Artificial Intelligence (AI) and Operational Performance of Selected Manufacturing Firms in Lagos State, Nigeria

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DOI: https://doi.org/10.51244/IJRSI.2026.1307000111

Received: 13 July 2026; Accepted: 18 July 2026; Published: 31 July 2026

ABSTRACT

This study examined the effect of Artificial Intelligence techniques on Operational Performance of manufacturing firms in Lagos State, Nigeria. Using a Survey Research Design, data were collected from 250 respondents and analysed with SPSS using regression analysis. The findings revealed that Machine Learning significantly affects Operational Efficiency ($\beta = 0.558$, $p < 0.05$), Deep Learning significantly affects Product Quality and Defect Detection ($\beta = 0.527$, $p < 0.05$), and Computer Vision significantly affects Waste Reduction and Quality Control ($\beta = 0.495$, $p < 0.05$). The study concluded that Artificial Intelligence significantly enhances operational performance. It was recommended that manufacturing firms should invest in ML, DL, and CV technologies, while government should provide incentives and training to support AI adoption in the manufacturing sector.

Keywords: Artificial Intelligence, Machine Learning, Deep Learning, Computer Vision, Operational Performance and Manufacturing.

INTRODUCTION

The Fourth Industrial Revolution has brought about rapid transformation in the way firms operate globally. At the centre of this transformation is Artificial Intelligence (AI), which simply suggest the ability of machines to perform tasks that typically require human intelligence. AI has become a new technique globally today, its' application to organisational operations which is generally believed to reduce costs, enhance operational efficiency and increase customer satisfaction (Audu & Aziwe 2025). Within AI, specific techniques such as Machine Learning (ML), Deep Learning (DL), Computer Vision (CV) among others are driving innovation in manufacturing, operations and industries. Machine Learning enables systems to learn from data and make predictions without explicit programming. Deep Learning, a subset of ML, uses neural networks to detect complex patterns, especially in images and large datasets. Computer Vision allows machines to "see" and interpret visual information for quality control. Globally, manufacturing firms in the US, China, Germany Japan and so on are leveraging these AI techniques to achieve predictive maintenance, automated quality inspection, optimised production scheduling and faster decision-making which seems to have led to increased productivity, reduced costs and improved product quality (Audu and Aziwe 2025). Today, AI application is gradually gaining ground around the world and Nigeria is not an exception. In achieving corporate goals and objectives, with a view to reducing operational costs and improve organizational performance, the application of AI becomes imperative (Chan et al., 2019; Jabłońska & Pólkowski, 2017; Ulas, 2019; Ulrich, Frank, & Kratt, 2021; Ebuka, Dibua, & Idigo, 2023, Udeogu, Arinze & Okoye,2024).

In Nigeria, the manufacturing sector contributes significantly to GDP and employment. However, the sector is faced with challenges such as frequent machine breakdowns, high defect rates, production inefficiencies, energy costs, and slow decision-making processes. Despite the potential of AI techniques to address these challenges, adoption remains low due to factors such as poor infrastructure, lack of skills, and limited awareness (Audu & Aziwe 2025). Given the competitive pressure and the need for industrial growth in Nigeria, it is important to examine how specific AI techniques can be applied to improve operational performance in the manufacturing sector.

Operational Performance either in the manufacturing subsector or other subsectors is usually determined by some specific Metrics which includes; operational efficiency, effectiveness, Quality, speed with accuracy, Cost, reliability, innovation, productivity, safety among others. (Dawes, 1999; Harris, 2001; Atalay et. al, 2013; Ziyaminyana & Pwaka, 2019). Hence, concerned with the dwindling performance of the Manufacturing subsector of the Nigerian economy, Manufacturing organizations went to search for how to improve operational performance through; reducing costs, increasing operational efficiency, and enhance customer satisfaction of the subsector. The readily available option in a dynamic competitive manufacturing environment was Artificial Intelligence (AI).

Statement of Problem

The Nigerian Manufacturing sector continues to experience operational inefficiencies that limit its growth and global competitiveness. Problems such as unplanned equipment downtime, poor quality control, waste in production and delay in decision-making are common Ebuka, Emmanuel and Idigo (2026). Traditionally, firms rely more on manual monitoring, scheduled maintenance and human inspection which are often error-prone and costly.

