Ilaro Journal of Humanities and Management (IJOHAM) 2024
Published Online October 2024 (https://fpihumanitiesjournal.federalpolyilaro.edu.ng/)
Volume 3, 2024 Edition
ISSN: 2682- 6577

The Influence of Automation on Job Security in Nigeria Quoted Manufacturing Firms

Abayomi O. Ogunsanwo
The Federal Polytechnic, Ilaro. Department of Procurement and Supply Chain Management. Ogun State, Nigeria.
E-mail: abayomi.ogunsanwo@federalpolyilaro.edu.ng

Azeez A. Oyelekan
The Federal Polytechnic, Ilaro. Department of General Studies, Ogun State, Nigeria.
E-mail: azeez.oyelekan@federalpolyilaro.edu.ng

Abstract

This study examines the complex dynamics of automation's effects on employment within Nigeria's burgeoning manufacturing sector, with a close attention to Lagos cluster, the hub of the nation's economic activity. A thorough survey study design was used to collect data from 320 respondents who worked for three manufacturing organizations. The Structural Equation Model (SEM) was used to analyze the intricate relationship between automation technologies—Artificial Intelligence (AI), Internet of Things (IoT), and Data Analytics (DA)—and employment levels. AI has the most influence, closely followed by IoT and DA. The regression weights showing the size of effect of relationship between Employment and Internet of Things was (0.287), Employment and Artificial Intelligence was (0.563), as well as Employment and Data Analytics to be (0.309). Additionally, a convincing analysis using Squared Multiple Correlations reveals a correlation of 0.840. This coefficient indicates that the combined effects of the automation factors, including IoT, AI, and DA, account for 84% of the variation in employment levels. The research's conclusions confirm that each of the three automation technologies has a statistically significant and overwhelmingly favourable impact on employment by emphasizing the urgent need for proactive governmental measures that would create an environment that will allow Small and Medium-sized Enterprises (SMEs) to easily adopt automation technologies. The study therefore recommends the adoption of automation technologies in Nigeria's manufacturing sector to help stakeholders, business leaders, and policymakers to navigate the complex world of automation in Nigeria's industrial sector and provides an effective road map for successfully utilizing automation's promise while resolutely preserving the well-being and livelihoods of the workers.

Keywords: Artificial Intelligence, Data Analytics, Employment Levels, Internet of Things, Structural Equation Model.

Introduction

Automation has always been a key factor in rising productivity and economic expansion. Early mechanization during the Industrial Revolution resulted in some manual labour positions being replaced, but it also opened up new opportunities in manufacturing and other industries (Acemoglu & Restrepo, 2019). However, the current wave of automation, driven by advances in AI, robots, and machine learning, has caused serious concerns about how it will affect the labour market (Bessen, 2019).

Nigeria's manufacturing industry has played a significant role in both job creation and economic expansion. In recent years, concerns have been expressed over the influence of automation technology on employment in this industry (NESG, 2019). The manufacturing sector in Nigeria has the potential to become more productive and competitive through automation. A research from the Nigerian Economic Summit Group NESG,

(2019) claims that automation can boost production process efficiency, which may therefore encourage the expansion of the manufacturing sector. Particularly in higher-skilled occupations connected to the design, maintenance, and operation of automated systems, this expansion may result in new employment possibilities.

Automation in industry, however, has the potential to displace workers. Automation technologies, as noted by Amadi and Ezejiofor (2018), can replace human labour in some routine and repetitive operations, potentially reducing the number of job prospects for low-skilled individuals in the industry. If not properly managed, this displacement effect could make Nigeria's unemployment problems worse.

There are various obstacles in the way of Nigeria's manufacturing sector's automation change. The risk of a skills gap, where the workforce may not have the necessary skills to operate and maintain automated systems, as well as the need for significant investment in infrastructure and workforce development are among the main causes for concern (Umeokafor *et al.,* 2020).

