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Effect of Intelligent Manufacturing System on Organisational Performance: A study of Chi Limited

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Abstract

Despite the increase of innovative technologies during the Fourth Industrial Revolution (4IR), there are few quantitative and empirical studies that deal with the recently intelligent manufacturing system (IMs). The objective of the study was to examine the effect of intelligent manufacturing system on the performance of manufacturing organisation, a study of Chi Limited in Lagos state. The study adopted a survey research method. The population comprised 921 employees. The sample size of the study was 279. The stratified sampling technique was used and 210 copies of the questionnaire were returned and valid. Regression analysis was utilized and the findings showed that intelligent manufacturing systems have a significant effect on competitive advantage; intelligent manufacturing systems is statistically significant and may be used to predict production efficiency, while the performance of the organisation is influenced by IMs parameters. This study concluded that IMs (intelligent employees and intelligent technologies) has significant effect on organisational performance (competitiveness and production efficiency). This study recommended that more businesses need to engage intelligent employees in order to improve the competitiveness of the organisations. Manufacturing organisations ought to embark on the adoption and expansion of advanced manufacturing system because it will enhance production efficiency. This is influenced by IMs parameters.

Keywords: Competitive Advantages, Intelligent Manufacturing System, Intelligent Employees, Intelligent Technologies, Performance

1.0 Introduction

The manufacturing sector is the cornerstone of a humane, civilised lifestyle in today's globalised society and is crucial to sustainable development (Kumar *et al.*, 2024). Emerging nations often face significant questioning and repercussions from their fortune not to establish sustainable manufacturing industries due to their reliance on the service sector, mining, and agriculture (Atieh *et al.*, 2022). In the traditional manufacturing system, the

state and dynamic nature of customer orders, the unpredictability of resource acquisition, the intricacy of the manufacturing process, and the dynamic liquidity of production chains and logistics information are all worse (Mata *et al.*, 2026). High-end intangible products are added to low-end tangible products in the traditional manufacturing system, which is primarily driven by large-scale and standardised product demand, which takes the rationalisation of the manufacturing industry structure (Jianjiang *et al.*, 2022).

Since recovering from the COVID-19 pandemic, the manufacturing sector's performance has been weak and sluggish. As a result, the sector's average annual contribution to Nigeria's GDP falls well short of levels that are globally competitive (Olajide *et al.*, 2026). Traditional manufacturing firms are facing challenges due to the global competitive environment, including scheduling difficulties, high tooling costs, excess scrap, quality control issues, and long setup times. Nigerian manufacturers are particularly affected by high energy costs, limited credit access, reduced consumer purchasing power, unstable government policies, heavy taxation, inflation, and a depreciating currency. These issues have an impact on production efficiency (Kolawole, 2026).

In many ways, modern human-machine interaction differs from the interaction between humans (employees) and machines (technologies) in traditional manufacturing (Moring, 2022). Major obstacles to sustaining the current industrial revolution include the lack of the requisite capabilities, the skills gap in manufacturing, and the high cost of investment (Atieh *et al.,* 2022). In most societies, modern technology plays a critical role in the daily operations of various business organisations. Conventional technologies were created with distinct goals in mind, catering to the needs of users and businesses. According to Serrano (2023), contemporary intelligent technologies integrate various functionalities into identical physical technologies.

Due to its flexibility, intelligent technologies (IT) have emerged as the manufacturing industry's focal point and future direction (Verma *et al.*, 2026). As such, IT is now an essential component of IMs. Unlike conventional technologies, this data-based technology can effectively reduce related costs and ease the demands on goods for intelligent functions. The development and deployment of such a system may be significantly impacted by the cost of implementing IT (Liu *et al.*, 2022). Furthermore, if the difference in manufacturer frontiers is taken into account, the non-adopters of IT, an emerging technology, will have an impact on production efficiency (Hwang & Kim, 2022). This will inevitably have a negative impact on organisational performance. IMs, contemporary technologies improve an organization's production efficiency by not using excessive amounts of resources (Li & Ling, 2023)

