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ARTIFICIAL INTELLIGENCE AND EMPLOYEE PERFORMANCE IN MANUFACTURING FIRMS IN SOUTH-|SOUTH, NIGERIA.

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ABSTRACT

This study examined the influence of Artificial Intelligence on employee performance in the manufacturing firms in South-South Nigeria. Specifically, the study investigated the extent to which machine learning systems and smart production systems influence employee productivity and efficiency within manufacturing organizations. The study adopted a cross-sectional survey research design. The population of the study comprised 272 employees drawn from selected manufacturing firms in South-South Nigeria. Using the Krejcie and Morgan sample size determination formula, a sample size of 153 respondents was obtained. Data for the study were collected through a structured questionnaire, while descriptive statistics and simple linear regression analysis were used for data analysis with the aid of SPSS Statistics. The findings revealed that machine learning systems and smart production system significantly improve employee performance. The regression analysis showed a strong positive relationship between machine learning systems and employee performance ($R = 0.830$, $R^2 = 0.688$, $p < 0.05$) and smart production systems and employee performance with ($R = 0.819$, $R^2 = 0.671$, $p < 0.05$). Based on the findings, the study concluded that artificial intelligence-driven technologies significantly enhance employee productivity and efficiency in manufacturing firms. The study therefore recommended that manufacturing organizations should invest more in machine learning and smart production technologies, provide continuous employee training programmes, and strengthen technological infrastructure to improve operational efficiency and employee performance.

KEYWORDS: Artificial Intelligence**,** Machine Learning**,** Smart Manufacturing**,** Employee Performance, Employee Efficiency, Manufacturing Firms, South-South Nigeria.

INTRODUCTION

The emergence and rapid advancement of Artificial Intelligence have significantly transformed organizational operations and employee activities across industries globally. Artificial Intelligence refers to computer systems and digital technologies designed to perform tasks that traditionally require human intelligence, including learning, reasoning, decision-making, speech recognition, and problem-solving (Russell & Norvig, 2021). AI technologies such as machine learning, robotics, predictive analytics, and automation systems are increasingly being integrated into organizational processes to improve efficiency, productivity, and competitiveness (Brynjolfsson & McAfee, 2022). In recent years, manufacturing firms have adopted AI-driven technologies to optimize production processes, reduce operational costs, improve product quality, and enhance employee effectiveness (Lee *et al.* . 2023; Sharma & Patel, 2024).

Globally, the manufacturing sector is experiencing major transformation through the adoption of smart technologies associated with Industry 4.0. AI-enabled systems now assist organizations in predictive maintenance, quality control, inventory management, supply chain coordination, and production automation (Kumar *et al.* . 2023). These technologies help employees perform tasks faster, minimize human errors, and improve decision-making processes within organizations (Ivanov & Dolgui, 2022). Studies have shown that AI adoption positively influences organizational resilience, operational efficiency, and firm performance when properly implemented (Bag *et al.* . 2024; Sony & Naik, 2023).

Businesses today operate in a competitive environment (Uwa & Johnson, 2017). In Nigeria, the manufacturing sector remains an important contributor to economic growth, industrial development, and employment generation (Manufacturers Association of Nigeria, 2024). However, many manufacturing firms continue to face operational challenges such as low productivity, inefficient production systems, poor technological infrastructure, and intense market competition (Adebayo & Nwankwo, 2023). To remain competitive and improve operational performance, several manufacturing firms in Nigeria have increasingly embraced

Artificial Intelligence technologies and automation systems. Organizations now utilize AI-powered tools for process automation, data analysis, smart monitoring systems, and production management to enhance efficiency and employee output (Okeke *et al.* 2024).

The growing adoption of AI in Nigerian manufacturing firms has significantly altered workplace practices and employee responsibilities. Employees need greater level of resilience to be able to adapt to changes in their responsibilities (Ekutu *et al.* 2020). AI technologies are changing how employees communicate, make decisions, solve problems, and execute assigned tasks (Eze & Ibrahim, 2023). When introducing new AI tools, management must give employees adequate and timely information to enable them to cooperate with the organization (Johnson *et al.* 2024). Recent studies in Nigeria indicate that AI adoption improves operational efficiency, reduces production errors, and strengthens organizational competitiveness (Ogunleye & Salami, 2024). For instance, studies conducted on manufacturing firms in Enugu State and North-Central Nigeria revealed that AI management and automation systems significantly influence organizational performance and productivity (Ugwuanyi *et al.* 2024; Yakubu & Danjuma, 2023).

Statement of the Problems

The increasing adoption of Artificial Intelligence in modern organizations has transformed operational processes and workplace practices across the manufacturing sector. Manufacturing firms now utilize AI-driven technologies such as automation systems, robotics, predictive analytics, and smart monitoring tools to improve productivity, reduce operational costs, and enhance organizational competitiveness. Despite these perceived benefits, the integration of AI into organizational operations has created several behavioural and managerial concerns that may negatively affect employee performance and workplace stability.

