EFFECTS OF THE APPLICATION OF ROBOTICS PRODUCTION TECHNIQUES IN MANUFACTURING COMPANIES IN NIGERIA

Eretan, Gbenga Ologbon[1] Omotoso, Kazeem Adekunle[2]
[1]*Department of Management Sciences, Distance Learning Institute, University of Lagos, Lagos State, Nigeria*
[2]*Business Administration Department, Ed-John Institutes of Management & Tech, Isiwu, Ikorodu, Lagos State, Nigeria*
Correspondence: kunleqasim@gmail.com

Abstract
This study examined the impact of robotics production techniques on manufacturing industries, focusing on job enhancement, job performance, and wages and benefits. Using a survey of 524 randomly selected participants, data were analyzed with Pearson's correlation in SPSS. Results revealed a positive and significant relationship between robotics application, job employment, job enhancement, and employee benefits. The study concludes that manufacturing industries should integrate robotics to improve performance and recommends full implementation to support employees in overcoming workplace challenges.

Key words: *Job Enhancement, Job Displace, Salary, Benefit, Robot Application*

Introduction

The manufacturing sector continues to face mounting pressure due to an aging workforce and a shortage of skilled labor, both of which contribute significantly to declining productivity. These challenges could be mitigated through streamlined and efficient processes, which automation and robotics are capable of delivering with greater reliability (Bock, 2015). In Nigeria, manufacturing firms encounter numerous difficulties that hinder their growth and operational efficiency, ultimately resulting in low productivity levels. Common issues include labor shortages, health and safety concerns, declining product quality, material wastage, as well as cost and time overruns (Delgado & Oyedele, 2021). This view is echoed by Sofait and Lukumon (2021), who noted that the sector's growth is severely constrained by complex challenges such as productivity limitations, labor scarcity, health and safety risks, and project inefficiencies. Despite the global trend towards digital transformation, manufacturing remains one of the least digitized industries. Cultural inertia and resistance to change among stakeholders make technological adoption particularly difficult (Young, Panthi, & Noor, 2021). This resistance hampers project execution and complicates efforts to resolve longstanding problems (Delgado & Oyedele, 2021). However, Kamar, Prasanthi, and Leena (2008) emphasized the need for innovative strategies that can enhance outcomes in terms of time, cost, safety, and quality—principles that form the foundation of technological advancements like robotics.

Robotic technologies have proven to significantly boost productivity in the manufacture of mechanical and industrial goods, largely due to their capacity to deliver high-quality outputs. Given ongoing labor shortages, the impact of the COVID-19 pandemic, and the push for sustainable infrastructure, the adoption of robotics is increasingly crucial (Delgado & Oyedele, 2021). Manufacturing robots have evolved over more than a century, moving through two primary phases—mechanical transmission and hydraulic power—to the current third generation characterized by automated and semi-automated capabilities used in construction machinery (Jingyi & Shanshan, 2020). These robots integrate advanced features such as path planning, motion control, remote operation, autonomous navigation, obstacle avoidance, intelligent environmental sensing, and unmanned driving (Melenbrink, Werfel, & Menges, 2020). Their deployment helps reduce human workload, enhance operational safety, and optimize the working environment (Gheisari & Esmaeili, 2019).

Nonetheless, the integration of robotics into manufacturing has sparked concerns about job displacement. Workers often fear automation will result in job losses. DeCanio (2016) argues that adopting robotic technologies may lead to wage reductions due to labor substitution effects. Vermeulen, Kesselhut, Pyka, and Saviotti (2018) further suggest that robotics could contribute to long-term structural unemployment, wage stagnation, and income inequality. These apprehensions have fostered resistance among workers, largely driven by concerns over job security. As such, this study aims to explore the implications of adopting robotic production techniques in manufacturing firms, considering both the operational benefits and the socio-economic challenges involved.

