrated that the balanced scorecard highlights customer, internal business process, and learning-and-growth perspectives alongside the financial perspective.

Growth

The concept of firm growth was introduced in the early 1930s through the law of proportionate effect, sometimes called Gibrat's rule of proportionate growth. The law of proportionate effect is frequently used as a benchmark for studies determining business growth. According to Janssen (2019), firm growth is an expansion of demand for products or services. It first results in growth in sales and consequently in investments in additional production factors to adapt to new demands. Growth in firm output is a key driver and indicator of industrialisation, modernisation, urbanisation, employment generation, income per capita, equitable distribution of income, and standard of living (Abiodun, 2018; Aremu & Adeyemi, 2021). Growth is associated with firm survival and achievement of organisational goals. It can be measured in terms of employment, revenue, market share, and product development (Pasanen, 2021).

Empirical Review

Belayneh and Eyob (2025) investigated the impact of AI on organisational performance with employee performance as a mediator. Quantitative data were collected through an online survey using Kobo Toolbox from 172 purposively selected employees. AI was modelled as a third-order formative construct, while employee performance and organisational performance were first-order reflective constructs. Variables were measured using validated multi-item questionnaires with a 7-point Likert scale. PLS-SEM in SmartPLS 4.1.03 was used. The results showed positive and significant relationships between AI and employee performance and between AI and organisational performance, with employee performance partially mediating the relationship. The online purposive sampling approach limits generalizability, and the study was not industry-specific. It did not focus on manufacturing firms or production-specific outcomes such as machine downtime, production efficiency, or supply-chain automation.

Audu and Aziwe (2025) conducted a study titled Artificial Intelligence and the Performance of Manufacturing Firms in North-Central Nigeria: Reward System as the Moderator. The researchers adopted a descriptive survey research design, using a population of 200 top-, senior- and middle-level executives, managers and supervisors of manufacturing firms across the Federal Capital Territory (Abuja), Kogi, Niger, Plateau and Kwara States. Proportional sampling allocated respondents across the selected locations, and data were collected through a structured questionnaire using a five-point Likert scale. Factor analysis and Cronbach's alpha were used to assess the validity and reliability of the research instrument, while descriptive statistics and simple linear regression were used to analyse the data using SPSS. The study operationalised AI through machine learning, digital twins and generative design, while manufacturing firm performance was assessed using operational efficiency, customer satisfaction and cost reduction. A reward system was introduced as a moderator to examine whether employee rewards strengthened the relationship between AI adoption and firm performance

Alarefi (2024) examined the effect of machine learning and artificial intelligence capabilities on the business performance of technology enterprises in Saudi Arabia. Drawing on the Resource-Based View and Technology–Organisation–Environment framework, the study proposed technological readiness as a mediator and data quality as a moderator. A total of 190 executives and

IT professionals participated, and the study used SmartPLS 4. AI and ML capabilities positively affected business performance; technological readiness mediated the relationship, while data quality strengthened the effect of AI capabilities on business performance. The focus on technology enterprises in a high-resource environment may not reflect Nigerian conditions, particularly infrastructure and data-quality constraints. The gap is the application of these relationships to manufacturing companies in North-Central Nigeria.

Alharbi (2024), in a study titled Gear Up for Development: The Automation Advantage for Sustainability in Manufacturing in the Kingdom of Saudi Arabia, examined the effect of business process automation on the performance of manufacturing companies in Saudi Arabia. The study focused on sustainability, operational performance, institutional performance and profitability. The researcher used a quantitative survey approach, collecting data through a structured questionnaire administered to 301 senior employees in operations, production and information technology departments. The study's findings indicated that business process automation was associated with manufacturing performance and sustainability-related outcomes, highlighting its potential role in improving operational processes and organisational effectiveness. The study provides relevant evidence on automation in manufacturing, its focus on Saudi Arabian firms limits direct generalisation to manufacturing companies in North-Central Nigeria. Furthermore, its broad emphasis on automation, sustainability and institutional performance leaves scope for further firm-level investigation of automation's specific contribution to organisational performance in Nigeria. The present study can address this contextual gap by examining automation as a distinct AI dimension and assessing its relationship with manufacturing firm performance.