One major concern associated with AI adoption is employees' fear of job displacement due to automation. Many workers perceive AI technologies as threats to job security because intelligent systems can perform repetitive and routine tasks previously handled by humans. This situation often creates uncertainty, anxiety, resistance to technological change, and psychological stress among employees. In many organizations, workers struggle to adapt to emerging technologies because of inadequate digital competencies, insufficient training opportunities, and limited organizational support systems. Consequently, employees may become less motivated, less committed, and less productive in the workplace.

Furthermore, the successful implementation of AI technologies largely depends on employees' willingness and ability to effectively interact with technological systems. In situations where employees lack adequate technological knowledge and adaptability, organizations may experience operational disruptions, communication challenges, reduced work efficiency, and poor employee performance during the transition process. Although AI technologies are generally introduced to improve efficiency and productivity, studies have shown that organizations often experience short-term performance difficulties before long-term benefits are achieved.

In Nigeria, particularly within the manufacturing sector, many firms continue to face challenges related to poor technological infrastructure, inadequate employee training, resistance to innovation, and low digital literacy among workers. While several manufacturing firms have begun integrating AI technologies into their operations, there is still uncertainty regarding the extent to which AI adoption influences employee performance outcomes such as productivity, efficiency, quality of work, and task accomplishment. Existing studies in Nigeria have focused more on technological innovation and organizational performance with limited attention given to the behavioural implications of AI on employees within manufacturing firms. It is against this backdrop that this study seeks to examine the influence of Artificial Intelligence on employee performance in manufacturing firms in South-|South Nigeria.

Objective of the Study

The study aims to determine whether AI adoption significantly influences employee productivity, efficiency, and overall job performance within the manufacturing sector. Specific objectives includes;

1. To examine the influence of machine learning systems on employee performance in manufacturing sector, south-south Nigeria.
2. To examine the influence of Smart production systems on employee performance in manufacturing sector, South-South Nigeria.

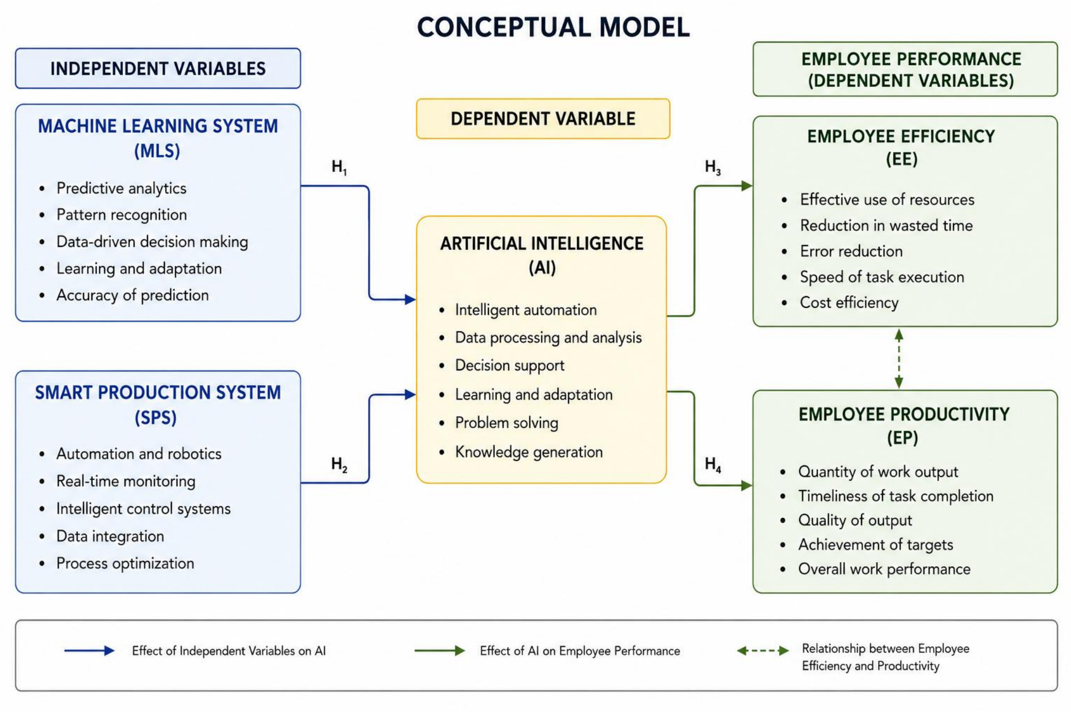
Statement of Hypothesis

H_{01}: Machine learning systems has no significant influence on employee performance in manufacturing sector, South-South Nigeria.

H_{02}: Smart production systems has no significant influence on employee performance in manufacturing sector, South-South Nigeria.

Literature Review

Conceptual Framework



Artificial Intelligence

Manufacturers all over the world have recently adopted cutting-edge technologies, particularly artificial intelligence (AI), to speed up digital transformation and implement agile response techniques to improve organizational performance. AI is a cutting-edge technology that could help businesses maintain and improve their organizational performance and competitive advantage (Wong and Ngai, 2023). The manufacturing industry has made extensive use of AI technologies, which streamline operational procedures and support decision-making tasks like product design and research & development. A comprehensive research providing an in-depth analysis of the global smart (or intelligent per se) manufacturing industry was just released by industry Research (2023). This analysis indicates that the worldwide intelligent manufacturing market is expected to rise quickly due to the growing demand for smart automation and the increasing acceptance of innovative technologies (Zhu *et al.*2024). There is mounting evidence that AI enhances industrial systems' capacity for learning by gathering and analyzing pertinent production and contextual data. Consequently, producers are able to accomplish their production goals, satisfy performance standards, and efficiently adjust to changing market needs (Haenlein and Kaplan, 2019). All AI procedures must be in line with acceptable ethical conduct.