The complexity of the manufacturing process, the state and dynamic nature of customer orders, the unpredictable nature of resource acquisition, the dynamic liquidity of the production chains, and logistics information are all worse in the traditional manufacturing system (Li *et al.*, 2026). In the conventional manufacturing system, high-end intangible products are paired with low-end tangible products. This is mainly due to large-scale, standardised product demand, which necessitates the rationalisation of the manufacturing industry structure (Jianjiang *et al.*, 2022). The challenge of equipping the workforce with digital skills is significant as businesses shift to a digital workspace; this could lead to a skills gap and bottlenecks for companies. An increasing number of manufacturing organisations are implementing modern manufacturing systems as part of industry upgrading and to strengthen their competitive advantage (Cooke *et al.*, 2022). In Nigeria's manufacturing industries, a stronger link between new design and manufacturing

processes, like IMs, is required to improve organisational performance (Okokpujie *et al.*, 2023).

Despite the increase of innovative technologies during the 4/5IR, there are few quantitative and empirical studies that deal with the recently intelligent manufacturing system (IMs). This study examines the effect of IMs (IE and IT) on organisational performance (competitive advantage and production efficiency).

2.0 LITERATURE REVIEW

2.1 Conceptual Review

IMs has emerged as a necessary trend in the development of the manufacturing industry due to the new generation of ITs rapid development and deep integration with the sector. This presents a chance to lessen remanufacturing system uncertainty (Tu *et al.*, 2025). IMs is a manufacturing system that performs various functions in design, production, management, and service, as well as self-awareness, self-learning, self-decision, self-execution, and self-adaptation (Jianjiang *et al.,* 2022). In order to protect the environment, IMs reduce pollution, help get rid of old equipment, and provide low-cost opportunities for new technological innovation (Nleya & Velempini, 2024). IMs aim to increase the autonomy, adjustability, and configurability of the production process in order to advance production processes flexibly and to realize the efficiency of individual customization (Hammad *et al.,* 2024).

According to Yang and Shen (2023), IMs has realised the innovation of manufacturing mode and established the framework for the new development of the industry by integrating artificial intelligence and advanced manufacturing technology. It is a manufacturing technique that aims to maximise product production and trading by increasing process flexibility through the use of cutting-edge IT and manufacturing technologies. It adapts to the ever-changing dynamics of the world market (Rozhok *et al.,* 2023). According to Atieh et al. (2022), in order to achieve the best possible manufacturing result, IMs consists of a mix of people, machines, and equipment connected by a common material and information flow. It is a new manufacturing structure that combines the benefits of manufacturing and information technology.

With the widespread use of AI, industrialised nations and emerging economies have quickly turned to IMs as their primary tool for promoting the revival of manufacturing and competing in the globally (Yang & Shen, 2023). With little oversight or help from operators, this system can automatically adjust to shifting conditions and differing process requirements (Ma *et al.*, 2023). According to Wei (2025), it has been widely reported that instant messaging (IMs) can help businesses achieve agility, virtualization, lean, integration, and collaboration. It can also improve the efficiency, dependability, and safety of their manufacturing processes. According to Weiss (2026), countries' economies can no longer expand independently without relying on the rapid expansion of manufacturing.