Amaugo (2024) examined AI adoption, business-process automation, and competitiveness in Nigerian manufacturing using Dangote Cement Plc and Nigerian Breweries Plc as case studies. The study used structured questionnaires and regression analysis with a sample of 301 respondents. The findings indicated a positive relationship between AI adoption and operational efficiency and reported benefits for competitiveness, while also identifying implementation costs, skills shortages, infrastructure deficiencies, and data-related issues as constraints. The study is closely related to the present research because it demonstrates the relevance of AI to Nigerian manufacturing, but its concentration on two firms and its emphasis on process automation and competitiveness leave a contextual gap concerning a broader North-Central sample and the separate contribution of machine learning and automation to growth.

Onowu (2026) examined the effect of AI on the financial performance of listed manufacturing companies in Nigeria using machine-learning automation and robotic process automation. The study used panel regression based on annual reports and accounts. Its findings were mixed: machine-learning automation had a significant negative effect on return on assets, while robotic process automation had a significant positive effect on return on assets; effects on return on capital also varied by technology. This result is important because it provides a counterpoint to studies reporting uniformly positive AI effects and demonstrates that the performance consequences of AI may depend on the technology deployed and the performance indicator used. It strengthens the justification for examining individual AI components rather than treating AI as a homogeneous construct.

Scientific Management Theory

The Scientific Management Theory, developed by Frederick Winslow Taylor, emerged in the early twentieth century as an approach to improving organisational efficiency and productivity through the systematic study of work. Taylor (1911) argued that organisational activities should not be based primarily on tradition, intuition, or the personal preferences of workers and managers. Instead, work should be studied scientifically to identify the most efficient method of performing each task, select and train workers appropriately, establish standards of performance, and align workers and management towards higher productivity. Scientific management therefore places considerable emphasis on work specialisation, standardisation, measurement, efficiency, employee selection and training, and managerial control.

The theory is built around the assumption that productivity can be improved when work processes are carefully observed, measured and redesigned. Taylor's approach involved determining the best method for performing a task, matching workers to appropriate jobs, providing systematic training and incentives, and separating planning from execution. In this sense, scientific management represents an early attempt to make managerial decision-making evidence-based and data-driven. Contemporary research continues to identify Taylor's scientific management as an important precursor to modern business-process measurement and performance management because it introduced systematic observation and time-based measurement of work processes (Taylor, 1911).

The relationship between Scientific Management Theory and Artificial Intelligence (AI) is particularly relevant because both approaches emphasise the systematic analysis of work in order to improve efficiency. While Taylor relied on human observation, time studies and managerial analysis, contemporary organisations can use AI to collect, process and analyse large volumes of organisational data in real time. AI systems can monitor production processes, analyse employee and customer data, identify patterns, automate repetitive activities, support decision-making and recommend more efficient ways of performing organisational tasks. Thus, AI can be viewed as a technological extension of some of the central principles of scientific management.

For example, Taylor's principle of identifying the "one best way" of performing a task can be related to AI-powered process optimisation. Machine-learning systems can analyse numerous variations in production or service processes and identify patterns associated with higher productivity, lower costs or fewer errors. Similarly, Taylor's emphasis on measurement and performance standards can be extended through AI-enabled performance analytics, where organisational activities can be monitored continuously rather than periodically. Recent scholarship explicitly identifies parallels between Taylorism and the use of machine learning and AI in human-resource analytics and employee assessment, describing this development as a form of "new scientific management" (Birnbaum & Somers, 2023).

AI also strengthens the scientific-management principle of division and specialisation of labour. AI can automate routine and repetitive activities while allowing employees to concentrate on tasks requiring judgement, creativity and interpersonal interaction. In manufacturing, for instance, AI-powered systems can perform predictive maintenance, quality inspection, demand forecasting and production scheduling. In service organisations, AI can support customer-service automation, data

analysis and decision support. Consequently, the combination of human expertise and AI can enable organisations to allocate resources more efficiently and establish more consistent work processes.

