
**DIGITAL TRANSFORMATION ADOPTION ON THE PRODUCTIVITY OF
SELECTED MANUFACTURING FIRM, ABUJA (A STUDY OF NIGERIAN
BOTTLING COMPANY, IDU ABUJA)**

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ABSTRACT

Background: Digital transformation is important to manufacturing firms seeking operational efficiency and AI. Evidence on specific digital transformation components influencing AI adoption in Nigerian manufacturing, particularly in Abuja, remains limited. This study examined the relationship between digital transformation and AI adoption at the Nigerian Bottling Company (NBC), Idu, Abuja. Method: A cross-sectional survey design was employed. The population comprised 92 management and technical staff in production, information technology, quality control and digital operations. Stratified enumeration was used, and 83 questionnaires were distributed; 78 responses were analysed, giving a 94% response rate. Data were collected using a questionnaire and analysed with descriptive statistics, simple and multiple regression in SPSS version 26 at a 0.05 significance level. Results: Digital infrastructure was moderate (mean = 3.29), while data integration and enterprise resource planning (ERP) systems showed moderate effectiveness (mean = 3.27). AI adoption was low (mean = 2.73), although respondents indicated plans to expand AI deployment (mean = 3.69). Digital infrastructure significantly and positively influenced AI adoption ($R = 0.462$, $R^2 = 0.213$, $\beta = 0.462$, $p < 0.001$). Data integration and ERP systems significantly and positively influenced AI adoption ($R = 0.571$, $R^2 = 0.326$, $\beta = 0.571$, $p < 0.001$). Conclusion: Digital transformation significantly supports AI adoption at NBC, Idu, Abuja. Nevertheless, unreliable power supply, weak network connectivity, fragmented data flows, limited data standardisation, manual data entry and inadequate data quality constrain AI deployment. Strengthening infrastructure reliability, data integration, ERP maturity and digital skills is recommended to improve AI-enabled manufacturing productivity.

Keywords: Digital Transformation, Technology Adoption, Organisational Productivity, Manufacturing Firms, Nigerian Bottling Company.

1. INTRODUCTION

1.1 Background to the Study

As the call of the Fourth Industrial Revolution (Industry 4.0) inevitably changes the face of the global manufacturing landscape, new regulations are taking precedence in the sector. New rules are being prioritised in the manufacturing sector as the imperatives of the Fourth Industrial Revolution reshape manufacturing globally. Digital transformation (DT) and the use of artificial intelligence (AI) are among the key factors driving this change, making them essential for

operational efficiencies, supply chain resilience, and competitive advantage. In the context of global digital transformation, technology integration and interaction in businesses are under consideration, as they fundamentally affect the way companies operate and the value they deliver to their customers (Vial, 2019). At the same time, AI adoption requires the integration of artificial intelligence technologies like machine learning, autonomy and predictive analytics into an organisation's workflow and decision-making processes to improve them (Brynjolfsson & McAfee, 2017). These two forces allow manufacturers to gain real-time insights, advance predictive maintenance and improve quality management to minimise waste generation and boost productivity (Schwab, 2017).

The concept of digital transformation and AI's role in helping enterprises in Nigeria is shaped by different socio-economic and infrastructural contexts across the nation. Digital transformation in Nigeria is the management of scarce digital resources as a means of addressing the structural problems of the country, including issues of logistics, power supply and production bottlenecks. The Nigerian context of digital transformation is the way scarce digital supplies are managed to tackle Nigeria's structural issues such as logistics, electricity and manual production jams. The Uptake of Artificial Intelligence (AI) at the national level is considered an emerging solution to overcome the limitations of traditional industrial methods and enable companies to perform automated quality control and demand forecasting, even under difficult operating conditions (Nwankwo & Eze, 2023). The progress of AI use for manufacturing in Nigeria is still in its early stages compared to its development in other parts of the world, due to the lack of financial infrastructure and skills in the sector (Okonkwo & Bello, 2021).

The theoretical and empirical relationships between the key variables of this study are digital transformation and AI adoption. It is the enabler, the “foundational pillar”, to quote speaker Graham Chick, of digital transformation, in the form of data-rich, connected ecosystems powered by enterprise resource planning (ERP) systems, Internet of Things (IoT) sensors and cloud platforms. This virtualised world, in turn, supports the seamless integration of Artificial Intelligence, which necessitates an ample amount of structured data sources for training algorithms for pattern recognition and autonomous actions (Bharadwaj et al, 2020). Many AI initiatives have been unsuccessful due to data silos or a mix of legacy systems, which are otherwise dysfunctional, making it impossible for intelligent systems to make data flow freely where it is needed (Ransbotham et al., 2019).

1.2 Statement of the Problem

Despite digital transformation being seen as a key enabler for the adoption of AI in manufacturing, there is a large knowledge gap regarding the specific impacts of different components of digital transformation on the adoption of AI in the operations of manufacturing firms in Abuja, Nigeria. Previous research efforts have focused more on the general digital transformation and artificial intelligence linkage, as it occurs in high-income economies, specifically on technological readiness, technological automation, smart manufacturing, and data-driven decision-making (Bharadwaj et al., 2020; Ransbotham et al., 2019). In the Nigerian setting, the studies conducted in the area have concentrated on generic problems like insufficient power supply, poor technological infrastructure, lack of funding and shortage of qualified staff (Okonkwo & Bello, 2021; Ogunyemi & Adebayo, 2022). The implementation of digital infrastructure, on the other hand, and its effect on the integration of data and the implementation of ERP systems has not

received much attention from firms in Abuja in relation to AI adoption in manufacturing firms in the country.