However, in advanced economies, manufacturers are solving similar problems using AI Techniques. Machine Learning is used for predictive maintenance, Deep Learning for defect detection, Computer vision for automated inspection, Reinforcement Learning for optimising production Schedules and Natural Language Processing (NLP)for analysing reports and improving communication.

Hence, in Nigeria, there is limited awareness, adoption and empirical evidence on the application and impact of these specific AI techniques in Manufacturing firms. Most studies on AI such as Financial Stability Board (2017); Finextra (2026); McKinsry (2026); Reuters (2026) and so on focuses generally on Fintech and Services, with little attention to how ML, DL, CV, in relation to how it can directly improve industrial operations.

This study therefore seeks to investigate the effect of Machine Learning, Deep Learning, Computer vision, Reinforcement on operational performance of manufacturing firms in Nigeria.

Objectives of the Study

The main objective of this study is to examine the effect of Artificial Intelligence (AI) techniques on operational performance of some selected manufacturing firms in Lagos State, Nigeria. While the Specific objectives are:

1) To examine the effect of Machine Learning on operational efficiency of selected manufacturing firms in Lagos State, Nigeria.
2) To assess the effect of Deep Learning on product quality and defect detection in selected Manufacturing firms in Nigeria.
3) To determine the effect of Computer Vision on Waste reduction and quality control in selected Manufacturing firms in Nigeria,

Statement of Hypothesis

H_o1: Machine learning has no significant effect on operational efficiency of Selected manufacturing firms in Lagos State, Nigeria.

H_o2: Smart Deep Learning has no significant effect on product quality and defect detection of Selected manufacturing firms in Lagos State, Nigeria.

H_o3: Computer Vision has no significant effect on Waste reduction and quality control in selected Manufacturing firms in Nigeria,

LITTERATURE REVIEW

Concept Of Artificial Intelligence

Artificial intelligence is a concept derived from natural human beings who employ their intellects to handle jobs that ordinary people cannot fathom (Udeogu, Okoye & Ikechukwu, 2024). While, Arakpogun et.al (2021); Rai, Constantinides & Sarker, (2019) described AI as the assemblage of Information and Communication Technologies (ICTs) that model human intelligence and hence perform duties that were hitherto undertaken by human beings. The primary purpose of the application of AI is to improve jobs, create greater operational efficiency, and drive performance and economic growth (Arakpogun, Olan, and Elsahn, 2021). AI can therefore be described as the design, application and usage of computer system to perform specific task in order to achieve a better result than what would have been achieved by ordinary human being. Firms deploy a range of AI tools which includes Machine Learning, Computer Vission, Reinforcement Learning, Natural Language Processing (NLP), Digital Twins, Generative Design technology among others.

Concept Of Machine Learning

Russell & Norvig (2021) described Machine Learning as a core component of modern artificial intelligence that enables systems to automatically learn from data, identify patterns, and make decisions with minimal human intervention. It is a branch of computer science concerned with the development of algorithms that improve their performance over time through experience and exposure to data. While, Burian (2020) Described Machine Learning as AI tools designed to improve the level of precision in forecasting and solving of logistic problems. In organizational and industrial contexts, Machine Learning Systems (MLS) have become essential tools for enhancing decision-making, optimizing processes, and improving operational (Ekanem, Effiong, Ekanem and Udom, 2026).

Concept Of Deep Learning

Deep Learning (DL) is a subset of Machine Learning that utilizes artificial neural networks with multiple hidden layers to automatically learn hierarchical representations from large volumes of data (LeCun, Bengio & Hinton, 2015). While, Zhao and Wang (2024) maintained that deep learning-based data augmentation enables accurate virtual data for defect identification in manufacturing.