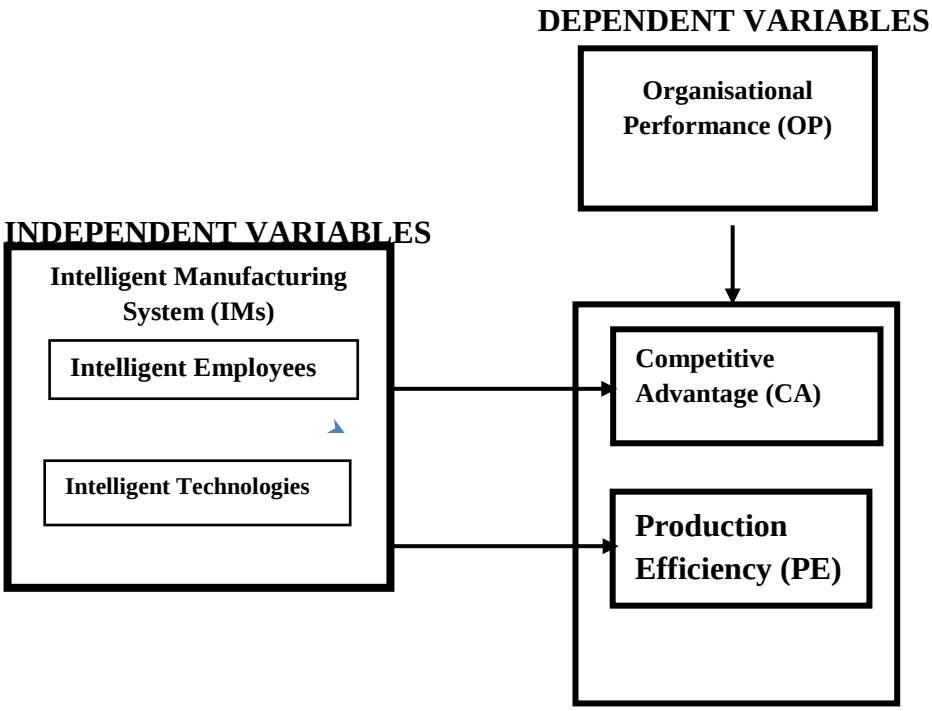
Building a productive manufacturing system is therefore now a pressing issue for the manufacturing company that must be handled quickly (Shahin *et al.*, 2026). IMs have the ability to precisely identify operations and compute direct costs, and it will lower the percentage of direct labour and manufacturing costs (Dui *et al.,* 2026). But in this environment of competitive advantage, a number of essential components of IMs are represented in intelligent devices, IE, intelligent processes, intelligent connectivity, and intelligent infrastructures. These components can actually and effectively improve product design, increase manufacturing resource efficiency, and lower waste percentages in

business organizations, all while satisfying customer demands for quality and delivery (Ahmed & Kareem, 2019).

2.2.0 Hypotheses Formulation

This study examines the effect of intelligent manufacturing system (IMs) on organisational performance, as well as the organisational performance metrics of competitive advantages and production efficiency. Intelligent Employees (IE) and Intelligent Technologies (IT) are used to measure Intelligent manufacturing System (IMs), underscoring the significance of taking everything into account.

The authors connected the independent variables of IMs with the dependent variable of organisational performance in order to conceptualize this study.



Source: Developed through extant Research (2026).

Figure 1: Conceptual Model of the effect of intelligent manufacturing system (IMs) on organisational performance in Chi Limited.

2.2.1 IMs Component: Intelligent Employees (IE)

Anglim et al. (2022) claim that a high intelligence quotient (IQ) is correlated with intelligence. The ability to grasp and manage abstract concepts, learn from experiences, adjust to new circumstances, and use knowledge to influence one's surroundings is referred to as intelligence. It encompasses abilities like critical thinking, problem-solving, quick learning, and comprehending intricate concepts (Satarkar, 2026). One important factor in explaining differences in employees' mental performance is their intelligence. Gunke (2025) endorsed the idea that there are various forms of human intelligence, each of which reflects a unique employee's optimal method of processing information to produce noteworthy or significant results.

Employees with intelligence possess the knowledge, abilities, competence, and experience necessary to carry out extraordinary deeds. One important source of competitive advantage

is the accumulation of intelligent personnel. Employees' cognitive ability and flexibility allow them to quickly acquire the professional knowledge and skills they need and apply them to real-world tasks (Lin *et al.*, 2022).

In most manufacturing organisations, employees are being replaced by machines due to continuous automation development (Ogu & Opara, 2026). However, intelligent employees can learn and adjust to these changes (Mikołajczyk, 2022). In an objective setting, they adopt a similar personal mastery strategy (Williams, 2022). However, since they are crucial to the success, management should encourage IE whose potentials will enhance the production efficiency of any organization (Zhenjing *et al.*, 2022). In this study, it can be deduced that intelligent employees are denoted by human knowledge, experience, and equally have modern technological capability.