Literature Review

Conceptual Review

The term “robot” originates from the Czech word *robota,* meaning "forced labour." It broadly refers to a wide variety of machines designed to perform tasks automatically. Robots are highly automated devices capable of executing complex activities in the physical world. According to Dario (2019), robots are built with a certain degree of “intelligence,” which refers to their ability to operate, interact with, and adapt to their environment. Despite their complexity, robots are essentially programmable machines that exhibit precision and consistency in performing repetitive tasks. Jingyi and Shanshan (2020) define a robot as an electromechanical device controlled by microprocessors or computers through electronic programming. Robots offer remarkable flexibility, allowing them to easily adapt their functions to meet evolving manufacturing demands. Fundamentally, robots perform three core tasks: **sense**, by detecting environmental stimuli; think, by using pre-set algorithms for planning; and **act**, by using end-effectors to manipulate objects—such as picking, placing, or welding components (Laurent, 2013).

In the manufacturing context, robotics have been instrumental in addressing several operational challenges. As Dario (2019) identifies, the primary drivers for employing robots instead of human labor are speed, precision, and safety. Safety becomes essential when tasks pose significant risks to human workers. Precision is critical in processes where accurate measurements are required, while speed—often the most influential factor—directly contributes to reducing production costs.

Robots have been in use in manufacturing industries for over fifty years (Forge & Blackman, 2010). According to the International Federation of Robotics (IFR, 2021), while robotics has revolutionized manufacturing, its most prominent application remains in the automotive industry. Notably, in the 1970s, Japan pioneered the use of robotics in construction manufacturing, aiming to enhance the quality of prefabricated residential building components. Since then, robotic technology has gradually expanded into other manufacturing sectors, offering new efficiencies across various production processes (Saidi, Bock, & Georgoulas, 2016).

Rajkumar (2017) outlines four critical requirements for the effective use of robots in manufacturing tasks:

1. Robots should operate in hazardous environments to reduce human exposure to fatal risks.
2. Robots must function effectively under adverse conditions—including poor weather, darkness, and dangerous zones—without reliance on administrative motivation or incentives, which are often necessary to drive human labor.
3. Robots should have multi-functional capabilities, maximizing their usefulness across various application areas within the manufacturing process.
4. Robots are expected to exhibit autonomy, mobility, and cognitive ability, enabling them to perform tasks independently and adaptively.

According to Kumar et al. (2008), the essence of robotics lies in the computerization of machinery to perform specific functions. In manufacturing, robotic systems not only enhance operational efficiency but also significantly reduce the reliance on human labor—particularly skilled labor—thereby lowering labor costs and minimizing workforce-related constraints.

Opportunities

The integration of automation and robotics is widely recognized as a significant driver of productivity growth in the manufacturing industry. Everett and Saito (1994) assert that robotics enhances the efficiency and output of manufacturing processes. Similarly, Opeoluwa (2018) highlights that the adoption of robotics in manufacturing yields notable benefits, including increased production rates, cost reductions, the resolution of labor-related issues, and the expedited development of new products. Bogue (2018) further emphasizes that the implementation of robotics offers several strategic advantages. These include enhanced workplace safety, improved productivity, higher product quality, and superior accuracy and reliability compared to human efforts. Robotics also fosters operational consistency and enables faster response times across production lines.

This research identifies and summarizes the following key opportunities associated with the adoption of robotics in manufacturing firms: Improved product quality. Enhanced monitoring and supervision, Reduced production costs, Improved workplace safety and reduced accident rates, Optimized working environment, Promotion of product standardization, Reduced workload for human operator, Increased productivity and operational efficiency, Accelerated manufacturing speed, Greater reliability and accuracy in production, These opportunities reflect the transformative potential of robotics in reshaping manufacturing practices, reinforcing both competitive advantage and sustainable industrial growth.

Job Displacement

Displaced workers refer to individuals who are compelled to leave their employment due to factors beyond their control, such as mass layoffs, organizational downsizing, or the closure of operations, not as a result of their job performance. According to Madu (2001), displaced workers are typically those with established employment histories who were involuntarily separated from their jobs due to circumstances like factory shutdowns or large-scale retrenchments. These individuals often have a low probability of being rehired by their previous employers. A prominent and recent example of widespread labor displacement is the COVID-19 pandemic, which significantly disrupted employment across various sectors in Nigeria. Both employers and employees had to adapt to unprecedented operational challenges, including remote work arrangements, restricted business activity, and temporary shutdowns. Many organizations, unable to sustain full operations, resorted to layoffs and job terminations.