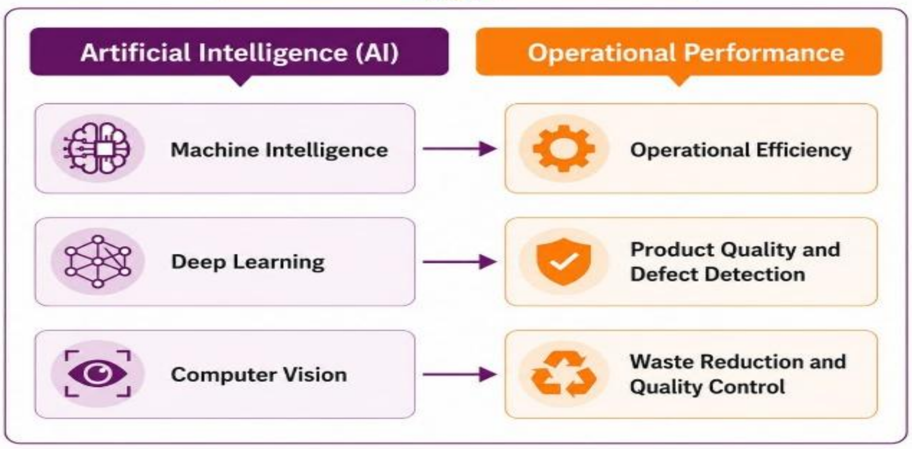
Concept Computer Vision

Computer Vision (CV) is a subfield of Artificial Intelligence that enables machines to interpret, analyse, and understand visual information from images and videos (Szeliski, 2022). Unlike traditional image processing, Computer Vision (CV) systems use deep learning models to automatically extract features and make decisions without human intervention (Goodfellow, Bengio & Courville, 2016).

Concept Of Operational Performance

Operational Performance is defined as the efficiency and effectiveness of an organization's resources, internal processes, and operations in accomplishing its strategic goals It reflects how well a manufacturing firm transforms inputs into outputs across key competitive priorities (Adeniji et al., 2024 cited in MDPI, 2025).

Fig. 1: CONCEPTUAL FRAMEWORK



Source: Researcher's Conceptualisation, 2026.

THEORETICAL FRAMEWORK

This research work is being anchored on Technology Acceptance Model (TAM) by Davis (1989). The theory posits that an individual's acceptance and use of technology depend primarily on two core beliefs: perceived usefulness and perceived ease of use (Davis, 1989). This proposition is drawn from the Technology Acceptance Model, which explains how users come to accept and utilize new technologies within organizational settings. Perceived usefulness refers to the extent to which an employee believes that using a particular technology will enhance job performance, while perceived ease of use refers to the degree to which the technology is expected to be free of effort i.e easy to use (Davis, 1989). These two factors jointly influence the attitude toward using Artificial intelligence (AI), which ultimately determines actual usage behaviour.

EMPIRICAL REVIEW

Ekanem, Effiong, Ekanem and Udom (2026) conducted a study on Artificial Intelligence and employee performance in the manufacturing firms in South-South Nigeria. The research tried to find out the degree to which machine learning and smart production affect employee productivity and efficiency in manufacturing organizations. Cross sectional survey research design was employed with the population of 272 workers captured from manufacturing firms in South-South Nigeria. The study made use of Krejcie and Morgan for sample size determination, where a sample of 153 was achieved with the use of structured questionnaire. The research was analysed with the use of descriptive statistics and simple linear regression through SPSS. It was found out that that machine learning and smart production significantly impact positively on employee performance.

Audu and Aziwe (2025) Conducted descriptive research using reward system as moderator to find out the relationship between AI and organizational performance. The sample size was 200 respondents from Manufacturing Firms. Completed questionnaire was analysed with the use of descriptive statistics and Linear regression. The findings revealed a positive and significant influence of AI on Manufacturing Firms performance. Also, there was more improvement in performance of the Manufacturing Firms with the introduction of the moderating value

Ebuka, Emmanuel and Idigo (2023) conducted a descriptive research to find out the role of AI in small business operations in Nigeria. In the objective of the study, application of AI and its' barriers to the deployment of AI in SMEs were stated. The population was made up of 27,546 small businesses in Nigeria duly registered with Corporate Affairs Commission (CAC). Krejcie and Morgan formular was used to determine the sample size. Personal interviews and structured questionnaire were used to gather the data while, descriptive statistics was used to analyse the data. The study found out that, Nigerian SMEs are currently operating manually, therefore they do not benefit from the massive opportunities that AI deployed hence, remain small in size.

Himanshu, Chaudrika and Rabindra (2022) researched om the influence of AI on the operating performance of companies in Bhubaneswar, India. The aim of the study was to establish the relationship between AI and performance of companies from different sectors in India. The study made use of primary data generated from annual reports of selected companies from the period of 2004 to 2018. Regression were used to analyse the data through E- View. The The study found out that AI has a significant influence on companies operating costs and operating profits.