Nigeria's manufacturing industry is vital to the nation's economy, making a considerable contribution to job creation, revenue production, economic diversification, industrialization, and economic growth (Agu, 2015). Over the years, the manufacturing industry in Nigeria has grown and changed, driven by both internal and international economic influences. Recent developments in automation technology have brought about a transformational wave, nonetheless, prompting concerns about their impact on employment in this area (World Economic Forum., 2023). To address the difficulties and opportunities this transition provides ground for it is crucial to comprehend its context and dynamics.

In Recent years, automation technologies like robotics, artificial intelligence (AI), the internet of things (IoT), and data analytics have begun to proliferate in Nigeria's manufacturing sector (DigiInternational, 2023; Copper Digital, 2023). These technologies have the power to completely alter how goods are produced, increase productivity, and raise standards of quality (Ejemeyovwi et al., 2020). They present chances for cost-cutting and more market competition on a global scale. The effects of AI, IoT, and data analytics on the employment landscape are complicated (McKinsey & Company, 2021). Despite the possibility of employment creation, these technologies also present issues with job displacement and income inequality. An analytical and digitally skilled workforce is required by the changing labour market and empirical research is still essential for guiding policies and strategies to address the complex effects of these technologies on employment and society as technology develops further.

However, there are difficulties in integrating automation into Nigeria's manufacturing industry. The possible displacement of human labour is one of the main worries (Frey & Osborne, 2017). As normal and repetitive jobs are replaced by automation technologies, the livelihoods of low-skilled workers may be impacted by this displacement effect, making the unemployment problem worse (Amadi & Ezejiofor, 2018). In contrast, the adoption of automation technology may result in the creation of jobs in positions connected to the design, upkeep, and management of automated systems (NESG, 2019). The manufacturing industry is changing, and skilled people who can use and manage these technologies may discover new opportunities.

The policies and programmes of the Nigerian government have a big impact on how automation develops in the manufacturing industry (World Economic Forum, 2020). To maximize the advantages of automation while tackling its possible drawbacks, a key strategy is needed (Umeokafor *et al.,* 2020). To inform decisions and enable a smooth transition to an automated future, a thorough analysis of the impact of automation on employment in Nigeria's industrial industry is necessary.

There is a need for a deeper knowledge of how automation affects certain industries, the skills needed in the changing labour market, and the efficacy of reskilling programmes despite the constant conversations and studies on the effects of automation on employment. Additionally, little research has been done on the long-term effects of automation on income disparity and employment quality. This research seeks to fill these gaps by examining the complex interactions between automation and worker well-being, skill demands, and employment, as well as the opportunities and challenges presented by the quickly evolving workplace.

A crossroads of opportunity and difficulty exists for Nigeria's industrial sector as AI, IoT, and Data Analytics gain prominence. The symbiotic relationship between employment and automation technologies emphasizes the need for a balanced strategy. Realizing the full potential of AI, IoT, and Data Analytics while maintaining the vibrancy of employment in Nigeria's industrial sector requires making use of automation's advantages while also assisting workers in adapting to this changing landscape. Against this background, the study aims within Nigeria manufacturing firm context to examine the relationship between Automation and employment generation, evaluate the influence of Artificial Intelligence on employment creation, assess the impact of Internet of Things on employment generation and examine the effect of Data Analytics on job security.

Literature Review

The Internet of Things (IoT), Artificial Intelligence (AI), and Data Analytics are three separate technological disciplines, each with its own specialties and applications. This conceptual analysis investigates the synergy that results from their intersection, illuminating how the combination of AI, IoT, and Data Analytics is reshaping industries, improving decision-making procedures, and influencing the future of technology-driven solutions.

The phrase "artificial intelligence" (AI) refers to a collection of technologies, such as "computer vision," "machine learning," and "natural language processing," that enable computers to imitate human intellect. Russell and Norvig, (2021) conceptualize Artificial intelligence as a systems that use patterns and algorithms to make predictions about the future or decisions based on facts from the past.