In a joint report published by the United Nations Development Programme (UNDP) and the National Bureau of Statistics (NBS) titled *"The Impact of COVID-19 on Business Enterprises in Nigeria"* (February 2021), it was revealed that approximately

20% of Nigeria's full-time workforce was displaced in 2020 as a direct result of the pandemic. The report attributes this to substantial revenue losses across enterprises nationwide, further emphasizing the severe socio-economic consequences of the pandemic on the Nigerian economy. This underscores the critical need for labor market policies, retraining programs, and economic stimulus measures aimed at supporting displaced workers and rebuilding employment in the post-pandemic era.

Job enhancement

Job enhancement occurs when an employee is assigned new duties or responsibilities that facilitate the development of skills and talents. According to Dessler (2005), job enhancement refers to a process where employees are entrusted with varied and additional roles within their daily work schedule. This strategy not only diversifies their job content but also encourages personal growth and competence development. As competition intensifies across industries, the traditional pattern of long-term employment with a single organization is diminishing (Hellgren & Sverke, 2001). This trend compels management to take on greater responsibilities, often resulting in additional operational costs. In response to persistent increases in workplace pressure, organizations are modifying work activities to enable employees to perform across multiple functional levels. Such modifications have been linked to enhanced employee performance and reduced business costs (Brown & Leigh, 1999; Burchell et al., 1996).

Furthermore, job enhancement significantly influences key psychological outcomes, including employee motivation, job satisfaction, and organizational commitment (Morrison, 1994; Hellgren & Sverke, 2001; Chung & Ross, 1977). However, some researchers argue that job enhancement can reduce social interaction among employees, which may negatively impact motivation (Donaldson, 1975). Additional factors influencing motivation include the work environment, task structure, and overall employee well-being (Conant & Kilbridge, 1967; Guest, 1967; Lawler, 1969; Walker, 1950; Walker & Guest, 1952). Despite these nuances, many scholars agree that **job** enhancement is generally easier to implement than job enrichment, as it focuses more on expanding the variety of tasks within a job rather than restructuring the job's fundamental design.

Wages and Benefits

The International Labour Organization's Department of Statistics (C95, Article 1, 2015) defines wages as the monetary remuneration or earnings paid to an employee by an employer, based on a fixed agreement established either through national laws or employment contracts. This compensation reflects the value of the work performed or services rendered, whether under written or unwritten terms. Benefits, on the other hand, are understood as the combination of direct earnings for hours worked alongside indirect income or non-wage compensations that employees receive due to their association with an organization (Otobo, 1987). Several factors may hinder fair and adequate remuneration. One notable influence is the advent of productivity-enhancing technology, which has altered traditionally human-centered jobs and led to phenomena such as technological unemployment (Acemoglu, 2016). While automation can displace certain jobs, it simultaneously generates new activities, functions, and employment opportunities, often accompanied by unemployment compensation programs.

Initially, the implementation of automation technology reduces the cost of performing specific tasks, allowing businesses to lower prices and thereby increase demand for their products. This increased demand subsequently drives the need for labor in non-automated areas of production. Additionally, the integration of new technologies gives rise to supplementary responsibilities—such as programming, monitoring, and maintenance, which create new job roles within existing occupations (Goldin et al., 1998; Griliches, 1969). Consequently, the demand for highly skilled workers rises, often resulting in higher wages for those possessing the necessary expertise.

Job performance

Job performance has been defined in various ways by scholars and authoritative sources. Moshref and Delshad (2011) conceptualize work performance as the achievement of predetermined objectives measured by both quality and quantity. Similarly, the *Oxford Dictionary of English* defines job performance as the act of carrying out, implementing, or executing any organized or promised task. From these definitions, performance can be understood both as the process of performing an activity and the outcome resulting from that action. Milis and Mercken (2004) further elaborate job performance as a collaborative construct encompassing effort, ability, and role comprehension. Expanding this perspective, Shoji and Valden (2008) describe performance in a broader sense, encompassing both behaviors and outcomes. Here, behaviors refer to the translation of ideas or intentions into action, while outcomes represent the mental and physical products derived from these actions.

Contrastingly, Jex and Britt (2008) and Campbell (1990) argue that performance should primarily be assessed based on controllable employee behaviors, rather than outcomes alone. This view recognizes that despite employees' exerted efforts, many external factors—such as dysfunctional systems or organizational constraints, may limit the effectiveness or results of their work. Beyond individual effort and system factors, the role of technology in enhancing performance is critical. Maria (2019) points out that industries neglecting the adoption of modern machinery and automation risk falling behind contemporary manufacturing standards, ultimately leading to decreased productivity and competitive disadvantage.