Yulia and Wamba (2022) researched on how AI influence firm resilience to supply chain disturbances which consequently increased firms' performance in Europe. The study generated data from107 organizations in Europe using a research survey and then analysed. The study found out that the usage of AI has a direct impact on business resilience and that firm resilience totaly mediates between AI application and firm performance.

Wechie and Opigo (2020) investigated the effect of AI on organizational performance of Manufacturing Firms in Port Harcourt Nigeria. The study made use of Survey research design with the help of structured questionnaire. The study made use of 56 General Managers as the population of the study. Pearson Product Moment coefficient of correlation were used to analyse the data. The study found out that there is significant positive effect on AI and organizational performance

RESEARCH METHODOLOGY

This study adopted a descriptive survey and explanatory research design. The descriptive aspect describes the extent of AI adoption in manufacturing firms, while the explanatory aspect examines the cause-effect relationship between specific AI techniques and operational performance. This design is suitable because it allows collection of primary data to test hypotheses and generalize findings to the population of manufacturing firms in Lagos State.

The population comprises selected manufacturing firms in Lagos State, Nigeria. Lagos is the industrial hub of Nigeria with the highest concentration of manufacturing firms. The target population includes Production Managers, Operations Managers, IT/AI Managers, and Quality Control Managers in firms that have either adopted or are aware of AI techniques.

Krejcie & Morgan formular was employed to determine the sample size of 250 respondents across 15 manufacturing firms in Lagos State. Multi-stage sampling was used. Purposive sampling to select manufacturing firms in Lagos that use/are aware of AI, ML, DL, CV. Stage, stratified random sampling to select respondents across departments: Production, Quality, Maintenance, IT. Stage and Simple random sampling within each department.

Structured questionnaire administered to managers and technical staff. Secondary Data which includes; journals and existing literature on AI and manufacturing were equally used.

The questionnaire was divided into 3 sections: Section A: Demographics - firm size, years of operation, department, role Section B: Extent of AI Adoption - 5-point Likert scale measuring use of ML, DL, CV, 1=Strongly Disagree to 5=Strongly Agree Section C: Operational Performance Metrics - measures of efficiency, quality, waste reduction, cost, reliability using 5-point Likert scale Validity: Face and content validity test was conducted to ensure the instrument was valid through expert review by 2 lecturers in AI/Operations. Reliability: Cronbach's Alpha test was conducted. A coefficient ≥ 0.70 was considered reliable. Questionnaires was administered via Google Forms to managers in selected firms in Ikeja, Apapa, and Oshodi industrial zones in Lagos. With permission from HR/Operations heads.

Data collected was coded and analysed using SPSS v26. Descriptive Statistics: Frequency, Percentage, Mean, and Standard Deviation to answer research questions and describe demographics and extent of AI use. While, Inferential Statistics was employed to test the 3 hypotheses.

Simple Linear Regression was used to determine the effect of each specific objective as well as the broad objective. ANOVA and T-test was used to test the strength of relationship between AI techniques and performance metrics. Hypotheses was tested at 0.05 level of significance. If p-value < 0.05, reject H0

Model Specification:

$$OP = \beta_0 + \beta_1 ML + \beta_2 DL + \beta_3 CV + \varepsilon$$

Where:

OP = Operational Performance

ML = Machine Learning

DL = Deep Learning

CV = Computer Vision

β_0 = Constant,

β_1-β_3 = Coefficients,

ε = Error term

Descriptive Statistics on AI and Operational Performance of Manufacturing Firms in Lagos State.

N=250, 5-Point Likert Scale: 1=SD, 5=SA. Decision Mean ≥ 3.0

AI Technique	N	Mean	Std. Dev	Min	Max
Machine Learning (ML)	250	4.12	0.684	2.00	5.00
Deep Learning (DL)	250	3.98	0.721	2.20	5.0
Computer Vision (CV)	250	4.05	0.698	1.80	5.0
Operational Efficiency	250	3.91	0.771	2.00	5.0
Product Quality &Defect Detection	250	4.08	0.804	1.60	5.0
Waste Reduction & Quality Control (WRQC)	250	3.96	0.821	1.80	5.0

Source: Field Survey (2026)

Interpretation:

The table shows that all variables had mean scores above 3.50 on a 5-point Likert scale. This indicates that respondents agreed to a high extent that AI techniques are adopted and have affected operational performance in selected manufacturing firms in Lagos State. The standard deviations are all below 1.0, showing consensus among respondents

Test of Hypotheses $H_0 1$:

Machine learning systems has no significant effect on Operational Efficiency in Manufacturing Lagos State, Nigeria.