The term "Internet of Things" (IoT) refers to a network of physically connected devices, such as machines, buildings, and vehicles that are also linked to the internet. According to Atzori *et al.* (2010), the use of these devices to collect and transfer data makes it feasible to monitor and manage physical systems in real time.

Data analytics involves doing in-depth research in order to identify important tendencies, patterns, and insights hidden within the data (Couchbase, 2023). According to Davenport and Harris (2007), it incorporates a number of different approaches, such as descriptive, diagnostic, predictive, and prescriptive analytics, in order to bolster decision-making and improve operations.

Automation is the use of technology and systems to complete tasks or processes with the least amount of human involvement (Smith, 2018). Robotics, software, and artificial intelligence are just a few of the technologies that fall under this umbrella notion and are utilized to streamline and optimize numerous tasks in enterprises, industries, and daily life (Jones, 2020). In several industries, including manufacturing, logistics, customer service and data analysis, automation is used to increase efficiency, accuracy and productivity (Brown, 2019; Davis, 2017; Wilson, 2020; Johnson, 2021).

Through the lens of labour substitution theory, it is better comprehended how technology and work are interacting in the modern workforce. Its theoretical underpinnings highlight the potential for robots and AI to transform entire sectors, levels of production, and occupations. Addressing the socioeconomic ramifications and adopting a balanced approach to labour substitution will be vital as sectors adjust to the changing environment. According to World Economic Forum (2023), the fundamental tenet of labour substitution theory is that automation and technology improvements have the potential to cause robots and AI systems to take the place of workers. The law of diminishing returns and capital-labor substitution are two traditional economic theories that serve as inspiration for this one (Solow, 1957). In more recent study, the importance of robotics and information technology in promoting labour substitution has been highlighted (Acemoglu & Restrepo, 2020).

Labour replacement theory is based on the premise that as technology develops, jobs that were previously performed by human employees can be done more effectively and efficiently by machines. This idea covers a broad spectrum of businesses where repetitive and routine work can be automated, from manufacturing to services (Autor, 2019). This theory's components include the identification of jobs that can be automated, the development of the necessary technology and potential workforce effects.

Labour substitution theory has important societal and industrial ramifications for businesses looking to boost productivity and save costs. Processes could be streamlined, precision could be improved, and mistake rates could be decreased with the help of automation and AI-driven systems (Brynjolfsson & McAfee, 2014). The need for labour upskilling and worries about job displacement, however, have become crucial issues (Acemoglu & Restrepo, 2020). Additionally, the theory raises moral concerns over the fair distribution of benefits and their propensity to worsen income inequality.

The following empirical studies contribute to a better understanding of the intricate dynamics at play in the labour market by providing insightful information about the diverse relationship between automation technology and employment.

Arntz *et al.* (2016) examined the probability of job automation in OECD nations in their empirical study. The study intended to pinpoint the industries and jobs most at risk from automation using data from several nations. The study used a thorough comparative investigation to determine how automation has affected employment in various nations. According to the research, the risk of automation varies by industry and employment, with regular and manual jobs being more vulnerable. The study provides interesting and useful information about the complicated effects that automation has had on labour markets all around the globe.

Another empirical research that focuses on the significance of demand in the link between artificial intelligence and employment was conducted by Bessen (2019). The study investigates how the implementation of AI impacts the demand for labour in a variety of different sectors. Using historical data, the research investigates how changes in employment numbers, increases in salaries, and job prospects have occurred in sectors that make use of AI technology. The study highlights the necessity of understanding the demand side of the labour market as an important step in determining how artificial intelligence affect employment opportunities. According to the findings of the study, while automation may result in the loss of certain jobs, it also provides new opportunities for employment in fields that make use of artificial intelligence.