Most manufacturing organisations want to build an edge over their rivals. The ability of an organisation to produce a good or service more effectively than its rivals is known as a competitive advantage. It is crucial everywhere because it gives customers the freedom to select from a wide range of options and get what they need. To increase market share, manufacturers use quality improvement and competitive advantage (Majeed, 2025). However, modern organisations must contend with increased competition, environmental changes that happen more quickly, globalisation, and complex customer requirements (Ujam, 2025). The industry's tendency towards perpetual change, rivalry, and open markets puts pressure on all participating organisations to maintain a competitive advantage by introducing ideas like innovation, flexibility, and differentiation from rivals (Ogunniyi, 2025).

Hypothesis ($H_0$1): IMs components do not significantly affect competitive advantage in Chi Limited.

2.2.2. IMs Component: Intelligent Technologies (IT)

Technology is the application of scientific principles to various spheres of life, encompassing the utilisation of materials, tools, techniques, and power sources to enhance productivity and make life easier or more enjoyable (Stephen *et al.*, 2024). Originally, it was employed to replace labourers by automating tedious, filthy, hazardous, or disjointed jobs. Subsequently, it was then employed to supplement employees, working with them as a tool that offered new or improved skills and insights (Kamen *et al.*, 2023). As a result of the influence of modern IT, technology has entered the Intelligent Era. A paradigm shift is also occurring in conventional technology (Mansour *et al.*, 2026). One way to characterise the Industrial Revolution is as the replacement of old industrial methods with new, prevailing techniques by the technologies available at that time (Raja Santhi & Muthuswamy, 2023).

Leading technologies, IT, which are related to the current trend of automation and data exchange in manufacturing and other industries, emerge as a result of the fourth industrial revolution, or 4.0 Industry (Ali *et al.*, 2023). Smarter technologies related to manufacturing, computing, virtualization, connectivity, data handling, and other areas are integrated by it (Hussein & Ibnkahla, 2025). The range of technologies has expanded as a result of their interoperability, which offers advantages like flexibility, remote monitoring, cost-effectiveness, time-saving, ease of configuration, improved understanding, and quick response to market demands (Salehi *et al.*, 2026). According to Ali et al. (2023), it also helps manufacturing facilities produce more customised and globalised goods to boost production efficiency and improve an organization's competitive advantage. The term

"intelligent technologies" in this study refers to connected devices, automated procedures, and machines that are sensor or data driven.

ITs are produced to improve cost, quality and efficiency. While maintaining the highest possible level of production efficiency is always the ultimate goal, manufacturing organisations must address the critical issue of production efficiency. Achieving optimal performance is the main goal of the pursuit of production efficiency in the manufacturing sector, although this is not an easy task (Singh, 2023). It involves producing the greatest amount of goods with the fewest resources possible. These resources consist of costs associated with labour, planning, overhead expenses, inventory, raw materials, and other things like contemporary technology (Afwika *et al.*, 2026). In order to assess the efficacy of a manufacturing system and to determine profitability, customer satisfaction, and the long-term viability of a business, production efficiency is an essential metric (Handoyoa *et al.*, 2023).

Hypothesis (H_{02}): IMs components do not influence production efficiency in Chi Limited.

2.3 Theoretical Review

This study is underpinned by Human Computer Interactive Theory

2.3.1 Human Computer Interactive Theory

Card, Newell, and Moran popularised the term "Human Computer Interactive" Theory in 1983 (Brown, 2026). Man-machine or human-machine interaction is also occasionally employed (Chouhan *et al.*, 2026). Human-computer interactive (HCI) refers to the exchange of information and interaction between people and computerised systems through a user interface (Ge, 2026). In order to accomplish organisational objectives, HCI aims to comprehend and enhance human-computer interaction, making technology more comprehensible, effective, and enjoyable (Dreyer, 2026). It has been more than ten years since this field was founded. But as engineering and technology have advanced recently, it has become indispensable in a number of sectors, such as manufacturing, transportation, and healthcare (Li *et al.*, 2026).

In the current digital environment, human-computer interaction (HCI) is a key factor in determining how staff members within a company use technology (Prasad, 2026). The usability principle is represented by HCI, which focuses on making user experiences intuitive, effective (production efficiency), and pleasurable. This will ultimately increase productivity and satisfaction by giving users a competitive edge, improving their general well-being, and fostering pleasurable interactions between people and computers (IT) (Setiawan & Yatim, 2026). That being said, the modern digital world is what gave rise to the idea of instant messaging. According to Daou et al. (2026), IMs is a collaborative manufacturing system that is fully integrated with various components and can adapt in real time to changing demands and conditions in the manufacturing process, supply chain, and customer needs.