ANALYSIS

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-watson
1	.558a	.312	.309	.65123	1.874
a.Predictors: (Constant), ML b.Dependent Varriable: OPEF					

Source: SPSS V26

R=0.558 shows a moderate-strong positive relationship. R Square=0.312 means 31.2% of variation in Operational Efficiency is explained by Machine Learning. Durban-Watson=1.874 is close to 2, hence, no autocorrelation problem.

ANOVA

Model	Sum of Square	Df	Mean Square	F	Sig
Regression	46.082	1	46.082	108.612	.000b
Residual	101.918	248	.424		
Total	148.000	249			

a.Dependent Variable: OPEF				
b.Predictors: (Constant), ML				

Source: SPSS V26

Coefficients a

Model		Unstandardized Coefficients		Standardized Coefficients	T	sig	95% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	Constant	1.420	.210		6.762	.000	1.008	1.832
	ML	.604	.058	0.558	10.421	.000	.490	.718
a. Dependent Variable: OPEF								

Source: SPSS V26

The model is significant with F=108.61, p=0.000. R^2=0.312 implies that 31.2% of the variation in Operational Efficiency is explained by Machine Learning. Beta=0.558, p=0.000 means a 1-unit increase in ML adoption leads to 0.558unit increase in operational efficiency. Therefore, H01 is rejected. Also, the 95% confidence interval for Machine Learning (0.490, 0.718) does not include zero, further confirming the statistical significance and reliability of the effect on Operational Efficiency at $p < 0.05$.

Hypotheses H_o2

Model	R Square		Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.527a	.278	.275	.69245	1.921
a. Predictors: (Constant), DL b. Dependent Varriable: PQDD					

Source: SPSS V26

R= 0.527 shows a moderate positive relationship. R Square= 0.278 means 27.8% of variation in product Quality and Defect Detection is explained by Deep Learning. Adjusted R Square= 0.275 is close to R Square, then the model is stable.

ANOVA

Model	Sum of Square	Df	Mean Square	F	Sig
Regression	44.892	1	44.892	93.563	.000b
Residual	116.108	248	.468		
Total	161.000	249			
a.Dependent Variable: PQDD					
b.Predictors: (Constant), DL					

Source: SPSS V26

Coefficients b

Model		Unstandardized Coefficients		Standardized Coefficients	T	sig	95% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	Constant	1.685	.231		7.294	.000	1.230	2.140
	DL	.538	.056	.527	9.673	.000	.428	.648
a. Dependent Variable: PQDD								

Source: SPSS V26

The model is significant with F=93.56, p=0.000. R^2=0.278 implies that 27.8% of the variation in Product Quality and Defect Detection is explained by Deep Learning. Beta=0.527, p=0.000 means a 1-unit increase in DL adoption leads to 0.527 unit increase in quality/defect detection. Therefore, H02 is rejected Also, the 95% confidence interval for Deep Learning (0.428, 0.648) does not include zero, further confirming the statistical significance and reliability of the effect on Product Quality and Defect Detection at $p < 0.05$.

Hypotheses H_o3

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.495a	.245	.242	.71890	1.856
a. Predictors: (Constant) CV b. Dependent Varriable: WR&QC					

Source: SPSS V26

R=.0.495 which shows a moderate positive relationship. R Square= 0,245 means 24.5% of variation in Waste Reduction and quality control is explained by Computer Vision. Std Error= 0.71890 is low, indicating good model fit.