Frey and Osborne (2017) carried out a ground-breaking empirical investigation to determine the degree to which different types of work are vulnerable to being done by machines. Using extensive data on the characteristics of various vocations, the research investigated the possibility of certain occupations being replaced by robots. The concept of a "technological automatability index" was developed in order to categorize different types of work according to the degree to which they may be performed by machines. In order to determine which industries and professions are most at risk, the research classified employment into three categories based on the degree of automation risk they posed: high, medium, and low. The research provides a comprehensive analysis of job loss brought on by automation, which makes a significant addition to our comprehension of how technology influences the labour market.

In another empirical study "The Second Machine Age," Brynjolfsson and McAfee (2014) examined how digital technologies, such as artificial intelligence (AI) and data analytics, are changing the nature of work and the economy. To demonstrate how automation technologies have impacted job growth, productivity, and income distribution, the authors drew on comprehensive data and case studies. They made the case that, despite the possibility of job displacement, automation may also result in the creation of higher-skilled, better-paying positions, highlighting the need for a workforce with adaptive abilities.

Methodology

This research investigates the effects of automation on employment in Nigeria's manufacturing sector, with a particular focus on Lagos, which is widely seen as the principal financial and commercial hub of the nation. A thorough survey research design was created to accomplish this. The 320 respondents who participated in the data collection were carefully chosen from a pool of the top ten manufacturing enterprises in Nigeria. Both parametric and non-parametric sample methods were used in the sampling operation.

In the first step, stratified sampling method was used to purposefully choose ten leading manufacturing companies. Three of these businesses—with a combined population of 15,466—were randomly selected. Dangote Cement Plc, Nigeria Breweries Plc, and Unilever Nigeria Plc made up the chosen trio. The sampling frame for these companies were 12,020, 2,671, and 775 respectively. The selection of the sample was carried out, with 279, 62, and 18 questionnaires chosen, correspondingly, depending on the populations of the aforementioned companies, since the sample size of 359 was determined by Cochran formular for large samples.

A four-point Likert scale questionnaire was used to collect the data. Component factor analysis and Cronbach's alpha statistics were used to establish the instrument's psychometric qualities, which include validity and reliability. An excellent response rate of 345 surveys were returned from the 360 that were distributed. 320 of these responses were found to be valid after going through rigorous validation procedures and were then used for the study's analyses. Structural Equation Modelling (SEM), utilizing Amos Graphic Version 26, was used for data analysis.

Results

The analysis of this study is based on the results obtained from the structural equation model (SEM) analyzed using AMOS Graphics Version 26.

Figure 1: Unstandardized Structural Equation Modelling

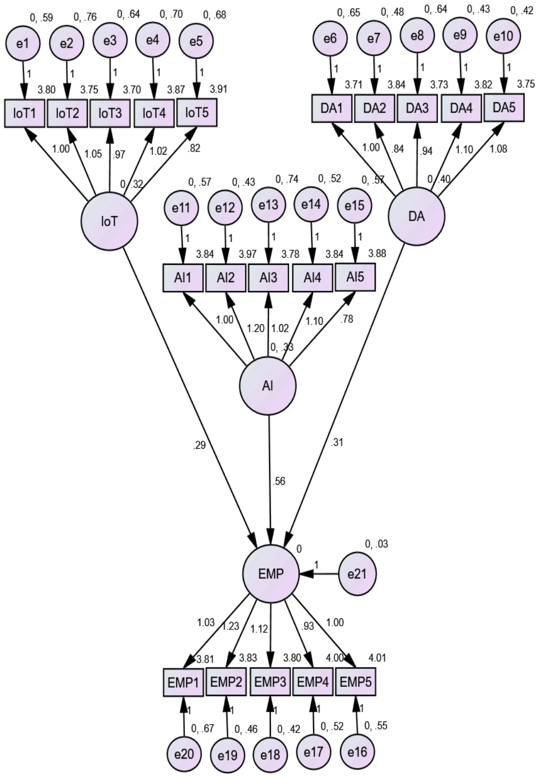
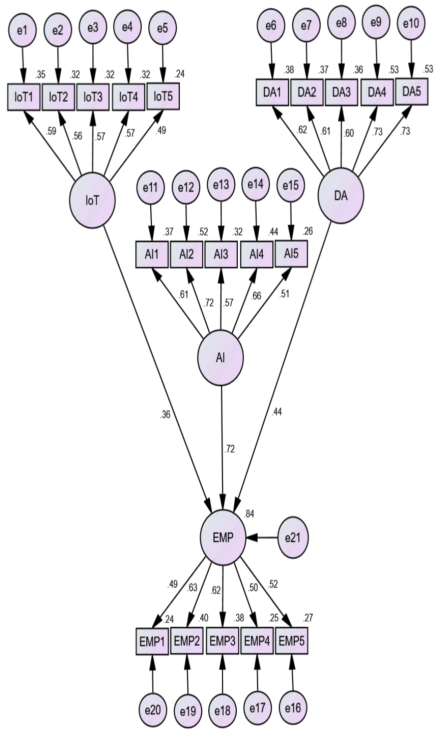