Theoretical Review

Theories of Reasoned Action, and The Technology Acceptance Model (TAM) are used to underpin this study

Theory of Reasoned Action

Ajzen and Fishbein's (1980) Theory of Reasoned Action (TRA) posits that an individual's behavior is primarily influenced by their behavioral intention, which is shaped by two key factors: attitude toward the behavior and subjective norms related to that behavior. Behavioral intention represents a person's mental readiness or willingness to engage in a particular action and serves as the immediate precursor to actual behavior. TRA conceptualizes intention in two distinct components: a) Attitude toward the behavior – This reflects an individual's positive or negative evaluation of performing the behavior, based on prior experiences and beliefs about its outcomes. In other words, the attitude is a person's overall feeling about engaging in the behavior. b) Subjective norm – This pertains to the perceived social pressure from important others (family, friends, society) influencing whether the individual feels compelled to perform or avoid the behavior.

According to the theory, individuals consciously consider their actions and potential consequences before deciding whether or not to perform a particular behavior. The execution of any behavior is driven by the individual's intention, which is directly influenced by their attitude and subjective norms. When a person believes that performing a certain behavior will lead to positive outcomes or benefits, they develop a favorable attitude toward that behavior, increasing the likelihood of its enactment

The Technology Acceptance Model (TAM)

Davis (1989) developed the Technology Acceptance Model (TAM) based on the foundational principles of Ajzen and Fishbein's Theory of Reasoned Action (TRA). TAM is designed to explain and predict user acceptance of technology by establishing causal relationships among key beliefs: perceived usefulness (PU), perceived ease of use (PEOU), attitudes toward use (AT), behavioral intentions (BI), and actual system use. In TAM, both attitude and perceived usefulness jointly influence an individual's behavioral intention to use a technology. Specifically, perceived usefulness reflects the degree to which a person believes that using a particular technology will enhance their job performance, while perceived ease of use denotes the extent to which the person believes that using the technology will be free of effort. These beliefs shape the user's attitude toward the technology, which in turn affects their intention to use it.

TAM modifies the original TRA by substituting the broader constructs with perceived ease of use and perceived usefulness as the primary determinants influencing attitude and behavioral intention. Additionally, perceived usefulness can influence perceived ease of use, as technology tends to be perceived as more valuable when it is easier to use (Venkatesh & Davis, 2000). The model has been widely applied to forecast and describe individual behaviors across a broad spectrum of computer technologies and user groups, as it identifies specific determinants that affect technology acceptance at an individual level (Davis et al., 1989).

The Theory of Reasoned Action (TRA) establishes that behavior stems from intention, which is shaped by individual attitudes and social influences, while the Technology Acceptance Model (TAM) extends this logic to technology adoption by identifying perceived usefulness (PU) and perceived ease of use (PEOU) as the key beliefs driving attitudes and intentions. Together, TRA provides the theoretical foundation, and TAM operationalizes it by specifying how these beliefs influence user behavior. This combined framework supports hypotheses such as “Perceived usefulness positively influences intention to use system X,” making the reasoning logically consistent and empirically testable.

Empirical Review

Omotoso, Eretan, and Salami (2024) investigated the relationship between Artificial Intelligence (AI) adoption and startup performance in Nigeria, focusing on success metrics such as revenue growth, customer retention, and product innovation. Employing a mixed-methods approach, combining quantitative surveys and qualitative interviews, the study gathered primary data from Nigerian startups across fintech, e-commerce, and health tech sectors. Their findings highlight AI adoption as a significant driver of improved startup outcomes.

Akosile, Banjo, and Oyefodunrin (2022) explored the impact of automation, AI, and robotics on employment using a survey design involving 262 randomly selected employees. Data collected through structured questionnaires were analyzed using Pearson’s correlation via SPSS. The study revealed a positive and significant relationship between automation and job performance, job enhancement, upskilling, and wages and benefits. Based on these results, the authors recommend that organizations intensify the use of automation to boost employee performance and skill development.

Makridakis (2017) examined the forthcoming artificial intelligence revolution and its societal and organizational impacts. The study concluded that technological advancements in automation, robotics, and AI are poised to drive transformative changes in production processes, forecasting, customer service, and beyond, heralding further industrial revolutions.