ANOVA

Model	Sum of Square	Df	Mean Square	F	Sig
Regression	41.015	1	41.015	79.421	.000b
Residual	126.985	248	.512		
Total	168.00	249			
a.Dependent Variable: WRQC					
b.Predictors: (Constant), CV					

Source: SPSS V26

Coefficients C

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig	95% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	Constant	1.902	.248		7.669	.000	1.414	2.390
	CV	.513	.058	.495	8.912	.000	.399	.627
a. Dependent Variable: WRQC								

Source: SPSS V26

Decision: H_o3 Rejected. CV has significant positive effect on waste Reduction and Quality Control

The model is significant with F=79.42, p=0.000. R^2=0.245 implies that 24.5% of the variation in Waste Reduction and Quality Control is explained by Computer Vision. Beta=0.495, p=0.000 means a 1-unit increase in CV adoption leads to 0.495-unit increase in waste reduction/quality. Therefore, H03 is rejected Also, the 95% confidence interval for Computer Vision (0.399, 0.627) does not include zero, further confirming the statistical significance and reliability of the effect on Product Quality and Defect Detection at $p < 0.05$."

DISCISSION OF FINDINGS

H01: Machine Learning and Operational Efficiency Result Shows R^2=0.312, β=0.558, p=0.000 < 0.05. This means Machine Learning has a significant positive effect on operational efficiency. 31.2% of the variation in efficiency is explained by ML. We therefore reject H01. This supports Audu and Aziwe (2025) that ML enables predictive maintenance and reduces downtime.

H02: Deep Learning and Product Quality Result Shows R^2=0.278, β=0.527, p=0.000 < 0.05. This means Deep Learning has a significant positive effect on product quality and defect detection. 27.8% of variation in quality is explained by DL. We reject H02. This implies firms using DL neural networks can detect defects faster and more accurately than manual inspection. This finding agrees with Zhao and Wang (2024) who reported that deep learning techniques enable real-time defect prevention in manufacturing processes.

H03: Computer Vision and Waste Reduction Result Shows R^2=0.245, β=0.495, p=0.000 < 0.05. This means Computer Vision has a significant positive effect on waste reduction and quality control. 24.5% of variation in waste reduction is explained by CV. We reject H03. This confirms that CV systems for automated inspection help reduce defective products and material waste. The result is consistent with previous studies from MDPI (2024), that computer vision systems provide immediate feedback for corrective action which minimizes waste in manufacturing firms.

Hence, all 3 hypotheses were rejected. This means specific AI techniques significantly improve operational performance of manufacturing firms in Lagos State. The highest impact comes from Machine Learning. This is consistent with global studies in US, China, Germany where AI drives productivity. The findings suggest that increasing adoption of DL, CV, and ML will directly lead to better cost, quality, and efficiency in Nigerian manufacturing.

CONCLUSION

The study concluded that Artificial Intelligence techniques significantly enhance Operational Performance of manufacturing firms in Lagos State. Specifically, Machine Learning improves Operational Efficiency, Deep Learning improves Product Quality and Defect Detection, and Computer Vision improves Waste Reduction and Quality Control. Therefore, AI adoption is critical for manufacturing firms to remain competitive in the Industry

RECOMMENDATIONS

Based on the findings, the following recommendations are made: Manufacturing Firms should invest more in Machine Learning for process optimization, adopt Deep Learning for real-time defect detection, and deploy Computer Vision systems to minimize waste and ensure quality control. Also, government should provide tax incentives and establish AI training centres to build capacity for AI adoption in the manufacturing sector. Finally, Management should invest more in data infrastructure and train staff to effectively operate AI-driven systems for improved performance

CONTRIBUTION TO KNOWLEDGE

This study contributes to existing literature by providing empirical evidence from Lagos State that ML, DL, and CV individually and significantly improve different dimensions of operational performance. It also provides a practical framework for manufacturing firms in Nigeria to prioritize AI investments.

REFERENCES

1. Arakpogun, E. O., Elsahn, Z., Olan, F., & Elsahn, F.(2021). Artificial Intelligence in Africa: Challenges and Opportunities. The Fourth Industrial Revolution: Implementation of Artificial Intelligence for Growing Business Success, 375-388.
2. Atalay, M., Anafarta, N. & Sarvan, F. (2013). The Relationship between Innovation and firm performance: An Empirical evidence from Turkish automotive supplier industry. Proceeding Social and Behavioural Sciences, (75), 226 – 235.
3. Audu & Aziwe (2025*)* Artificial Intelligence and the Performance of Manufacturing Firms in North-Central Nigeria: Reward System as the Moderator. *International Journal Of Research And Innovation In Social Science*, *9*(I), 1739-1755. DOI: 10.47772.
4. Burian, J. (2021). The complex choreography of supply chain resilience. Retrieved fromhttps://www.industryweek.com/supplychain/article/21163467/supply-chain-resilienceis-amultilevel-challenge. On July 11, 2026.