Figure 2: Standardized Structural Equation Modelling



The Internet of Things, artificial intelligence, and data analytics were the automation proxies used in this study to examine employment in Nigerian manufacturing companies. This is shown in the structural equation model. The model produced a number of statistics, including the mean of the observed variable(s), the impact of the latent independent variable (the Internet of Things, AI, and data analytics), and the residual (error term), which represents the discrepancy between the observed values of the dependent variable and the values predicted by the regression model. The study looked at the links between three latent independent variables—Automation, namely Internet of Things (IoT), Artificial Intelligence, and Data Analytics (DA)—and a latent dependent variable—Employment (EMP), based on the structural equation modelling (SEM) methodology.

With an effect size of 0.56 in the unstandardized model and 0.72 in the standardized model, the analysis discovered that AI had a significant beneficial impact on employment. This means that there will be a large increase in job levels as AI technologies are embraced and incorporated. The significant impact of AI, especially in the standardized model, emphasizes how important it is in determining employment patterns. In addition, an effect size of 0.29 in the unstandardized model and 0.36 in the standardized model, IoT also showed a favourable impact on Employment. Even

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while the effect size is a little bit smaller than it is for AI, the adoption of IoT technology still has a beneficial impact on employment, albeit to a considerably reduced amount. Data Analytics also had a favourable impact on employment, with an effect size of 0.34 in the standardized model and 0.31 in the unstandardized model, similar to IoT. DA has a major impact on employment, albeit less so than AI.

Table 1: Regression Weights (From the Unstandardized Equation)

Variables	Estimate	S.E.	C.R.	P-Value	Decision
Employment □Internet of Things	.287	.064	4.507	***	Signific nt
Employment □Artificial Intelligence	.563	.087	6.508	***	Signific nt
Employment □Data Analytics	.309	.057	5.438	***	Signific nt

Source: Extracted from AMOS Text Output

Table 1 displays the findings of a regression analysis that was done to determine the correlations between particular variables, more especially the regression weights. The focus in this instance is on the correlation between the dependent variable "Employment" and the three independent variables "Internet of Things," "Artificial Intelligence," and "Data Analytics

The association between Employment and Internet of Things is assessed to have a regression weight of 0.287. This implies that there is an expected gain of 0.287 units in employment for every unit rise in the Internet of Things (IoT). With respect to this estimate, the standard error is 0.064. Three asterisks (***) signify a high level of statistical significance, and the critical ratio (C.R.) for this association is 4.507 whereas the p-value is indicated by a single asterisk (*). Therefore, there exists a statistically significant correlation between employment and Internet of Things, which implies a statistically significant positive impact on employment levels.

The estimated regression weight for the relationship between employment and Artificial Intelligence is 0.563. This implies that for every one-unit increase in Artificial Intelligence (AI), there is an estimated increase of 0.563 units in Employment. The standard error (S.E.) for this estimate is 0.087. The critical ratio (C.R.) for this relationship is 6.508, and the p-value is denoted by three asterisks (***), indicating high statistical significance. This signifies that the relationship between employment and Artificial Intelligence is statistically significant. Hence, the presence and growth of AI technologies have a substantial and statistically significant positive impact on employment levels.