Organizations that aim for optimum performance cannot ignore ethical standards in their daily operations (Uwa *et al.* 2018).

AI applications in manufacturing have proven effective in a variety of business processes, each offering a multitude of benefits (Dubey *et al.* 2020). These applications, for example, fall into three categories: AI for cognitive engagement, AI for process automation, and AI for cognitive insights (Davenport and Ronanki, 2018).

Artificial Intelligence (AI) is described as the capacity of machines to interact with humans through electronic systems and perform tasks in ways that simulate human intelligence without necessarily revealing that they are not human, where decision-making may often be based on logical or binary processes (Russell & Norvig, 2021). One of the pioneers of artificial intelligence, Marvin Minsky, described AI as the science of making machines perform tasks that require human intelligence, such as reasoning, learning, and problem-solving (Minsky, 1967). According to the symbolic school of AI, intelligent systems operate through the manipulation of symbols, where basic symbols represent real-world objects and concepts in structured forms of reasoning (Newell & Simon, 1976).

While there are many different ways to define Artificial Intelligence, it is generally accepted as the field of study concerned with theories, techniques, tools, and applications that aim to mimic, enhance, and extend human intelligence (Russell & Norvig, 2021). In contemporary times, AI has become increasingly influential in human existence and organizational systems, serving as a foundational technology of the modern digital era. Its role is often compared to earlier technological revolutions such as steam engines in the industrial age, electricity in the electrical age, and computers in the information age (Brynjolfsson & McAfee, 2014; Schwab, 2016).

Dimensions of Artificial Intelligence

Machine Learning System

Machine Learning is a core component of modern artificial intelligence that enables systems to automatically learn from data, identify patterns, and make decisions with minimal human intervention. It is a branch of computer science concerned with the development of algorithms that improve their performance over time through experience and exposure to data (Russell & Norvig, 2021). In organizational and industrial contexts, Machine Learning Systems (MLS) have become essential tools for enhancing decision-making, optimizing processes, and improving operational efficiency.

Machine Learning Systems refer to integrated computational frameworks that use statistical models and algorithms to analyze large volumes of data, detect patterns, and generate predictive insights that support organizational decision-making. These systems are capable of self-learning and continuous improvement, making them highly valuable in dynamic environments such as manufacturing firms where production processes and market demands frequently change (Jordan & Mitchell, 2015).

In manufacturing industries, Machine Learning Systems are widely applied in predictive maintenance, quality control, demand forecasting, supply chain optimization, and production scheduling. For instance, ML algorithms can predict machine failures before they occur, thereby reducing downtime and improving productivity. Similarly, they assist managers in analyzing production data to improve efficiency and reduce operational costs (Wuest *et al.* 2016). These capabilities make Machine Learning Systems a critical driver of Industry 4.0 transformation.

From an organizational behaviour perspective, the adoption of Machine Learning Systems influences how employees perform their tasks, make decisions, and interact with technology. Employees working in ML-enabled environments often experience enhanced productivity due to automation of repetitive tasks and improved access to real-time data. However, the effectiveness of these systems depends on employees' digital literacy, acceptance of technology, and ability to adapt to data-driven decision-making processes.

Smart Production systems

Smart production systems represent the integration of advanced digital technologies such as automation, robotics, artificial intelligence, the Internet of Things (IoT), and real-time data analytics to optimize manufacturing processes. These systems are designed to create highly efficient, flexible, and intelligent production environments where machines, systems, and humans interact seamlessly to improve operational performance. Smart Production Systems are a core component of Industry 4.0 and are increasingly being adopted by manufacturing firms to enhance productivity, reduce operational costs, and improve product quality (Lasi *et al.* 2014; Kagermann *et al.* 2013).

In modern manufacturing environments, Smart Production Systems play a critical role in transforming how employees perform their tasks. Through the use of automated machines, real-time monitoring systems, and intelligent control technologies, production processes become faster, more accurate, and less dependent on manual intervention. This allows employees to focus on supervisory, analytical, and decision-making roles rather than repetitive physical tasks. Studies have shown that the integration of smart production technologies improves operational efficiency, reduces production errors, and enhances overall workplace performance (Zhong *et al.* 2017; Frank *et al.* 2019).

From an organizational behaviour perspective, Smart Production Systems significantly influence employee performance by reshaping job roles, work processes, and skill requirements. Employees operating in smart manufacturing environments are required to develop digital competencies and adapt to technologically advanced systems. While this enhances productivity and efficiency, it may also create challenges such as skill gaps, resistance to change, and job insecurity concerns among workers. Therefore, the effectiveness of Smart Production Systems in improving employee performance largely depends on the level of employee training, technological readiness, and organizational support provided during implementation.