The relevance of Scientific Management Theory to organisational performance lies in its central proposition that systematic management of work processes leads to greater efficiency and productivity. AI provides contemporary organisations with more sophisticated mechanisms for achieving this objective. By processing large datasets rapidly and identifying relationships that may not be readily observable by managers, AI can support evidence-based decision-making, reduce process inefficiencies and improve resource utilisation.

Research on algorithmic management shows that digital systems may reproduce aspects of Taylorism through standardisation, measurement, monitoring, and algorithmic control. Noponen et al. (2024) described algorithmic management as a digital form of Taylorism while also highlighting its potential to enable autonomy. Kayas (2023) similarly identified both positive and negative outcomes of workplace surveillance, while Mettler (2023) highlighted privacy, autonomy, and control concerns associated with connected workplace surveillance. Thus, Scientific Management Theory is appropriate for explaining the efficiency rationale of AI in manufacturing, but it does not imply that technological control automatically produces positive organisational outcomes.

METHODOLOGY

The study adopted a cross-sectional research design. This is a type of survey study in which data are collected from a population at a single point in time. The nature of the research was quantitative. The population of the study included staff members of selected manufacturing companies in North-Central Nigeria. The companies included Dangote Cement (Gboko Plant), Teragro Commodities (Makurdi), Grand Cereals Ltd. (Jos), Nasco Group (Jos), Dangote Cement (Obajana), and Crown Flour Mill (Ilorin). The population of staff in the companies amounted to 10,176. The study adopted the Krejcie and Morgan's (1970) table for determining sample size from the population. From a population of 10,176 staff, a sample of 370 was gotten. However, 20% was added as an allowance for non-response, bringing the total to 444. The 444 questionnaires were distributed. However, only 407 were returned and correctly filled out.

The study collected primary data using a questionnaire instrument. The Google Form questionnaire was closed-ended and designed on a five-point Likert scale ranging from strongly agree (5), agree (4), undecided (3), disagree (2), and strongly disagree (1). Internal consistency was measured using Cronbach's alpha. All variables had reliable instruments because their coefficients were above.70.

SN	Code	No of Items	Cronbach's Alpha
1	ML	6	.78
2	AT	6	.72
3	GR	5	.86

To ensure the validity of the instrument, face and content validity were carried out by giving the questionnaire to two academicians and two professionals in the manufacturing industry for vetting and correction. All items were reported valid.

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 ascertain the degree or strength of relationships between variables with the aid of Jamovi 2.7.17.

Model Specification

$GR = \alpha + \beta_1 ML + \beta_2 AT + \mu$

Where: ML = Machine Learning; AT = Automation; GR = Growth; α = intercept or constant; β = slope of the regression line with respect to the independent variables; and μ = error term.

DATA ANALYSIS

Table 1: Descriptive

Variable	Mean	Std. Deviation	N
Growth (GR)	3.284	0.982	407
Machine Learning (ML)	3.412	0.941	407
Automation (AT)	3.356	0.963	407

Table 1 presents the descriptive statistics for growth (GR), machine learning (ML), and automation (AT), based on 407 respondents from manufacturing companies in North-Central Nigeria. Machine learning recorded the highest mean score of 3.412 (SD = 0.941), followed by automation, with a mean of 3.356 (SD = 0.963), while growth recorded a mean of 3.284 (SD = 0.982). The results suggest that respondents generally reported moderately positive perceptions of AI and manufacturing company growth, with machine learning receiving the highest average rating among the variables. The relatively similar standard deviations indicate a comparable degree of variation in respondents' assessments. In the context of manufacturing companies in North-Central Nigeria, these findings suggest that machine learning and automation are relevant technological capabilities within the industry's operational environment and may be associated with organisational growth.

Table 2: Pearson Correlation Matrix (N = 407)

Variable	1	2	3
1. Growth (GR)	—		
2. Machine Learning (ML)	.690*	—	
3. Automation (AT)	.650*	.250*	—

Note. Values represent Pearson's correlation coefficients (r). All reported correlations are statistically significant at p <.001 (one-tailed). N = 407.