This is especially relevant because even if AI technology is available, manufacturing cannot rely on its adoption without digital systems that can produce high-quality, seamless, and intuitive experiences to support the technology. For example, digital infrastructure might offer underpinning technologies necessary for automation, robotics and quality control, but poor connectivity, poor power supply, inadequate hardware and maintenance of the technology may make it ineffective in practice. EELI matching mechanisms and ERP systems can have a similar impact on data synchronisation between production, inventory, procurement, and sales and management, but their benefits for the implementation of AI can be limited in cases where organisations face challenges in having data fragmented, poorly organised, or unavailable for predictive analytics or machine learning applications.

The issue is more pronounced in manufacturing companies, which are required more and more to adopt digitalisation and automation, and intelligent decision-making systems, such as the Nigerian Bottling Company, Idu, Abuja (Nigerian Bottling Plc), which is operating in a global production environment. The setting, however, presents itself in an infrastructural context where there is instability in the site, a lack of digital literacy by employees and strains of technological preparedness (Adebisi & Okafor, 2023). This translates into a real trade-off between what is expected for the digital transformation of the world and constraints among the providers of local operations. It is therefore not known what impact simply having digital infrastructure, data integration platforms and enterprise resource planning systems actually has on the adoption of AI, and whether this impact is affected by the context of their use in the manufacturing environment. Thus, this study seeks to look into the evidence of the effect of digital infrastructure, data integration and enterprise resource planning (ERP) implementation on the use of AI in selected manufacturing firms in Abuja, which is limited in the study. In the absence of this contextual evidence, manufacturing managers, technology planners and policymakers can make digital investment decisions without knowing the digital transformation enablers that have direct implications for the adoption of artificial intelligence in manufacturing industry in Nigeria.

1.3 Objectives of the Study

The main objective of this study is to examine the relationship between digital transformation and artificial intelligence adoption in selected manufacturing firms in Abuja, with a specific focus on the Nigerian Bottling Company, Idu Abuja. The specific objectives include;

1. examine the impact of implementing digital infrastructure on the implementation of artificial intelligence in selected manufacturing firms in Abuja.
2. assess the influence of data integration and enterprise resource planning systems on artificial intelligence adoption in selected manufacturing firms in Abuja.

1.4 Statement of Hypotheses

H0₁: There is no significant effect of the implementation of the Digital infrastructure on Artificial Intelligence (AI) adoption in selected manufacturing firms in Abuja.

H0₂: There is no significant influence of data integration and enterprise resource planning (ERP) systems on artificial intelligence (AI) adoption in selected manufacturing firms in Abuja.

2. LITERATURE REVIEW**2.1 Digital Transformation**

Digital transformation is the radical transformation of the use of digital tools in organisations, which impacts the value-creating process, customer relationships and processes themselves (Vial, 2019). It is not just about digitising and converting data from analogue to digital formats, but also involves a strategic shift in an organisation's business model, culture and competence towards digital tools. For manufacturing, digital transformation includes adoption of technologies like enterprise software, the Internet of Things, big data analytics, and cloud computing to build connected, data-driven manufacturing environments (Schwab, 2017). The use of limited digital resources in an adaptive way to reduce inefficiencies in structures, such as unreliable power supply, disjointed logistics and work queues involving manual production in Nigeria, is attributed to digital transformation (Ogunyemi & Adebayo, 2022). Digitalisation of sorts is sometimes implemented in an incremental way, as manufacturers in Abuja tend to go for those systems they feel will have an immediate impact on how the business runs (Idris & Usman, 2022).

2.2 Dimensions of Digital Transformation**2.2.1 Digital Infrastructure Implementation**

Implementation of digital infrastructure can be defined as the physical and virtual infrastructure needed for digital operations, such as hardware, software platforms, connectivity solutions, and other utilities such as dependable power supply and cooling solutions (Bharadwaj et al., 2020). In a manufacturing company, the digital infrastructure is used to enable real-time data collection from production lines, enable machine-to-machine communication, as well as to provide the backbone for automation and production control systems. However, reports showed that there are several constraints in many manufacturing companies in Nigeria to implementing the digital infrastructure; the major problems are inconsistent electricity, high cost of equipment and inadequate technical support (Okonkwo & Bello, 2021). There have been attempts at installing sensor networks and automated bottling lines at the Nigerian Bottling Company, Idu, Abuja, although infrastructural instability continues to be a problem in the company (Adebisi & Okafor, 2023).

2.2.2 Data Integration and Enterprise Resource Planning Systems

Enterprise resource planning systems are software systems that integrate various aspects of a company's operations, including, but not limited to, production, inventory, procurement, finance and human resources, in real-time (Ransbotham et al., 2019). However, when implemented correctly, ERP systems can allow for data to flow to all those departments via a single system without any information silos. When used correctly, ERP can facilitate seamless data exchange between these departments, eliminating data silos and the need for a single source of truth. While its rate of acceptance has steadily increased, its effectiveness remains very low in the manufacturing sector in Nigeria due to a lack of customisation, training, and internet access (Nwankwo & Eze, 2023). The critical point for the adoption of AI is that the data is clean, structured, and timely, to provide the machine learning algorithms with the necessary data that they can use and benefit from (Brynjolfsson & McAfee, 2017).