Employee performance

The word performance is derived from job performance or actual performance, which refers to an individual's actual accomplishment at work. The definition of performance (work performance) is the quantity and quality of work that an employee completes while performing his duties in line with his assigned obligations. Performance, according to Al Mehrzi and Singh (2016), is the outcome or degree of success of an individual as a whole throughout a specific time period in completing duties in comparison to other alternatives, such as work standards, targets, or established criteria that have been mutually agreed upon. Additionally, according to Yang *et al.* (2016), performance is essentially what workers do or do not do. The complete process used to raise an organization's or company's performance, including each employee's and work group's performance, is known as performance management. Employee performance, according to Shmailan (2016), is what workers accomplish to complete the tasks assigned to them by the firm. Performance in doing its duties is not independent; rather, it is always correlated with employee job satisfaction and the amount of compensation offered, and it is impacted by personal qualities, talents, and abilities.

Organizational Behaviour defines employee performance as a key construct used to assess how effectively individuals contribute to the achievement of organizational goals. It refers to the extent to which employees successfully carry out assigned duties in line with job requirements, organizational standards, and performance expectations. Employee performance is not only concerned with the completion of tasks but also with the quality, efficiency, and consistency of work output over a specified period. It reflects how well employees convert organizational resources, skills, and effort into productive outcomes that support institutional effectiveness and competitiveness.

Employee performance is commonly measured using indicators such as productivity, efficiency, quality of work, timeliness, and goal attainment. Productivity refers to the volume of output produced by an employee within a given period, while efficiency relates to the ability to complete tasks using minimal time and resources without compromising quality. Employee's efficiency usually measures their usefulness to the organization as it shows the value that such employee adds to the organization (Johnson, *et. al.,* 2024) Quality of work reflects the accuracy, precision, and standard of outputs produced, whereas timeliness measures how quickly tasks are completed within deadlines. While employees are expected to exercise their skills to achieve goals, the organization should also create an atmosphere which enables employees to socialize and share ideas to stimulate actualization of assigned task (Johnson, *et. al.* 2024). Goal attainment evaluates the extent to which employees meet predetermined targets and performance benchmarks set by the organization. According to Armstrong (2021), employee performance is a combination of both behaviour (how work is performed) and results (what is achieved), making it a critical factor in organizational success.

From a behavioural perspective, employee performance is influenced by several factors including motivation, skills, work environment, leadership style, and access to technology. In modern organizations, especially manufacturing firms, technological systems such as automation, digital tools, and intelligent systems increasingly shape how employees perform their tasks. High-performing employees are typically those who can adapt to technological changes, apply their skills effectively, and maintain consistent output under varying workplace conditions. Therefore, employee performance remains a central determinant of organizational productivity, efficiency, and competitive advantage.

Artificial Intelligence and Employee Productivity

Artificial Intelligence has become a transformative force in modern organizations, significantly influencing employee productivity across various sectors, particularly in manufacturing firms. AI refers to the ability of machines and systems to perform tasks that typically require human intelligence, such as learning, reasoning, decision-making, and problem-solving. In organizational settings, AI technologies such as machine learning, robotics, predictive analytics, and intelligent automation are increasingly used to streamline operations, reduce manual workload, and enhance task execution speed, thereby improving employee productivity (Brynjolfsson, Rock, & Syverson, 2017; Davenport & Ronanki, 2018).

Artificial Intelligence improves employee productivity by automating repetitive and routine tasks, allowing employees to focus on more strategic, creative, and value-added activities. For instance, AI-powered systems in manufacturing firms can handle production scheduling, quality control, and predictive maintenance, which reduces delays and minimizes human error. This leads to faster completion of tasks and improved output levels. According to Chui, Manyika, and Miremadi (2016), organizations that integrate AI technologies into their operations experience significant productivity gains due to improved decision-making processes and enhanced operational efficiency.

Furthermore, AI enhances employee productivity by providing real-time data analytics and intelligent decision-support systems that improve accuracy and reduce uncertainty in workplace operations. Employees working alongside AI systems are able to make faster and more informed decisions, which increases overall work efficiency. However, the productivity benefits of AI depend on factors such as employee digital skills, organizational readiness, and the level of technology adoption. Studies also suggest that while AI can significantly boost productivity, its effectiveness is maximized when employees are adequately trained and supported in adapting to new technologies (Makridakis, 2017; Dwivedi *et al.* . ., 2021).

In addition, AI fosters continuous improvement in organizational processes through learning algorithms that optimize workflows over time. This creates a more efficient working environment where employees can achieve higher output with fewer resources. Consequently, AI is widely regarded as a key driver of productivity growth in the modern digital economy, reshaping how employees perform tasks and contribute to organizational success.

Machine Learning Systems and Employee Performance

Machine Learning systems have a significant influence on employee performance in modern organizations, particularly in manufacturing environments where precision, speed, and productivity are essential. Machine Learning enhances employee performance by automating repetitive and routine tasks, thereby allowing employees to focus on higher-level and more strategic responsibilities. Through predictive analytics and real-time data processing, ML systems support employees with accurate and timely information that improves decision-making, reduces operational errors, and enhances overall work quality. Studies show that organizations adopting machine learning technologies experience improved productivity and operational effectiveness because employees are better supported by data-driven insights and intelligent systems (Chui *et al.* . ., 2023; Davenport & Ronanki, 2024). In manufacturing firms, ML systems also contribute to improved monitoring of production processes, leading to faster problem detection and better task execution outcomes.