The calculated regression coefficient for the association between Employment and Data Analytics is 0.309. As a result, there is an anticipated gain of 0.309 units in employment for every unit rise in data analytics (DA). This estimate's standard error (S.E.) is 0.057. The p-value for this association is indicated by three asterisks (***), which denote high statistical significance, and the critical ratio (C.R.) is 5.438. This indicates that the association between Employment and Data Analytics is statistically significant. However, the development and use of Data Analytics technology has a statistically significant positive effect on employment levels.

In conclusion, Table 1 presents compelling evidence for the statistically significant positive connections between the independent variables Internet of Things, Artificial Intelligence, and Data Analytics, and the dependent variable Employment. The implication is that as these technologies—IoT, AI, and DA—develop and spread, they are linked to higher employment levels. These findings suggest that these technologies may potentially result in job growth and possibilities, have significant ramifications for sectors of the economy and organizations that are using or evaluating these technologies.

Table 2: Squared Multiple Correlations

Variables	Estimate
Employment □ Automation	.840

Source: Extracted from AMOS Text Output

Table 2 provides the results of the Squared Multiple Correlations analysis, specifically for the relationship between the dependent variable Employment and a combined set of independent variables referred to as Automation. The Squared Multiple Correlations coefficient estimates the proportion of variance in the dependent variable that can be explained by all the independent variables together.

The association between Employment and Automation is projected to have a squared multiple correlation coefficient of 0.840 and this shows that the combined effects of the Automation variables, which include Internet of Things (IoT), Artificial Intelligence (AI), and Data Analytics (DA), may explain a significant 84% of the variance in the

Employment variable. The large coefficient indicates that IoT, AI, and DA—are present and have an impact on employment levels, and that these three technologies account for a sizeable share of the variation in employment levels. It therefore suggests that automation technologies are important contributors to changes in employment.

The cumulative impact of automation technologies, represented by IoT, AI, and DA, is highly important in explaining variances in employment levels, as shown by Table 2. The significant Squared Multiple Correlations coefficient of 0.840 highlights the significant impact on employment dynamics and offers insightful information for sectors and organizations navigating the adoption of automation in their processes.

Conclusion

This study highlights the symbiotic intricate dynamics of work between automation technology and employment in the ever-changing Nigerian manufacturing industry. The research shows that AI, IoT, and DA boost employment, proving their potential as economic drivers that can change the work environment. The empirical results show that these technologies significantly increase sector employment which indicates that automation may boost economic development, job creation, and competitiveness by providing people with digital and analytical abilities for an increasingly automated world. However, this research stresses the necessity for balance and strategy as Automation may replace low-skilled labour, requiring reskilling and upskilling. It also advocates for aggressive governmental interventions and investments to help Nigeria's industry capitalize on automation's advantages and overcome its obstacles. This revolutionary path requires politicians, industry leaders, and stakeholders to follow the study's conclusions to a future where automation and employment coexist, while protecting workers' well-being and livelihoods.

Recommendations

Based on the findings of the study, the Nigerian government and private sector should:

- Promote research and innovation in Nigeria-specific automation technologies by collaborating with universities, research institutions, and industry actors that can help develop automation solutions that correspond with the country's unique manufacturing challenges and opportunities.
- Address the issue of restricted access to advanced automation technologies by forming partnerships with international organizations, providing financial incentives for technology adoption, and facilitating the import of essential automation equipment.
- Encourage, develop and spread use of AI, IoT, and DA as economic drivers that can change the work environment to boost employment economic development, job creation, and competitiveness among people with digital and analytical abilities for an increasingly automated world.
- Adopt a strategy to replace Automation with low-skilled labour, requiring reskilling and upskilling.
- advocates for aggressive policy interventions and investments to help Nigeria's industry capitalize on automation's advantages and overcome its obstacles, through the use of tax incentives, grants, and affordable automation solutions

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