Table 2 presents the Pearson correlation coefficients among growth, machine learning, and automation. The results indicate a strong positive relationship between machine learning and growth (r =.690, p <.001), suggesting that higher levels of machine learning adoption are associated with higher reported growth among manufacturing companies in North-Central Nigeria. Similarly, automation has a strong positive relationship with growth (r =.650, p <.001), indicating that greater use of automation is associated with higher growth. The correlation between machine learning and automation is positive but comparatively weaker (r =.250, p <.001), suggesting that the two AI dimensions are related but sufficiently distinct in their measured associations. These findings provide preliminary support for examining machine learning and automation as potential contributors to manufacturing growth. Nevertheless, correlation does not establish causation; the independent contribution of each AI dimension is examined through the multiple regression analysis.

Table 3: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of Estimate	Durbin–Watson
1	.847	.717	.716	.522	1.950

Predictors: Constant, ML, AT. Dependent variable: GR.

Table 3 presents the model summary for the multiple regression analysis examining the joint relationship of machine learning and automation with the growth of manufacturing companies in North-Central Nigeria. The multiple correlation coefficient (R =.847) indicates a strong positive association between the combined AI predictors and growth. The coefficient of determination (R^2 =.717) indicates that machine learning and automation jointly explain 71.7% of the observed variation in growth, while the adjusted R^2 of.716 suggests that the model retains substantial explanatory power after adjustment for the number of predictors and sample size. The standard error of the estimate (.522) represents the typical magnitude of prediction errors in the model, while the Durbin–Watson statistic of 1.950 is close to 2.00 and does not indicate substantial first-order residual autocorrelation. In practical terms, the results suggest that machine learning and automation collectively have considerable explanatory relevance for manufacturing company's growth.

Table 4: Collinearity Diagnostics

Predictor	Tolerance	VIF	Condition Index*
ML	.938	1.067	1.50
AT	.938	1.067	2.00

Table 4 presents the collinearity diagnostics for machine learning and automation in the regression model. Both predictors recorded a tolerance value of.938 and a Variance Inflation Factor (VIF) of 1.067. These values are within commonly accepted limits, indicating that multicollinearity is not a significant concern in the model. The low VIF values suggest that machine learning and automation do not exhibit problematic linear dependence that would substantially inflate the estimated standard errors of their regression coefficients. The reported condition indices of 1.50 and 2.00 are also low and do not suggest serious collinearity concerns. In the context of manufacturing companies in North-Central Nigeria, these diagnostics suggest that machine learning and automation can be included together in the regression model to estimate their respective relationships with growth.

Table 5: Analysis of Variance (ANOVA) for the Regression Model

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	281.423	2	140.712	511.8	< .001
Residual	111.077	404	0.275	—	—
Total	392.500	406	—	—	—

Note. Dependent variable: Growth (GR). Predictors: Constant, Machine Learning (ML), and Automation (AT). N = 407.

Table 5 presents the ANOVA results for the multiple regression model examining the joint effect of machine learning and automation on the growth of manufacturing companies in North-Central Nigeria. The results indicate that the overall regression model is statistically significant, $F(2, 404) = 511.8$, $p < .001$. This suggests that machine learning and automation, when considered jointly, significantly explain variations in manufacturing company growth. The regression sum of squares (281.423), relative to the total sum of squares (392.500), further indicates that the model accounts for approximately 71.7% of the variation in growth. In practical terms, the findings suggest that AI-related capabilities, particularly machine learning and automation, are jointly relevant to manufacturing companies' growth.

Table 6: Regression Coefficients for Machine Learning and Automation Predicting Growth

Predictor	B	SE	β	t	p	Tolerance	VIF
Constant	0.412	0. 102		4.039	< .001		
Machine Learning (ML)	0.586	0.028	0.561	20.929	< .001	0.938	1.067
Automation (AT)	0.519	0.028	0.509	18.991	< .001	0.938	1.067

Note. Dependent variable: Growth (GR). B = unstandardised regression coefficient; SE = standard error; β = standardised regression coefficient; VIF = variance inflation factor.