Furthermore, Machine Learning Systems enhance employee efficiency by improving workflow coordination, optimizing resource allocation, and reducing downtime in production processes. By analyzing large and complex datasets, ML technologies assist organizations in forecasting demand, scheduling production activities, and improving supply chain operations, which indirectly enhances employee performance (Wamba-Taguimdje *et al.* 2023; Agrawal *et al.* 2022). However, despite these benefits, the influence of ML systems on employee performance may be moderated by challenges such as employee resistance to technological change, fear of job displacement, and inadequate digital skills. Recent studies emphasize that the successful impact of machine learning on performance depends largely on employee training, organizational readiness, and effective change management strategies (Dwivedi *et al.* 2023). When properly implemented, ML systems serve as a catalyst for improving employee productivity, efficiency, and overall organizational competitiveness.

Smart Production Systems and Employee Performance

Smart Manufacturing systems significantly influence employee performance in modern manufacturing firms by transforming production processes through automation, real-time monitoring, robotics, and integrated digital technologies. These systems enhance the speed and accuracy of production activities, thereby enabling employees to complete tasks more efficiently and with reduced error rates. By automating repetitive and routine functions, smart production systems allow employees to shift their focus toward supervisory, analytical, and problem-solving roles, which improves overall productivity and job performance (Frank *et al.* 2019; Zhong *et al.* 2017). As a result, employees in smart manufacturing environments tend to achieve higher output levels and improved quality of work due to streamlined operational processes.

Furthermore, Smart Production Systems improve employee efficiency by optimizing workflow coordination, minimizing downtime, and ensuring better utilization of organizational resources. Real-time data analytics and intelligent production control systems help employees make faster and more informed decisions, reducing delays and operational bottlenecks. However, despite these advantages, the adoption of smart production systems may also present challenges such as increased technological complexity, skill mismatch, and resistance to change among employees. Studies indicate that the positive impact of smart production systems on employee performance is largely dependent on effective training, digital skill development, and organizational support structures that facilitate employee adaptation to advanced technologies (Kagermann *et al.* 2013; Lasi *et al.* 2014). When properly implemented, smart production systems serve as a critical driver of improved employee productivity, efficiency, and overall organizational effectiveness.

Theoretical Review

Technology Acceptance Model (TAM) by Davis (1989).

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

In the context of Artificial Intelligence and employee performance, employees are more likely to adopt AI systems when they perceive that such technologies will improve their job effectiveness, productivity, and efficiency (Venkatesh *et al.* 2003). AI tools such as intelligent automation systems, predictive analytics, and machine learning applications provide employees with real-time information, reduce repetitive tasks, and enhance decision-making processes, thereby increasing task efficiency and overall output. Empirical studies have shown that when employees perceive AI as useful and easy to interact with, it leads to higher levels of adoption and improved performance outcomes in organizations (Dwivedi *et al.* 2021; Benbya *et al.* 2020).

However, when employees perceive AI systems as complex, difficult to use, or threatening to job security, resistance to adoption may occur, which negatively affects performance outcomes. Such resistance can manifest as anxiety, reduced motivation, and low engagement with AI-enabled systems, ultimately limiting productivity gains. Research further indicates that organizational support, training, and user-friendly system design significantly reduce perceived difficulty and enhance acceptance of AI technologies (Venkatesh *et al.* 2003;

Chatterjee *et al.* 2021). Therefore, the successful implementation of AI in improving employee performance largely depends on how positively employees perceive its usefulness and ease of use within the workplace context.

Empirical Review

Brynjolfsson *et al.* (2019) conducted a study titled Artificial Intelligence and the Modern Productivity Paradox to examine the impact of Artificial Intelligence and digital technologies on productivity and employee performance in firms. The objective of the study was to determine how AI adoption influences labour productivity and organizational output. The study adopted a quantitative research design using firm-level productivity data and econometric analysis. The findings revealed that AI-enabled technologies significantly improve productivity by reallocating human effort from routine tasks to more complex and creative activities. The study concluded that AI contributes positively to employee performance through efficiency gains and task optimization. It was recommended that organizations should invest in AI infrastructure and employee digital skills training to maximize productivity benefits.

Davenport and Ronanki (2018) conducted a study titled Artificial Intelligence for the Real World to assess how AI applications influence job performance and operational effectiveness in organizations. The objective was to evaluate the extent to which AI solutions improve work processes and employee output. The study employed a qualitative multiple-case study approach involving 152 AI projects across different industries. The findings showed that AI technologies such as robotic process automation and cognitive systems significantly enhance employee efficiency, reduce workload, and improve decision accuracy. The study concluded that AI improves employee performance when properly aligned with organizational processes. It recommended that firms should adopt a phased AI implementation strategy and ensure employee involvement in AI integration processes.

Chatterjee *et al.,* (2021) conducted a study titled Adoption of Artificial Intelligence in Organizations and Its Impact on Employee Performance to examine the relationship between AI adoption and employee effectiveness. The objective of the study was to analyze how AI-enabled systems influence employee productivity and decision-making. The study used a survey research design with quantitative analysis through structural equation modelling. The findings revealed that AI adoption positively influences employee performance by improving task accuracy, speed, and efficiency. The study concluded that AI systems enhance workplace productivity when employees perceive them as useful and easy to use. It recommended continuous employee training and organizational support to enhance AI acceptance.