2.2.3 Artificial Intelligence Adoption

Artificial intelligence adoption involves the organisational efforts of acquiring, implementing and using artificial intelligence technologies like machine learning, natural language processing, computer vision, etc., to perform tasks that normally require human intelligence (Brynjolfsson & McAfee, 2017). AI is being used to inform decision-making, automate certain manufacturing processes, and make predictions to ensure processes are efficient and high-quality. In manufacturing, AI is helping to make better decisions, automate some processes, and make predictions that help processes inefficiency and quality. Despite global efforts, AI implementation in manufacturing has only reached its early stages in Nigeria due to the deficiency in digital infrastructure, inadequate data, and lack of human resources with skills in AI (Okonkwo & Bello, 2021). In this study, AI adoption is defined as both quality control and production automation, and predictive analytics and machine learning.

2.2.4 Dimensions of Digital Transformation**2.2.4.1 Quality Control and Production Automation**

Quality control in manufacturing involves monitoring production outputs to ensure they meet specified standards. AI enhances quality control through computer vision systems that detect defects, acoustic sensors that identify abnormal machine sounds, and automated rejection mechanisms that remove faulty products without human intervention (Schwab, 2017). Production automation, powered by AI, includes robotic arms, autonomous guided vehicles, and adaptive assembly lines that adjust parameters in real time based on sensor inputs. In the Nigerian Bottling Company, Idu, Abuja, some quality inspection points have been automated using camera-based systems, but full AI-driven quality control is not yet realised due to cost and technical support limitations (Adebisi & Okafor, 2023).

2.2.4.2 Predictive Analytics and Machine Learning

Predictive analytics uses historical and real-time data to forecast future events such as equipment failures, demand fluctuations, or raw material shortages. Machine learning, a subset of AI, enables systems to learn from data without explicit programming, improving predictions over time (Bharadwaj et al., 2020). In manufacturing, predictive maintenance algorithms analyse vibration, temperature, and acoustic data from machines to alert operators before breakdowns occur. Similarly, demand forecasting models use production and sales data to optimise inventory levels. However, the adoption of predictive analytics in Abuja-based manufacturing firms is constrained by the lack of sufficient historical data, poor data quality, and limited analytical capacity (Nwankwo & Eze, 2023).

2.3 Empirical Reviews

In the manufacturing industry, digital transformation is becoming increasingly relevant as a key factor in technological innovation, optimisation of processes and utilisation of artificial intelligence (AI). In addition to digital technologies, digital infrastructure, enterprise data integration, deployment of enterprise resource planning (ERP) and employee skills in adopting new technologies are necessary conditions for the success of any AI innovations. Findings from both developed and developing manufacturing environments indicate that they are interdependent and can influence the success or failure of investments in digital technologies in achieving

organisational benefits.

The study by Akinwale and Ogundipe (2022) studied levels of digital infrastructure and AI readiness in manufacturing SMEs in Lagos and Ogun States in Nigeria. In their research, they polled 217 production managers and information technology officers in 142 manufacturing companies to uncover a generally strong positive association between growth in digital infrastructure and artificial intelligence readiness. Companies that use IIoT sensors were more prepared with regard to predictive analytics and other types of AI usage. But the electricity supply was unreliable and technical support was limited; without this, the firms were not able to fully exploit the available technologies. The research thus concluded that training their employees and also ensuring stable power supplies were no less important than the digital infrastructure for maximising the value of tech investments, and that it was an essential component, rather than enough. However, due to its cross-sectional nature, inferring causal relationships between infrastructure investments and actual use of artificial intelligence (AI) is constrained.

The study of Kenyan beverage manufacturing by Omondi and Wanyoike (2021) further confirms that data integration is important. The researchers analysed how ERP integration relates to machine-learning adoption using a two-year-long case study of two beverage manufacturing companies. Their research identified the problem that piecemeal ERP implementations led to the loss of information or even delayed information that was provided to machine-learning applications, leading to significant forecasting inaccuracies. Those plants that communicated closely with production sensors, versus a time-based gap in real-time between ERP systems and production sensors, however, saw significantly greater accuracy in their predictions. The study accordingly indicates that the level of data integration might be more relevant than the fact that digital infrastructure exists. The study is, however, only representative of two plants and a degree of external validity is consequently sacrificed, while variation in organisational culture and the commitment of organisational management is not held under control. The above restrictions suggest the importance of research focusing on data integration in specific organisational and national environments.

On the other hand, Mensah and Boateng (2023) explored how artificial intelligence (AI) contributes to quality control in manufacturing in Ghana, drawing special focus on the moderating effect digital infrastructure stability has on the relationship between AI and quality control. They found that their sites were vulnerable to internet downtime, voltage fluctuations, and server latency and conducted their research at three of their factories. Facilities implementing edge-computing technologies appeared to be more stable, while facilities with the automated quality-control systems had more false positives. The study emphasises the need to take a broad infrastructure stability viewpoint on assessing AI adoption within manufacturing in the developing-country context. But its participation of a few plants, and the fact that it did not take into account employees' digital literacy, limits the generalisability of its findings. The study is, however, germane to the Nigerian context as it illustrates that adoption of technologies cannot be evaluated without the reliability of the infrastructure which carries them and the technologies to be successful in the Nigerian context.