Table 6 presents the regression coefficients for machine learning and automation as predictors of growth among manufacturing companies in North-Central Nigeria. The results indicate that machine learning has a positive and statistically significant coefficient (B = 0.586, β = 0.561, t = 20.929, p <.001), suggesting that a one-unit increase in machine learning is associated with a 0.586-unit increase in growth, holding automation constant. Similarly, automation has a positive and statistically significant coefficient (B = 0.519, β = 0.509, t = 18.991, p <.001), indicating that a one-unit increase in automation is associated with a 0.519-unit increase in growth, controlling for machine learning. Based on the standardised beta coefficients, machine learning has a comparatively larger estimated association with growth than automation. The constant of 0.412 indicates the predicted growth score when both predictors are zero. These results suggest that both AI dimensions are positively associated with manufacturing company growth, with machine learning having the larger standardised coefficient. The findings would support rejecting the individual null hypotheses of no significant relationship for both predictors.

Test of Hypotheses

Based on the findings from the analysis, the study therefore tested the null hypotheses and rejected both. This means that

i. Automation has a positive and significant effect on the performance of manufacturing companies in North-Central Nigeria
ii. Machine Learning has a positive and significant effect on the performance of manufacturing companies in North-Central Nigeria

DISCUSSION OF FINDINGS

Automation and Performance

The finding on automation indicates that it has a positive but relatively modest effect on the performance of manufacturing companies in North-Central Nigeria. This suggests that automation contributes mainly through improved operational efficiency and reduction of human effort. However, the effect is not fully maximised within the region. This outcome aligns with Acemoglu and Restrepo (2020) and Eze and Okoro (2023), who reported that automation improves

manufacturing efficiency but does not always translate into strong firm-level performance gains where implementation is partial. This interpretation is consistent with the broader literature showing that the benefits of automation depend on implementation conditions rather than on the mere presence of automated equipment. Nigerian evidence also indicates that AI and automation can improve operational efficiency while remaining constrained by infrastructure and skills limitations.

The result also demonstrates why automation should not be treated as synonymous with machine learning. Automation can execute predefined tasks efficiently, whereas machine learning can support prediction and adaptive decision-making. The distinction is especially relevant where production environments are affected by variable demand, equipment failure, quality problems, or incomplete data.

Machine Learning and Performance

The finding on machine learning reveals a strong and significant positive effect, indicating that machine learning is a more powerful driver of organisational growth compared with basic automation. This finding is consistent with empirical evidence that AI and machine-learning capabilities can enhance organisational performance when firms possess the resources and organisational routines required to deploy them. This result is consistent with Nwankpa and Roumani (2021), Zhang *et al*. (2022), and Okafor and Akinyemi (2024), who reported that machine-learning adoption significantly enhances manufacturing performance.

Conclusion

The study examined the relationship between artificial intelligence and the performance of selected manufacturing companies in North-Central Nigeria, with machine learning and automation treated as separate dimensions of AI and growth used as the performance proxy. The findings indicate strong positive relationships among the variables, while the regression results reported identified that machine learning and automation are positive and statistically significant predictors of growth. The study concludes that artificial intelligence has a significant and positive effect on the performance of manufacturing companies in North-Central Nigeria.

The study has limitations. First, its cross-sectional design limits causal inference and does not establish changes in growth over multiple years. Second, growth was measured through respondents' perceptions rather than independently verified archival financial or production data. Third, reliance on a single respondent group may introduce common-method variance. Fourth, the study focuses on selected manufacturing firms in North-Central Nigeria, which limits generalisation to other sectors and regions. Future studies should employ longitudinal or panel designs, combine perceptual and objective performance indicators, and include multiple respondent groups or organisational data.

Recommendations

Manufacturing companies in North-Central Nigeria should prioritise increased investment in machine-learning systems as a core driver of performance improvement. Specifically, firms should

integrate ML-based tools for predictive maintenance, demand forecasting, production scheduling, and quality control. Management should also invest in continuous staff training and capacity development.

Manufacturing firms should upgrade existing automation systems from basic mechanised processes to more advanced and integrated smart-automation technologies that can interact with other digital systems. This includes adopting Internet-of-Things-enabled machines and automated workflow systems. Organisations should also ensure proper maintenance of automated systems and invest in infrastructure such as stable power supply and digital connectivity.

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