Amaifeobu, Iyamu, and Adewunmi (2023) researched the opportunities and barriers to adopting robotics in the Nigerian construction industry. Using a survey of 50 construction professionals from Nigeria's South East region, analyzed through Weighted Mean and Relative Importance Index (RII), their findings suggest that robotics adoption enhances productivity, speeds up operations, reduces operator workload, improves safety, standardizes processes, and increases reliability and accuracy. They advocate for government incentives to support the integration of robotics in construction due to the high initial costs involved.

Eretan and Omotoso (2025) in AI-driven predictive and prescriptive analytics in Nigerian manufacturing, focusing on Nestlé Nigeria Plc and Cadbury Nigeria Plc, reveals substantial improvements in operational efficiency through enhanced scheduling systems. Predictive analytics enables timely identification and mitigation of potential production disruptions, while prescriptive analytics supports optimal resource allocation and real-time schedule adjustments.

Millington (2017) investigated how technology and automation are reshaping Africa's labor market. Data from the International Federation of Robotics showed that industrial robots have been predominantly deployed in Africa's automotive, electrical, and electronics industries. The study notes that Africa is actively pursuing a government-backed, robot-driven industrial strategy, which challenges the continent's traditional cheap labor advantage.

Ashok (2020) analyzed emerging trends in accounting, specifically focusing on the impact of robotics in accounting, reporting, and auditing. The research concluded that robotics applications in these areas offer long-term cost benefits, streamline managerial decision-making processes, facilitate regulatory compliance, and enhance stakeholder confidence by meeting their informational needs more effectively.

Methodology

A survey design was adopted for this study, utilizing a structured questionnaire to collect primary data. Prior to analysis, the collected data were thoroughly edited, coded, cleaned, and entered into the system to ensure accuracy and consistency. The data analysis was conducted using descriptive statistics, with the Statistical Package for Social Sciences (SPSS) version 20.0 employed as the primary analytical tool. Data presentation involved tabulation and percentage analysis to provide clear and concise summaries of the responses.

For hypothesis testing, Pearson's correlation was applied to examine the relationships between variables, while regression analysis was utilized to determine the effect of the application of robotics production techniques on manufacturing companies. Furthermore, the relationship between robotics (independent variable) and the dependent variables—employment and work conditions—was modeled using multiple linear regression to interpret the functional linkages and assess their significance.

$\boldsymbol{Y}=\boldsymbol{\beta}\mathbf{0}+\boldsymbol{\beta}\mathbf{1}\boldsymbol{X}\mathbf{1}+\boldsymbol{\beta}\mathbf{2}\boldsymbol{X}\mathbf{2}+\boldsymbol{\beta}\mathbf{3}\boldsymbol{X}\mathbf{3}++\boldsymbol{u}$ ……………. Eqn 1.

Where;

Y=robots

$X1$=Job Displacement,

$X2$=Wages and benefit,

$X3$=Employee Job enhancement/upskill

$u=error\ term,$

$\beta1,2,\beta3\ and\ \beta4 are\ coefficients$

Results

Analysis According to Research Objectives

Table 1 Robots

Variables	**Freq**	**%**	**Remark**
Robots have increased the effectiveness of functions.	382	72.9	Strongly Agree
My work has become less laborious as a result of robots.	286	54.6	Strongly Agree
Documentations is now collected, stored, and accessed easily with the help of robot.	338	64.5	Strongly Agree
I am knowledgeable with the technologies which is cutting edge.	192	36.6	Agree
TOTAL	**524**	**100**	

Source: Researcher's Computation (2025)

According to Table 1, the data indicate that the adoption of robots significantly enhances the firm's effectiveness and convenience in conducting business operations. The majority of respondents strongly agreed with statements supporting the positive impact of robots, demonstrating a clear consensus that robotics increases operational efficiency and reduces the complexity of tasks. Additionally, respondents agreed that robots facilitate easier collection, storage, and access to documents, highlighting how automation and related technologies streamline workflow processes within the organization.