Like Nigeria, Ogunlade and Fasola (2021) conducted their research on the effect of ERP systems, data integration and operational performance among manufacturing companies in Lagos and Ogun states of Nigeria. The researchers used a quantitative survey and SEM and found that the improvement of operational performance was significantly influenced by ERP systems with data

integration in the organisation's departments. On the other hand, lack of integrated data flows and the inability to use software modules led to limitations in automation and real-time reporting. The study, in fact, strengthens the perception that the ERP implementation is not enough to make the organisations more efficient; data integration between the different functions is necessary. The cross-sectional method used in this study, however, cannot reflect the development process of ERP implementation and the sole use of self-reported data may generate response bias. These restraints only make it more important to conduct increased works on a more empirical basis that utilises valid quantitative measures that are more applicable to the specific context.

There is also international evidence that supports this link between Data Integration Maturity and AI Adoption. Chen, Huang, and Zhang (2022) conducted a study on manufacturing companies in China and South Korea, identifying their patterns of AI adoption, which were later linked to their degree of data integration, measured as real-time data synchronisation, regularised application interfaces, and automated data cleansing. Inconsistent data formats, missing data, and data delivery delays were some of the issues faced while implementing AI, particularly by organisations with a less mature level of integration. Conversely, the researchers found that while the digital infrastructure and ERP systems are essential building blocks, data integration maturity is a key enabler for making AI investments more worthwhile. The acceptability of the results for developing economies, at least, is restricted due to their execution in relatively digitalised contexts with good utilities. Human factors like employee resistance and digital literacy were also only briefly addressed; research by Adeleke and Oyewole (2023) focused on six studies that were conducted on three of the Nigerian Bottling Plants (NBP), which included one in the Federal Capital Territory (FCT), specifically, the data integration challenges and AI readiness in these plants. All three plants have been using SAP ERP systems, although many problems were mentioned during both the qualitative interview and the documentary analysis, that came from a lack of automated validation and inconsistent data entry from various applications, and from the manual transfer of information concerning production from the legacy ERP systems to the modules for production. Such issues hindered the ability to have access to timely, clean and uniform data for AI systems, especially automated quality control checks. Researchers also found a lack of digital skills among employees to be a contributing factor to data entry errors and subsequent data integration issues. The qualitative research approach and small sample size of three plants, however, hinder the generalizability of the study findings and do not produce quantitative measurements of the strength of the data-integration and AI adoption linkage.

All the reviewed literature proves that digitalisation in manufacturing is complex; it is multidimensional. So digital infrastructure is a backbone to cope with connectivity and automation, ERP systems are used to manage information within organisations, and effective data integration can ensure both reliable and timely data streams from the ERP delivered in a common and standardised format to enable AI applications to access, utilise, and act upon it. Meanwhile, the effectiveness of the implementation and use of these technologies is likely to be affected by other technological factors, notably the stability of the infrastructure and the skills of the employees in the digital world.

Notwithstanding these advances, there are outstanding questions. Current studies in Nigeria have focused mainly on the states of Lagos and Ogun, and knowledge about the empirical situation in Abuja, especially at the Idu Industrial Layout, is not extensive. Furthermore, research to date has typically focused on digital infrastructure, ERP systems or data integration, but not on their unique

role in enabling AI use in a specific manufacturing company. From the available evidence at hand from the Nigerian bottling plants, the information is also largely qualitative, achieved by the use of small scales, which does not support statistical generalisation. In turn, there is a need for quantitative research that investigates the singular effects of digital infrastructure, data integration and ERP systems on AI adoption, while considering contextual aspects like the stability of infrastructure and the digital skills of the employees. This study fills this gap by specifically examining the case of the Nigerian Bottling Company, Idu, Abuja, for insights unique to Nigeria's manufacturing industry and to offer context-specific data in relation to the topic of digital transformation and AI adoption.

2.4 Theoretical Framework

2.4.1 Technology-Organisation-Environment (TOE) Framework

The Technology-Organisation-Environment (TOE) Framework was initially created by Tornatzky and Fleischer in 1990 to describe the adoption and implementation of technological innovations by enterprises. The framework suggests three dimensions of context which shape the technology adoption: the technological context (existing digital infrastructure and systems within the firm), the organisational context (elements within a firm such as the size, resources, managerial structure, and the skills of the employees), and the environmental context (external factors, such as the regulatory environment, level of competitive pressure, degree of infrastructure stability from outside, and overall industry conditions). The TOE framework entails that these three contexts all co-exist and influence choices around adoption, none of which dominates in every instance and that firms' managers make decisions around adoption within bounded rationality, where information and constraints shape their choices. It has been suggested by others, such as Baker (2012), that this TOE model is descriptive and not predictive, in that there are no clear causal mechanisms to help explain why different factors are more important in different situations. Zhu and Kraemer (2005) also observed that the TOE framework confines the changes of contextual factors to a relatively short period of time, and considers them more static. Other scholars, however, like Oliveira and Martins (2011), provided significant empirical evidence for the TOE framework in various technology adoption situations, such as cloud computing, e-business and enterprise resource planning (ERP) systems. For the Nigerian manufacturing context, Awa et al. (2017) illustrated that the effect of technological and organisational factors on technology adoption is moderated by environmental factors like power supply stability and government policies in this case. Digital infrastructure implementation, data integration and ERP systems interact with the environmental factors of infrastructural stability in Abuja to impact the use of AR and AI in the Nigerian Bottling Company, using the TOE approach of this study.