Wamba-Taguimdje *et al.,* (2020) conducted a study titled Influence of Artificial Intelligence on Firm Performance and Employee Productivity to investigate the impact of AI-driven systems on organizational outcomes. The objective was to determine how AI technologies affect employee productivity and operational efficiency. The study adopted a mixed-method approach involving survey data and regression analysis. The findings indicated that AI adoption significantly improves employee productivity through automation and improved decision-making processes. The study concluded that AI enhances organizational performance indirectly by improving employee efficiency. It recommended that organizations should strengthen technological infrastructure and promote employee adaptability to digital systems.

METHODOLOGY

This study adopted a cross-sectional survey research design. A cross-sectional survey design is appropriate because it allows data to be collected from respondents at a single point in time in order to examine the relationship between variables without manipulating them. This design is suitable for this study because it enables the researcher to assess the influence of Artificial Intelligence on employee performance (productivity and efficiency) in manufacturing firms in South-South Nigeria as it exists in real workplace settings.

The population of the study consists of 272 employees drawn from selected manufacturing firms in Nigeria. These employees are considered appropriate respondents because they are directly involved in production processes and are exposed to AI-related technologies such as machine learning applications, and smart production systems within their organizations. The sample size for the study was determined using the Krejcie and Morgan (1970) formula/table for sample size determination.

The sample size for the study is 153 respondents. A simple random sampling technique was used to ensure that every employee in the population had an equal chance of being selected. This reduces bias and enhances the representativeness of the sample. Data were collected using a structured questionnaire designed on a 5 point Likert scale. The questionnaire captured information on Artificial Intelligence adoption and employee performance. Data collected were analyzed using descriptive statistics (mean and standard deviation) and inferential statistics (simple linear regression) to test the relationship between Artificial

Intelligence and employee performance. All analyses were conducted using SPSS Version 27. The empirical model for the study was specified as follows:

$EP = f(MLS, SPS) + \mu 1$ ……………………………………………………………….(1)

$EP = \beta 0 + \beta MLS + \mu 1$ …………………..……………………………………………(2)

$EP = f(MLS) + \mu 1$ ……….…………………………………………………………..(3)

$EP = \beta 0 + \beta_2 SPS + \mu 1$ ……………………………………………………………..(4)

$EP = f(MLS, SPS) + \mu 1$ ………………………………………………………… (5)

$EP = \beta 0 + \beta_1 MLS + \beta_2 SPS + \mu 1$--(6)

Where:

EP = Employee Performance

MLS = Machine Learning System

SPS= Smart Learning System

$\beta 0$ = intercept or regression constant term

$\beta 1$- $\beta 2$ = Regression coefficient

$\mu 1$ is the error term

4. Data Presentation, Analysis and Discussion

Descriptive statistics on Machine learning systems.

Items	**SA**	**A**	**U**	**D**	**SD**	**Total**
Machine learning systems improve the accuracy of work processes in my organization.	40 (26.1%)	55 (35.9%)	25 (16.3%)	20 (13.1%)	13 (8.5%)	153 (100%)
Machine learning technologies help employees complete tasks faster.	45 (29.4%)	60 (39.2%)	20 (13.1%)	18 (11.8%)	10 (6.5%)	153 (100%)
Machine learning systems reduce errors in production activities.	38 (24.8%)	52 (34.0%)	28 (18.3%)	22 (14.4%)	13 (8.5%)	153 (100%)
The organization effectively utilizes machine learning systems for decision-making.	42 (27.5%)	58 (37.9%)	25 (16.3%)	18 (11.8%)	10 (6.5%)	153 (100%)

Source: Field Survey (2026)

The result in the table shows respondents' perceptions regarding the influence of Machine Learning systems in the organization. On the statement that machine learning systems improve the accuracy of work processes in the organization, 40 respondents representing 26.1% strongly agreed, while 55 respondents representing 35.9% agreed. However, 25 respondents representing 16.3% were undecided, 20 respondents representing 13.1%

disagreed, and 13 respondents representing 8.5% strongly disagreed. This indicates that the majority of respondents believed that machine learning systems improve work accuracy within the organization.

Similarly, on the statement that machine learning technologies help employees complete tasks faster, 45 respondents representing 29.4% strongly agreed and 60 respondents representing 39.2% agreed. Meanwhile, 20 respondents representing 13.1% were undecided, 18 respondents representing 11.8% disagreed, and 10 respondents representing 6.5% strongly disagreed. This suggests that most employees perceived machine learning technologies as tools that enhance speed and timely completion of tasks.

Furthermore, regarding the statement that machine learning systems reduce errors in production activities, 38 respondents representing 24.8% strongly agreed, while 52 respondents representing 34.0% agreed. In contrast, 28 respondents representing 18.3% were undecided, 22 respondents representing 14.4% disagreed, and 13 respondents representing 8.5% strongly disagreed. The result implies that respondents generally agreed that machine learning systems contribute to error reduction in production processes.