5. Chan, C. M., Teoh, S. Y., Yeow, A., & Pan, G. (2019). Agility in responding to disruptive digital innovation: Case study of an SME. Information systems Journal, 29(2), 436-455.
6. Dawes, J. (1999). The Relationship between subjective and objective company performance Measures in market orientation research: further empirical evidence, marketing Bulletin, 10 pp. 65 – 75. https://doi.org/10.3390/su141912760.
7. Ebuka, Emmanuel & Idigo (2026). Artificial Intelligence as a catalyst for the Sustainability of Small and Medium Scale Business (SMEs) in Nigeria. *Annals of Management and Organisation Research 5*(1), 1-11.
8. Ekanem, G. U., Effiong, M.B., Ekanem, U. A & Udom, K. O. (2026) Artificial Intelligence and Employee Performance In Manufacturing Firms In South-South, Nigeria. *International Journal Advanced Research Publications, 2*(5), 1-24.
9. Financial Stability Board (2017). Some Studies in Machine Learning using the game of checkers. IBM Journal of Research And Development, 11(3), 170-179.
10. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.
11. Harris, L. C. (2001). Market orientation and performance: Objective and Subjective empirical evidence from UK Companies, Journal of Management Studies, 38(1), 17 – 43.
12. Himanshu, A., Chandrika, P. D., & Rabindra, K. S.(2022). Does Artificial Intelligence Influence the Operational Performance of Companies? A Study Atlantis Highlights in Social Sciences, Education and Humanities, 2, 59-69.
13. Jabłońska, M. R., & Pólkowski, Z. (2017). Artificial Intelligence-Based Processes In Smes. Studies & Proceedings of Polish Association for Knowledge Management (86).
14. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436-444.
15. McKinsey. (2026). Fintech industry trends: AI, digital assets, and more. Retrieved from www
16. Reuters. (2026). Wall Street banks ramp up digital assistants in bid to win productivity race.
17. Rai, A., Constantinides, P., & Sarker, S. (2019). Next generation digital platforms: toward human-AI hybrids. MIS quarterly, 43(1), iii-ix.
18. Russell, S., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (4th ed.). Pearson.
19. Szeliski, R. (2022). Computer Vision: Algorithms and Applications. Springer.
20. Udeogu, A.C; Okoye, I.E (2024). Artificial Intelligence and Competitive Advantage of Micro, Small & Medium Enterprises (MSMEs) in Anambra State. Cross Current InternationalJournal of Economics, Management and Media Studies,6 (1) 1-9.
21. Udeogu, A.C; Okoye, I.E (2024). Artificial Intelligence and Competitive Advantage of Micro, Small & Medium Enterprises (MSMEs) in Anambra State. Cross Current InternationalJournal of Economics, Management and Media Studies,6 (1) 1-9.
22. Ulas, D. (2019). Digital Transformation Process and SMEs. Procedia computer science, 158, 662-671. doi:https://doi.org/10.1016/j.procs.2019.09.101.
23. Ulrich, P., Frank, V., & Kratt, M. (2021). Adoption of Artificial Intelligence Technologies in German SMEs-Results from an Empirical Study. Paper presented at the PACIS.
24. Wechie & Opigo (2020) Artificial Intelligence and Organisational Performance of Manufacturing Firms in PortHarcourt, Nigerian. Journal of management Science. Retrieved from www. rsisinternational.org on 10 June, 2026.
25. Yulia, S., & Wamba, S. F. (2022). Artificial Intelligence, Firm Resilience to Supply Chain Disruptions, and Firm Performance. Proceedings of the 55th Hawaii International Conference on System Sciences. URI: https://hdl.handle.net/10125/80059.
26. Zhao, X., & Wang, Y. (2024). Computer Vision and Machine Learning Approaches for Defect Detection in 3D-Printed Cementitious Materials. MDPI. Retrieved from www.Reseaercgate.net on June10, 2026.