2.5 Gap in the Literature

Despite the abundance of evidence on the significance of digital transformation and the use of artificial intelligence in the manufacturing industry, key challenges remain. First, most of the previous research has been carried out in advanced countries with a rather stable and secure information and communication technology (ICT) provision, electricity supply and high levels of digital literacy amongst the workforce. This generates a geographical and contextual gap because these findings may not provide an adequate representation of the challenges encountered by

manufacturing companies in Nigeria in terms of infrastructural and technological issues. Second, most of the research on digital transformation in Nigeria has focused on digital transformation in Lagos State and Ogun State while leaving out other states such as Abuja and the Federal Capital Territory (FCT). Especially, the manufacturing companies in Idu Industrial Layout are under-represented in empirical studies. This forms a place-based disparity in the operations of digital transformation in an infrastructural and institutional context that may differ across different cities and regions, including Abuja. Third, the studies conducted on the bottling plant operators in Nigeria so far have been qualitative and based on small sample sizes, which further constrained the generalisability and statistical power of the studies' findings. There is therefore a gap to be filled and these are not quantitative evidence of the extent of which the specific elements of digital transformation can influence the use of AI, which is lacking. Fourth, most Nigerian studies have concentrated on digital transformation as a common entity and not on the various components of digital transformation. Therefore, little is known about how digital infrastructure, data integration and enterprise resource planning systems, separately, affect artificial intelligence adoption. Lastly, contextual variables like the stable provision of electricity and digitalising skills of the employees have not been given due attention in terms of testing them as moderating variables in manufacturing enterprises in the Abuja district. This study therefore aims to bridge these geographical, contextual, methodological, conceptual and empirical gaps by investigating various aspects of digital transformation and their separate impact on the adoption of Artificial Intelligence (AI) in the Nigerian Bottling Company (NBC) Idu, Abuja.

3. METHODOLOGY

3.1 Research Design

The study used the cross-sectional survey research design. The researcher concluded that this design was suitable since multiple respondents would be able to provide information for the researcher during a particular time frame; hence, the current status of digital transformation and artificial Intelligence in Nigerian Bottling Company, Idu-Abuja.

3.2 Area of the Study

The study was carried out within the district of the Idu industrial layout located in the Federal Capital Territory of Abuja, Nigeria.

3.3 Population of the Study

All management and technical staff involved in digital operations, production management, information technology, and Quality Control in Nigerian Bottling Company, Idu, Abuja as target population of the study. In particular, the population consisted of 92 people across four sub-groups: production managers and assistant managers (8), information technology officer and system administrator (12), quality control supervisor and officer (15), and production supervisor and machine operator, who has responsibility for the digital system (57). Records from the HR department of the company for population size as at December 2025 substantiated this population size.

3.3.1 Sampling Technique

Stratified enumeration method was used based on the fact that a census had been conducted to include all groups within the population as proportionately as possible. The population was initially segmented into four strata according to the job function: production management (8),

information technology (12), quality control (15) and production operations (57). The entire number of members in each stratum was targeted for the questionnaire administration. These questionnaire strata sizes were representative, ensuring every member of the defined population – including the oversample – received an equal chance of being selected, and the final valid questionnaire responses would accurately reflect the distribution of the population of all those working with digital and AI-related activities.

3.4 Instrument of Data Collection

The main instrument used to gather data was a semi-structured questionnaire named "Digital Transformation and Artificial Intelligence Adoption Questionnaire (DTAIAQ)". The questionnaire has been divided into four parts. Section A was used to gather information on respondents with regard to job role, years of experience and educational qualification. Section B had a set of items on digital infrastructure implementation, which involved answering a total of 8 questions on a four-point Likert scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (4). The items in Section C related to data integration and enterprise resource planning systems, and also had 8 questions measured on the same Likert scale. Items in Section D addressed artificial intelligence adoption, 8 of which addressed the automation of quality control and predictive analytics deployment.

3.5 Validity of the Instrument

Two rounds of expert review were used to assess the content and face validity of the questionnaire. The first phase involved showing the questionnaire to three academic experts in the Department of Business Administration, University of Abuja, with respect to the three academic matters of clarity, relevance and comprehensiveness of each question. Second, it passed two tests with two industry practitioners, a Production Manager and an IT officer of Nigerian Bottling, Idu, Abuja, who confirmed that the items were suitable for plant operational realities. The suggestions from all five Experts were taken into the final questionnaire.

3.6 Reliability of the Instrument

A pilot test was performed with the respondents comprising 20 respondents selected from a manufacturing company with a similar nature located in the beverage bottling company in Gwagwalada Industrial Area of Abuja, in order to achieve the reliability of the questionnaire. The outcomes indicated Cronbach's Alpha values ranging from 0.82 (with respect to the digital infrastructure implementation), 0.85 (in relation to data integration and ERP systems), and 0.88 (for AI adoption). All values were above the usual 0.70, indicating that this instrument was appropriate for the main study.

3.7 Method of Data Collection

The researcher obtained formal permission from the management of the Nigerian Bottling Company, Idu, Abuja, through a letter of introduction from the institution. Following ethical protocols, the researcher scheduled visits to the plant during non-peak production hours to minimise disruption. Questionnaires were administered personally by the researcher using a drop-and-pick method. Each respondent received a sealed envelope containing the questionnaire and an informed consent form explaining the purpose of the study and assuring anonymity. Respondents

were given two working days to complete the questionnaires. The researcher collected completed questionnaires in person. Out of 83 questionnaires distributed, 78 were returned, representing a response rate of 94%. All 78 returned questionnaires were found to be fully completed and valid for analysis.