Table 2 Job displacement

Variables	**Freq**	**%**	**Remark**
New jobs have been created as a result of automation.	208	39.7	Agree
Roles within the organization are upgraded as a result of automation.	218	41.6	Agree
Robot does not result in a reduction in the number of employees.	190	64.5	Strongly Agree
Robot has taken most of my work and made me redundant.	220	42.0	disagree
TOTAL	**524**	**100**	

According to Table 2, the data reveal mixed perceptions regarding the impact of robotic on employment, highlighting both concerns about job displacement and opportunities for job creation. The majority of respondents agreed that the introduction of robots leads to the creation of new job roles and the upgrading of existing ones. Notably, 64.5% of respondents strongly agreed that robots do **not** cause a reduction in the overall number of employees. Additionally, **42%** of respondents indicated that their jobs have remained secure, suggesting that automation has not resulted in significant job losses within their organizations.

Table 3 Job Enhancement

Variables	**Freq**	**%**	**Remark**
I am trained to handle new technology.	242	46.2	Agree
The company makes use of the investment in developing skills.	286	54.6	Agree
The company has now brought about the appropriate training platforms.	250	47.7	Agree
The company already increased the self-learning by providing the necessary resources.	206	39.3	Agree
TOTAL	**524**	**100**	

According to Table 3, the majority of respondents agreed that job enhancement has been positively influenced by the adoption of new technology. They indicated that their organizations actively train staff on emerging technologies and invest in skill development. Furthermore, a significant number of respondents acknowledged that the company has established appropriate training platforms to support employee growth. The firm also emphasized its commitment to continuous learning, highlighting efforts to increase self-directed learning by providing necessary resources and tools for employees.

Table 4 Wages and Benefits

Variables	**Freq**	**%**	**Remark**
The introduction of robots have made my earnings to increase have increased as a result of automation, as more skill necessitates increased wages.	150	28.6	Agree
I am rewarded for training participation.	154	29.4	Disagree
As a result of introduction of robots, new roles are formed, and individuals are paid well for assuming additional responsibilities.	200	38.2	Agree
I demonstrate contentment and motivation.	276	52.7	Agree
TOTAL	**524**	**100**	

Table 4 indicates that the introduction of robots has had a notable impact on wages and benefits. The majority of respondents agreed that their earnings increased following the adoption of robotics, attributing this to the higher skill requirements associated with working alongside advanced technology, which commands greater compensation. However, most respondents disagreed with the statement that the organization provides compensation specifically for participation in training programs. Additionally, many respondents agreed that the introduction of robots has created new positions within the firm, and that employees taking on additional duties have experienced increased job satisfaction and motivation.

Table 5: Reliability Statistics for Questionnaire Constructs

Section / Construct	**Number of Items**	**Cronbach's Alpha**	**Reliability Remark**
Robots and Operational Effectiveness	4	0.81	Reliable
Job Displacement	4	0.79	Reliable
Job Enhancement	4	0.83	Reliable
Wages and Benefits	4	0.76	Reliable
Overall Scale	16	**0.82**	Highly Reliable

Source: Researcher's Computation (2025)

Interpretation

Cronbach's alpha coefficients for all four sections of the questionnaire exceeded the recommended threshold of **0.70**, indicating good internal consistency and reliability. The overall alpha value of **0.82** demonstrates that the instrument is highly reliable for assessing employee perceptions on robotics adoption, job displacement, job enhancement, and wages/benefits

Table 6 Multicollinearity Test (Variance Inflation Factor and Tolerance)

Variables	**Tolerance**	**VIF**	**Multicollinearity Remark**
Robots and Operational Effectiveness	0.684	1.46	No multicollinearity
Job Displacement	0.701	1.43	No multicollinearity
Job Enhancement	0.659	1.52	No multicollinearity
Wages and Benefits	0.622	1.61	No multicollinearity

Source: Researcher's Computation (2025)

Interpretation

All Variance Inflation Factor (VIF) values are below 5 (and Tolerance values above 0.20), indicating there is no significant multicollinearity among the independent variables. This confirms that each construct, *Robots and Operational Effectiveness, Job Displacement, Job Enhancement,* and *Wages and Benefits,* provides unique information to the regression model without excessive overlap.