Finally, on the statement that the organization effectively utilizes machine learning systems for decision-making, 42 respondents representing 27.5% strongly agreed and 58 respondents representing 37.9% agreed. However, 25 respondents representing 16.3% were undecided, 18 respondents representing 11.8% disagreed, while 10 respondents representing 6.5% strongly disagreed. This finding indicates that the organization effectively utilizes machine learning systems to support managerial and operational decision-making processes.

Descriptive statistics on Smart Production Systems

Items	SA	A	U	D	SD	Total
Smart production systems improve the speed of production activities.	37 (24.2%)	58 (37.9%)	24 (15.7%)	20 (13.1%)	14 (9.2%)	153 (100%)
Automation technologies reduce manual workload in the organization.	40 (26.1%)	55 (35.9%)	22 (14.4%)	20 (13.1%)	16 (10.5%)	153 (100%)
Smart production systems improve the quality of products produced.	38 (24.8%)	57 (37.3%)	25 (16.3%)	20 (13.1%)	13 (8.5%)	153 (100%)
Real-time monitoring systems enhance operational efficiency.	42 (27.5%)	60 (39.2%)	20 (13.1%)	18 (11.8%)	13 (8.5%)	153 (100%)

Source: Field Survey (2026)

The result in the table shows respondents' perceptions regarding the influence of Smart Manufacturing systems in the organization. On the statement that smart production systems improve the speed of production activities, 37 respondents representing 24.2% strongly agreed, while 58 respondents representing 37.9% agreed. However, 24 respondents representing 15.7% were undecided, 20 respondents representing 13.1% disagreed, and 14 respondents representing 9.2% strongly disagreed. This indicates that the majority of respondents believed that smart production systems improve the speed of production activities within the organization.

Similarly, on the statement that automation technologies reduce manual workload in the organization, 40 respondents representing 26.1% strongly agreed and 55 respondents representing 35.9% agreed. Meanwhile, 22 respondents representing 14.4% were undecided, 20 respondents representing 13.1% disagreed, and 16 respondents representing 10.5% strongly disagreed. This suggests that most respondents perceived automation technologies as effective tools for reducing manual workload and enhancing operational convenience.

Furthermore, regarding the statement that smart production systems improve the quality of products produced, 38 respondents representing 24.8% strongly agreed, while 57 respondents representing 37.3% agreed. In contrast, 25 respondents representing 16.3% were undecided, 20 respondents representing 13.1% disagreed, and 13 respondents representing 8.5% strongly disagreed. The result implies that respondents generally agreed that smart production systems contribute positively to improving product quality within the organization.

Finally, on the statement that real-time monitoring systems enhance operational efficiency, 42 respondents representing 27.5% strongly agreed and 60 respondents representing 39.2% agreed. However, 20 respondents representing 13.1% were undecided, 18 respondents representing 11.8% disagreed, while 13 respondents representing 8.5% strongly disagreed. This finding indicates that respondents largely believed that real-time monitoring systems improve operational efficiency and support effective organizational performance.

Test of Hypotheses

H_{01}: Machine learning systems has no significant influence on employee performance in manufacturing sector, South-South Nigeria.

Model Summary[b]					
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**Durbin-Watson**
1	.830[a]	.688	.687	.43348	1.755

a. Predictors: (Constant), Machine learning systems						
b. Dependent Variable: employee performance						

ANOVA[a]						
Model		**Sum of Squares**	**Df**	**Mean Square**	**F**	**Sig.**
1	Regression	100.852	1	100.852	536.727	.000[b]
	Residual	45.660	152	.188		
	Total	146.512	153			
a. Dependent Variable: employee performance						
b. Predictors: (Constant), Machine learning systems						

Coefficients[a]						
Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
		B	**Std. Error**	**Beta**		
1	(Constant)	.638	.142		4.492	.000
	Machine learning systems	.824	.036	.830	23.167	.000
a. Dependent Variable: employee performance						

Hypothesis one was formulated to examine the effect of Machine learning systems on employee performance in manufacturing sector, South-South Nigeria. The simple linear regression result showed a strong positive relationship between Machine learning systems and employee performance in manufacturing sector, South-South Nigeria. The model summary revealed a correlation coefficient of R = 0.830, indicating a strong association between the variables. The coefficient of determination (R^2 = 0.688) showed that Machine learning systems explained about 68.8% of the variation in employee performance, while the adjusted R-square value (0.687) confirmed the stability of the model.

The ANOVA result further indicated that the regression model was statistically significant (F = 536.727, p = 0.000). The coefficient table showed that Machine learning systems had a significant positive effect on employee performance (B = 0.824, t = 23.167, p = 0.000), meaning that a unit increase in Machine learning systems increases employee performance by 0.824 units. Based on this, the null hypothesis was rejected, and the study concluded that Machine learning systems significantly improves employee performance in the ministry.

H_{02}: Smart production systems has no significant influence on employee performance in manufacturing sector, South-South Nigeria.