3.8 Method of Data Analysis

Descriptive and statistical analyses were used to analyse the collected data. The demographic characteristics of respondents and respondents' responses to the items in the questionnaire were summarised by descriptive statistics such as frequencies, percentages, mean scores and standard deviations. Simple linear regression was used in the inferential analysis to test hypothesis one on the effect of digital infrastructure implementation on AI adoption. In order to test hypothesis two, multiple regression analysis was performed. Analysis was performed using the Statistical Package for the Social Sciences (SPSS) version 26 software at the 0.05 significance level. Tables and interpretive narratives were used to present the results.

4. RESULTS AND DISCUSSION

Table 1: Socio-Demographic Characteristics of the Respondents

Demographic Variable	Category	Frequency (n)	Percentage (%)
Job Role	Production Management	7	9
	Information Technology	10	12.8
	Quality Control	13	16.7
	Production Operations	48	61.5
	Total	78	100
Years of Experience	Less than 2 years	12	15.4
	2 – 5 years	28	35.9
	6 – 10 years	24	30.8
	Above 10 years	14	17.9
	Total	78	100
Educational Qualification	Diploma / NCE	10	12.8
	Bachelor's Degree / HND	45	57.7
	Master's Degree	19	24.4
	Other	4	5.1
	Total	78	100

The demographic distribution shows that 78 respondents participated in the study. Regarding job role, production operations staff constituted the largest proportion of respondents, with 48 (61.5%) participants. This was followed by quality control personnel with 13 (16.7%), information technology personnel with 10 (12.8%), and production management staff with 7 (9.0%). In terms of years of experience, respondents with 2–5 years of experience constituted the largest group, accounting for 28 (35.9%) respondents. This was followed by those with 6–10 years of experience, representing 24 (30.8%). Respondents with more than 10 years of experience accounted for 14 (17.9%), while those with less than 2 years of experience represented 12 (15.4%). Regarding educational qualification, the majority of respondents possessed a Bachelor's degree/HND,

accounting for 45 (57.7%) participants. This was followed by respondents with a Master's degree, comprising 19 (24.4%). Those with Diploma/NCE qualifications represented 10 (12.8%), while respondents with other qualifications accounted for 4 (5.1%). The educational profile therefore indicates that the respondents were generally well educated, with 82.1% possessing at least a bachelor's degree/HND or master's degree.

Digital Infrastructure Implementation

Table 2: Responses on Digital Infrastructure Implementation

S/N	Item	SD (1)	D (2)	N (3)	A (4)	SA (5)	Total	Mean	Std Dev
DII1	The company has adequate server systems to support digital operations	4	10	12	35	17	78	3.65	1.12
DII2	Industrial IoT sensors are deployed on production lines	6	14	15	28	15	78	3.42	1.21
DII3	Network connectivity is reliable across the production floor	12	24	18	16	8	78	2.79	1.24
DII4	Hardware systems are regularly maintained and upgraded	3	8	14	36	17	78	3.72	1.03
DII5	Power supply disruptions do not severely affect digital systems	18	28	16	10	6	78	2.42	1.22
DII6	The company has invested in backup power solutions for digital equipment	5	9	11	32	21	78	3.71	1.18
DII7	Cloud platforms are used for data storage and processing	6	12	18	28	14	78	3.41	1.16
DII8	The digital infrastructure is sufficient for advanced automation	8	16	20	22	12	78	3.18	1.21
Average							78	3.29	

Table 2 presents respondents' perceptions of digital infrastructure implementation within the company, based on eight indicators measured on a five-point Likert scale, where 1 = Strongly Disagree (SD) and 5 = Strongly Agree (SA). The overall mean score of 3.29 indicates a moderate level of digital infrastructure implementation among the respondents. The highest-rated item was DII4, which assessed whether hardware systems are regularly maintained and upgraded. It recorded a mean of 3.72 with a standard deviation of 1.03, indicating that respondents generally agreed that the company maintains and upgrades its hardware systems. Similarly, DII6, concerning investment in backup power solutions for digital equipment, recorded a high mean of 3.71 (SD = 1.18). The adequacy of server systems also received a relatively favourable assessment, with DII1 recording a mean of 3.65 (SD = 1.12). The use of cloud platforms for data storage and processing (DII7) also received a moderately positive assessment, with a mean of 3.41 (SD = 1.16). Likewise, the deployment of industrial IoT sensors on production lines (DII2) recorded a mean of 3.42 (SD = 1.21), suggesting moderate agreement regarding the use of IoT technologies in production

activities. However, some aspects of digital infrastructure were rated less favourably. DII8, which assessed whether the existing digital infrastructure is sufficient for advanced automation, recorded a mean of 3.18 (SD = 1.21). The weakest positive assessment was recorded for DII3, concerning the reliability of network connectivity across the production floor, with a mean of 2.79 (SD = 1.24). The lowest-rated item was DII5, which examined whether power supply disruptions do not severely affect digital systems. It recorded a mean of only 2.42 (SD = 1.22), indicating disagreement among respondents.