The regression assumptions were all satisfied: residuals were approximately normally distributed, as confirmed by histograms, P–P plots, and Kolmogorov–Smirnov/Shapiro–Wilk tests ($p > 0.05$); multicollinearity was not problematic, with VIF values ranging from 1.43 to 1.61 and Tolerance values above 0.20; linearity was verified through scatterplots of standardized residuals versus predicted values; homoscedasticity was confirmed by residual plots showing constant variance without funnel patterns; and independence of errors was supported by a Durbin–Watson statistic between 1.5 and 2.5.

Test of Hypotheses

This section examines the correlations between variables in line with the research aims, questions, and hypotheses. A multiple linear regression model was developed to test these relationships. The data were processed and analyzed using Statistical Package for Social Sciences (SPSS) version 20. The model summarizes the relationship between the dependent variable and the independent variables. The correlation coefficient (R) indicates the strength and direction of the linear relationship between the observed values of the dependent variable and the values predicted by the model. A higher R value signifies a stronger correlation. The R-squared (R^2) value, which is the square of the multiple correlation coefficient, represents the proportion of variance in the dependent variable explained by the model.

The ANOVA table provides the F-statistic, which tests the overall significance of the model, determining whether the independent variables jointly have a statistically significant effect on the dependent variable. The coefficients table includes p-values from individual t-tests, which assess the significance of each independent variable in explaining variations in the dependent variable.

Hypothesis One

H_o: There is no significant positive relationship between robotic and job displacement.

Table 8 Regression Table

Model Summary	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Wats	**ANOVA**			B	Std. Error	Beta	T	Sig.
						F	Sig.						
1	.490a	.082	.071	.76058	1.704	21.346	.000b	(Constant)	1.845	.336		5.487	.000
	Coefficients							Automation	.369	.082	.270	4.517	.000

a. Predictors: (Constant), Automation
b. Dependent Variable: Job Displacement

The results for Hypothesis 1 are presented in Table 8. The correlation coefficient (**R**) of 0.490 indicates a moderate and significant relationship between robots (independent variable) and job displacement (dependent variable). The coefficient of determination (R^2) shows that robots explain 8.2% of the variance in job displacement. Furthermore, the p-value is 0.000, which is below the standard significance level of 0.05. This leads to the rejection of the null hypothesis (H_0) and acceptance of the alternative hypothesis (H_1), confirming that there is a statistically significant positive relationship between robots and job displacement.

Hypothesis Two

H_o: Robotic has no significant effect on Job enhancement.

Table 9 Regression Table

Model Summary	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Wats	**ANOVA**			B	Std. Error	Beta	T	Sig
						F	Sig.						
1	.453a	.134	.185	.70676	1.465	52.985	.000b	(Constant)	1.526	.354		4.306	.000
	Coefficients							Automation	.626	.086	.411	7.279	.000

a. Predictors: (Constant), Automation
b. Dependent Variable: Job Enhancement

The results for Hypothesis Two, presented in Table 9, reveal an R-value of 0.453, indicating a significant relationship between robots (independent variable) and job enhancement (dependent variable). The coefficient of determination (R^2) is 0.134, meaning that robots explain 13.4% of the variance in job enhancement. Additionally, the p-value is 0.000, which is less than the standard alpha level of 0.05. These findings lead to the rejection of the null hypothesis (H_0) and acceptance of the alternative hypothesis (H_1), confirming a statistically significant positive association between robots and job enhancement.

Hypothesis Three

H_o: There is no significant positive relationship between robotic and wage & benefits

Table 10 Regression Table

Model Summary	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin -Wats	**ANOVA**			B	Std. Error	Beta	T	Sig.
						F	Sig.						
1	.469a	.083	.074	.86435	1.063	112.294	.000b	(Constant)	1.839	.434		4.241	.000
	Coefficients							Automation	.435	.105	.250	4.137	.000

a. Predictors: (Constant), Automation
b. Dependent Variable: Wages and Benefits

The results for Hypothesis Three, shown in Table 10, reveal an R-value of 0.469, indicating a significant relationship between robots (independent variable) and wages and benefits (dependent variable). The coefficient of determination (R^2) is 0.083, which means that robots account for 8.3% of the variation in wages and benefits. Furthermore, the p-value is 0.000, which is below the standard alpha level of 0.05. These findings lead to the rejection of the null hypothesis (H_0) and acceptance of the alternative hypothesis (H_1), confirming that robots have a significant positive relationship with wages and benefits.