Model Summary[b]					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.819[a]	.671	.670	.44505	1.310
a. Predictors: (Constant), Smart production systems					
b. Dependent Variable: employee performance					

ANOVA[a]						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	98.382	1	98.382	496.714	.000[b]
	Residual	48.130	152	.198		
	Total	146.512	153			
a. Dependent Variable: employee performance						
b. Predictors: (Constant), Smart production systems						

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.171	.124		9.434	.000
	Smart production systems	.708	.032	.819	22.287	.000
a. Dependent Variable: employee performance						

The regression result indicated a strong positive relationship between Smart production systems and employee performance in the manufacturing firms in South-South Nigeria. The model summary revealed a correlation coefficient of R = 0.819, showing a strong association between the variables. The coefficient of determination ($R^2 = 0.671$) implies that Smart production systems accounted for about 67.1% of the variation in employee performance, while the adjusted R-square value (0.670) confirmed that the model remained stable after adjustment. The Durbin-Watson statistic of 1.310 suggests that autocorrelation is not severe, though it indicates a slightly weaker independence of errors compared to the ideal value of 2.

The ANOVA result showed that the regression model was statistically significant (F = 496.714, p = 0.000), confirming that Smart production systems is a significant predictor of employee performance. The coefficient table further revealed that Smart production systems had a significant positive effect on employee performance (B = 0.708, t = 22.287, p = 0.000), meaning that a unit increase in Smart production systems leads to an increase of 0.708 units in employee performance. Based on these findings, the null hypothesis (H_{02}) was rejected, and the study concluded that Smart production systems has a significant positive effect on employee performance in manufacturing sector, South-South Nigeria.

DISCUSSION OF FINDINGS

Based on the objective of the study which was to examine the influence of machine learning systems on employee performance in manufacturing sector, South-South Nigeria. The findings of the study revealed that machine learning systems significantly influence employee performance in the manufacturing sector in South-South Nigeria. Descriptive results showed that the majority of respondents agreed that machine learning systems improve the accuracy of work processes, help employees complete tasks faster, reduce production errors, and support organizational decision-making. This implies that employees perceive machine learning technologies as important tools for improving operational efficiency and enhancing workplace productivity. The regression analysis further supported this perception by revealing a strong positive relationship between machine learning systems and employee performance ($R = 0.830$). The coefficient of determination ($R^2 = 0.688$) indicated that machine learning systems accounted for 68.8% of the variation in employee performance, while the regression coefficient ($B = 0.824$, $p < 0.05$) confirmed that machine learning systems have a significant positive effect on employee performance. This finding aligns with the study of Davenport and Ronanki (2018), who found that AI-driven systems improve employee productivity and decision-making efficiency through automation and intelligent data processing. The finding is also consistent with Chatterjee *et al.* (2021), who reported that machine learning technologies enhance task accuracy, speed, and operational effectiveness in organizations.

Similarly, the second objective was to examine the influence of smart production systems on employee performance in manufacturing sector, South-South Nigeria. The findings showed that smart production systems significantly influence employee performance in manufacturing firms in South-South Nigeria. The descriptive statistics indicated that respondents generally agreed that smart production systems improve production speed, reduce manual workload, improve product quality, and enhance operational efficiency through real-time monitoring systems. The regression result further established a strong positive relationship between smart production systems and employee performance ($R = 0.819$). The coefficient of determination ($R^2 = 0.671$) showed that smart production systems explained 67.1% of the variation in employee performance, while the regression coefficient ($B = 0.708$, $p < 0.05$) revealed that smart production systems significantly improve employee performance. This suggests that the adoption of automation technologies and intelligent production systems contributes positively to employee productivity and efficiency in manufacturing organizations. The finding supports the study of Zhong *et al.* (2017), who found that smart manufacturing systems improve operational performance by enhancing production efficiency and reducing errors. It also agrees with Frank *et al.* (2019), who observed that smart production technologies significantly enhance workflow coordination, productivity, and organizational effectiveness in manufacturing environments.

CONCLUSION

This study examined the influence of Machine Learning systems and Smart Manufacturing systems on employee performance in the manufacturing sector in South-South Nigeria. Based on the findings, the study concluded that machine learning systems significantly improve employee performance by enhancing work accuracy, reducing production errors, supporting decision-making, and increasing the speed of task completion. The regression results further confirmed that machine learning systems have a strong positive and significant effect on employee performance in manufacturing firms.

The study also concluded that smart production systems significantly enhance employee performance through improved production speed, reduced manual workload, enhanced product quality, and better operational efficiency. The findings demonstrated that organizations utilizing smart production technologies experience improvements in employee productivity and efficiency due to automation and real-time operational monitoring. Overall, the study established that the adoption of artificial intelligence-driven technologies contributes positively to employee performance and organizational effectiveness within the manufacturing sector in South-South Nigeria.

Recommendations

Manufacturing firms in South-South Nigeria should invest more in Machine Learning systems to improve operational efficiency, reduce production errors, and enhance employee productivity and performance within the workplace. Management of manufacturing firms should organize regular training and digital skill development programmes to equip employees with the necessary competencies required to effectively utilize machine learning and smart production technologies. Manufacturing organizations should strengthen the implementation of Smart Manufacturing systems such as automation technologies and real-time monitoring systems in order to improve workflow coordination, production speed, and operational efficiency. Organizations should establish supportive work environments that encourage employees to accept and adapt to technological innovations, thereby reducing resistance to change and improving employee commitment toward AI-driven systems.

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