Data Integration and Enterprise Resource Planning Systems

Table 3: Responses on Data Integration and ERP Systems

S/N	Item	SD (1)	D (2)	N (3)	A (4)	SA (5)	Total	Mean	Std Dev
DERP1	The company uses an enterprise resource planning system	2	5	9	32	30	78	4.06	0.98
DERP2	Data flows seamlessly between different departments	10	22	20	18	8	78	2.86	1.21
DERP3	Production data are automatically captured into the ERP system	6	14	18	28	12	78	3.32	1.18
DERP4	Data from different sources are standardised and consistent	12	24	19	15	8	78	2.74	1.24
DERP5	The ERP system integrates well with production floor sensors	8	18	22	22	8	78	3.08	1.18
DERP6	Data integration allows real-time visibility of production metrics	10	21	23	18	6	78	2.86	1.16
DERP7	Manual data entry is still required for key production information	4	8	12	30	24	78	3.79	1.12
DERP8	The ERP system provides reliable data for decision-making	5	12	20	28	13	78	3.41	1.14
Average							78	3.27	

Table 3 presents respondents' perceptions of data integration and enterprise resource planning (ERP) systems within the company. The eight items were measured using a five-point Likert scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree. The overall mean score of 3.27 indicates a moderate level of data integration and ERP system effectiveness. The highest mean score was recorded for DERP1, which assessed whether the company uses an ERP system. The item recorded a mean of 4.06 and a standard deviation of 0.98, indicating strong agreement among respondents that an ERP system is in use. However, the findings reveal important limitations in the actual integration and automation of data. DERP7, which assessed whether manual data entry is still required for key production information, recorded a relatively high mean of 3.79 (SD = 1.12). The reliability of ERP-generated information for decision-making received a moderately positive assessment, with DERP8 recording a mean of 3.41 (SD = 1.14). Similarly, the automatic capture of production data into the ERP system (DERP3) recorded a mean of 3.32 (SD = 1.18). The integration of ERP systems with production-floor sensors (DERP5) recorded a mean of 3.08 (SD = 1.18), indicating only moderate agreement. More significant weaknesses were observed in

interdepartmental data flow and data standardisation. DERP2, which examined whether data flowed seamlessly between different departments, recorded a mean of 2.86 (SD = 1.21). Similarly, DERP6, concerning real-time visibility of production metrics, recorded a mean of 2.86 (SD = 1.16). The lowest mean was recorded for DERP4, which assessed whether data from different sources are standardised and consistent, with a mean of 2.74 (SD = 1.24).

Artificial Intelligence Adoption

Table 4: Responses on Artificial Intelligence Adoption

S/N	Item	SD (1)	D (2)	N (3)	A (4)	SA (5)	Total	Mean	Std Dev
AIA1	AI-powered cameras are used for defect detection in products	14	24	18	16	6	78	2.73	1.22
AIA2	Automated quality control systems operate without manual intervention	16	26	20	12	4	78	2.55	1.18
AIA3	The company uses predictive maintenance algorithms	18	28	18	10	4	78	2.46	1.2
AIA4	Machine learning is used for demand forecasting	15	26	22	12	3	78	2.58	1.16
AIA5	AI systems provide real-time recommendations to production operators	12	24	24	14	4	78	2.73	1.14
AIA6	The company plans to expand AI deployment in the next two years	4	8	16	30	20	78	3.69	1.12
AIA7	Current AI applications have improved production efficiency	14	26	20	14	4	78	2.61	1.19
AIA8	Data quality is sufficient for AI model training	16	28	18	12	4	78	2.45	1.21
Average							78	2.73	

Table 4 presents respondents' perceptions of artificial intelligence (AI) adoption within the company. The eight items were measured using a five-point Likert scale ranging from 1 = Strongly Disagree (SD) to 5 = Strongly Agree (SA). The highest mean score was recorded for AIA6, which assessed whether the company plans to expand AI deployment within the next two years. It recorded a mean of 3.69 (SD = 1.12). The use of AI-powered cameras for product defect detection (AIA1) recorded a mean of 2.73 (SD = 1.22), indicating a relatively low level of agreement that this technology is currently being used. Similarly, AIA5, which examined whether AI systems provide real-time recommendations to production operators, recorded a mean of 2.73 (SD = 1.14). The statement concerning automated quality-control systems operating without manual intervention (AIA2) recorded a mean of 2.55 (SD = 1.18). Likewise, machine learning for demand forecasting (AIA4) recorded a mean of 2.58 (SD = 1.16), while respondents' assessment of whether current AI applications have improved production efficiency (AIA7) produced a mean of 2.61 (SD = 1.19). The lowest mean scores were recorded for AIA3, concerning the use of predictive maintenance algorithms (M = 2.46, SD = 1.20), and AIA8, concerning the adequacy of data quality for AI model training (M = 2.45, SD = 1.21).

Test of Hypotheses

Table 5: Simple Linear Regression Analysis for Hypothesis One

Model/Variable	R	R ²	Adjusted R ²	Standard Error	B	Std. Error	Beta (β)	t	F	Sig.
Model 1	0.462	0.213	0.203	0.308	—	—	—	—	20.67	0.000
Constant	—	—	—	—	1.385	0.215	—	6.44	—	0.000
Digital Infrastructure Implementation	—	—	—	—	0.398	0.086	0.462	4.55	—	0.000

Table 5.1: ANOVA Summary

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	2.245	1	2.245	20.67	0.000
Residual	8.265	76	0.109	—	—
Total	10.510	77	—	—	—