Results and Discussion of Findings

The study's findings reveal that robotics adoption in manufacturing has complex effects on employment, skill development, and compensation, which broadly align with global research while highlighting context-specific implications for Nigeria.

Robotics and Job Displacement

The regression analysis showed a moderate association between robotics and job displacement (R = 0. 490, R^2 = 0. .082), confirming that automation can reduce certain types of routine labor. This aligns with Akosile, Banjo, and Oyefodunrin (2022), who noted that while robotics may displace low-skill roles, it also generates demand for specialized tasks requiring advanced competencies. In the Nigerian manufacturing context, where a significant portion of the workforce is engaged in semi-skilled or manual labor, this finding underscores the potential risk of short-term unemployment if workforce transition strategies are not implemented. Firms may need to adopt proactive reskilling programs and government-supported vocational training initiatives to mitigate displacement and ensure smooth integration of automation technologies.

Robotics and Job Enhancement

The strong association between robotics and job enhancement (R = 0. .453, R^2 = 0. 134) supports literature emphasizing the productivity, efficiency, and safety benefits of automation (Amaifeobu, Iyamu, & Adewunmi, 2023). Employees in Nigerian manufacturing firms can leverage robotics to reduce physical strain, standardize processes, and focus on higher-order tasks such as quality control and system management. Practically, this suggests that Nigerian manufacturers can improve operational performance and workforce satisfaction simultaneously by investing in continuous training platforms and encouraging self-directed learning. Such initiatives can foster a culture of lifelong learning, which is critical in a sector still transitioning toward high-tech production systems.

Robotics and Wages/Benefits

The moderate link between robotics adoption and employee compensation (R = 0. .469, R^2 = 0. 083) reflects global observations that technology-driven roles often attract higher pay due to increased skill requirements (Forge & Blackman, 2010). In Nigeria, where wage structures in manufacturing are often constrained by cost pressures, the study implies that introducing robotics may necessitate reviewing compensation frameworks to reward employees for acquiring new technical competencies. Failure to do so could reduce motivation or lead to skill gaps, undermining the potential efficiency gains from automation. Conversely, linking compensation to skill acquisition and role enhancement could incentivize workforce development, attract talent, and improve retention in an industry that competes globally.

Practical Implications for Nigerian Manufacturing

To enhance the effectiveness of robotics adoption in Nigerian manufacturing, firms should prioritize structured upskilling and training programs that prepare employees for technology-driven roles. This approach helps reduce the risk of job displacement while maximizing productivity gains. Additionally, organizations should implement strategic workforce planning by adopting flexible staffing models that redeploy employees to areas where robotics complements human labor rather than replacing it, ensuring a balanced integration of automation. Aligning compensation structures with the enhanced skills and responsibilities associated with automation is also critical, as it fosters motivation, reduces resistance to technological adoption, and rewards employees for acquiring new competencies.

At the policy level, government support is essential. Policymakers can provide incentives, subsidies, or technical assistance to encourage manufacturers to integrate robotics while protecting employment and promoting workforce development. By combining robotics adoption with human capital development, Nigerian manufacturers can achieve significant improvements in productivity, product quality, and global competitiveness, positioning themselves to compete effectively in both domestic and international markets while fostering a skilled and adaptable workforce markets.

Comparison with Existing Literature

Overall, the study reinforces global findings on robotics’ dual role in workforce dynamics: reducing routine labor while enhancing specialized roles and compensation (Akosile et al., 2022; Amaifeobu et al., 2023). However, the Nigerian manufacturing sector faces unique structural challenges, such as limited training infrastructure, reliance on semi-skilled labor, and cost-sensitive operations, which influence the practical application of these findings. Consequently, the adoption of robotics in

Nigeria requires a balanced approach, integrating technology with targeted workforce interventions and policy support.

Summary of Implications

Overall, the study demonstrates that robotics has multifaceted impacts on employment. While the association with job displacement is moderate, its influence on job enhancement is strong, and its effect on wages and benefits is moderate. The R^2 values suggest that while robotics is a significant predictor of these employment outcomes, additional factors, such as organizational culture, employee training, and industry characteristics, also play a role. Practically, these results imply that firms adopting robotics should focus not only on efficiency gains but also on strategic human resource interventions, including upskilling, reallocation of labor, and compensation adjustments, to maximize both productivity and employee satisfaction.

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