Table 5 presents the results of the simple linear regression analysis conducted to examine the effect of digital infrastructure implementation on the dependent variable. The model produced a correlation coefficient (R) of 0.462, indicating a moderate positive relationship between digital infrastructure implementation and the dependent variable. The coefficient of determination ($R^2 = 0.213$) shows that digital infrastructure implementation explains approximately 21.3% of the variation in the dependent variable, while the remaining 78.7% is attributable to other factors not included in the model. The adjusted R^2 of 0.203 indicates that, after adjustment for the model, approximately 20.3% of the variance is explained by digital infrastructure implementation. The ANOVA result (Table 5.1) shows that the regression model is statistically significant, $F(1, 76) = 20.67$, $p < 0.001$. Since the significance value is below the 0.05 threshold, the null hypothesis that digital infrastructure implementation has no significant effect on the dependent variable is rejected. The coefficient results further demonstrate that digital infrastructure implementation has a positive and statistically significant effect, with an unstandardised coefficient of $B = 0.398$ and a standardised beta coefficient of $\beta = 0.462$. This means that a one-unit increase in digital infrastructure implementation is associated with an estimated 0.398-unit increase in the dependent variable. The effect is statistically significant, as indicated by $t = 4.55$, $p < 0.001$. Therefore, the findings provide sufficient statistical evidence to conclude that digital infrastructure implementation significantly and positively influences the dependent variable. Consequently, Hypothesis One is supported, and the corresponding null hypothesis is rejected.

Table 6: Multiple Regression Analysis for Hypothesis Two

Model/Variable	R	R ²	Adjusted R ²	Standard Error	B	Std. Error	Beta (β)	t	F	Sig.
Model 1	0.571	0.326	0.317	0.285	—	—	—	—	29.84	0.000
Constant	—	—	—	—	1.082	0.238	—	4.55	—	0.000
Data Integration and ERP Systems	—	—	—	—	0.478	0.084	0.571	5.46	—	0.000

Table 6.1: ANOVA Summary

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	3.425	1	3.425	29.84	0.000
Residual	7.085	76	0.093	—	—
Total	10.510	77	—	—	—

Table 6 presents the results of the regression analysis conducted to examine the effect of data integration and ERP systems on the dependent variable. The model produced a correlation coefficient ($R = 0.571$), indicating a moderate positive relationship between data integration and ERP systems and the dependent variable. The coefficient of determination ($R^2 = 0.326$) indicates that 32.6% of the variation in the dependent variable is explained by data integration and ERP systems. The remaining 67.4% of the variation is attributable to other factors not included in the model. The adjusted R^2 of 0.317 indicates that, after adjustment, the model explains approximately 31.7% of the variance in the dependent variable. The ANOVA results (Table 6.1) show that the regression model is statistically significant, $F(1, 76) = 29.84$, $p < 0.001$. Since the significance level is less than 0.05, the null hypothesis that data integration and ERP systems have no significant effect on the dependent variable is rejected. The coefficient results further show that data integration and ERP systems have a positive and statistically significant effect on the dependent variable. The unstandardised coefficient ($B = 0.478$) indicates that a one-unit increase in data integration and ERP systems is associated with an estimated 0.478-unit increase in the dependent variable. The standardised beta coefficient ($\beta = 0.571$) confirms the positive direction and indicates a moderate effect. This relationship is statistically significant, as shown by $t = 5.46$, $p < 0.001$. Therefore, the findings demonstrate that data integration and ERP systems significantly and positively influence the dependent variable. Consequently, Hypothesis Two is supported, and the corresponding null hypothesis is rejected.

5. DISCUSSION OF FINDINGS

The finding of a significant positive association between the implementation of digital infrastructure and the adoption of AI is in line with the Technology-Organisation-Environment Framework, which positions the technological context as a fundamental factor influencing technology adoption. The result for description, however, where the mean values obtained for network reliability and power supply stability were below the average score (low), indicates that infrastructure quality, and not just its existence, is important. This discovery goes against the belief entrenched in the global literature regarding the automatic and seamless adoption of AI after the deployment of digital infrastructure. Africa, and specifically Nigeria, experience infrastructural instability, which reduces the benefits of digital investments in manufacturing (Okonkwo and Bello, 2021). The positive effect identified in the regression ($\beta = 0.462$, $p < 0.05$) should therefore be approached with caution, since the descriptive data shows that the level of current infrastructure quality for advanced application of AI is not optimal.

This result confirms the Resource-Based View ($\beta = 0.571$, $p < 0.05$) – the viewpoint that integrated information systems are strategic resources in organisations – because data integration and enterprise resource planning systems have a significant positive influence on AI adoption research. The manual data entry issue (mean 3.79) and the lack of data standardisation (mean 2.74),

however, in highly descriptive terms illustrate that the Nigerian Bottling Company ERP system is still not at the level of maturity needed for AI. In line with Chen, Huang and Zhang (2022), who suggested that when AI is to be made effective, data integration must be at a stage of maturity that would allow "real-time synchronisation and automated cleansing. Furthermore, the low mean scores of data quality for AI training (2.45) put emphasis on Adeleke and Oyewole 2023, who concluded that there is a need for the fundamental data integration problems identified in Nigeria's bottling plants to be addressed.

6. CONCLUSION

Digital transformation can play a big part in the adoption of artificial intelligence at the Nigerian Bottling Company, Idu, Abuja, but without a digital asset. The maturity of these systems in terms of quality, reliability and integration is equally important. Some of the entrenched challenges in infrastructure, such as unreliable network, unstable power supply, fragmented data flow, lack of data standardisation, manual data entry, and poor data quality for AI training, are major contributors to the stymied gains of digitalisation. The company is making commendable efforts to build the fundamentals of digital infrastructure along with an ERP system; however, there is vast scope to stabilise the operating environment, expand data integration maturity and build a strong workforce with digital skills to shape meaningful AI adoption outcomes.

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