Intelligent components, IE and IT can now communicate with each other through IMs. Its goal is to create entire IMs with a high degree of process digitization (Biswas, 2025). Businesses must transit to new and more efficient technologies due to a number of factors, including the need for digitalization, industry 4.0 adaptation, globalisation, market survival, and high costs (Deng *et al.*, 2026). One of the fundamental principles of the manufacturing sector is increasing production efficiency (Gayratovna, 2026). Manufacturing aims to achieve more than just efficient production; gaining a competitive edge over competitors is crucial for improving organisational performance. The manufacturing sector is under

constant pressure to increase production performance due to the strong competitive advantage (Chatti *et al.,* 2026). The manufacturing industry increasingly uses overall production efficiency and competitive advantage as common indicators of organisational performance (Jum'a *et al.*, 2026). The goal of IMS is to manage the impending digitalization transformation of the 4/5IR (Pan *et al.*, 2026), which is a crucial component of future survival and success.

2.4 Empirical Review

Yangjin et al. (2026) found that intelligent manufacturing (IM) significantly enhances ESG performance (ESGP) among Chinese A-share listed companies from 2010 to 2023, with results confirmed by various robustness checks. IM influences ESGP through two main channels: increasing technological innovation input (TII) and improving technological innovation output (TIO). Additionally, the effects of IM on ESGP are more pronounced in non-state-owned enterprises and firms in the Western region, indicating variation based on ownership and geography.

Zhang (2026) studied the enterprise digital strategy in the context of IM, focusing on the application and impact of artificial intelligence generated content (AIGC). The study employed empirical analysis of 268 valid questionnaires, leveraging chi-square tests, which revealed that AIGC technology significantly enhances enterprise transformation in intelligent manufacturing capabilities and data ecosystems, though its impact on the market ecosystem is less pronounced.

Ji et al. (2025) investigated how IM impacts urban green innovation efficiency using data from 279 prefecture-level cities. Employing a multiperiod difference-in-differences (DID) approach, the study found that IM enhances green innovation efficiency through scale, economic, and talent agglomeration. The positive relationship was established by robust testing methods and is moderated nonlinearly by financial development, particularly beyond a threshold of 3.817.

Wang et al. (2025) analysed the impact of IM on pollution emissions in China's manufacturing sector, utilizing firm-level tax data and a staggered difference-in-differences design. The study found that intelligent manufacturing aids in reducing pollution emissions through two main mechanisms: the technological progress effect, enhancing productivity, and the capital savings effect, optimizing energy consumption and lowering fixed capital intensity.

Guo et al. (2025) explored the connection between IM and local green development using panel data from 262 Chinese cities (2008-2019) with a panel smooth transformation regression model. The findings indicated that IM enhances urban green total factor productivity but experiences diminishing returns at higher application levels. It notably benefits non-resource cities, regions with advanced digital economies, and eastern cities. Additionally, optimal man-machine matching is crucial for maximizing the positive impact on green productivity.

Zi et al. (2025) examined the impact of IM on pollution emissions within Chinese listed manufacturing firms from 2012 to 2022. Employing an econometric model, the study revealed that industrial robots significantly affect emission intensity through technological progress and innovation. Additionally, factors such as pollution levels, regional environmental regulations, ownership type, and factor intensity exhibited varying effects on pollution abatement.

Based on the resource-based view, LI et al. (2024), intelligent manufacturing, industrial structure, and competitive advantage in the product market. Empirical tests of based regression were conducted utilizing data sourced from Chinese A-share listed companies in the manufacturing sector during the period 2011-2022. The findings of the study reveal that intelligent manufacturing significantly enhances the competitive advantage of enterprises in the product market; the enhancement impact is further amplified with higher levels of industrial structure supererogation and industrial structure rationalization; mechanism tests show that intelligent manufacturing enhances competitive advantages mainly through the channels of enterprise production efficiency and information efficiency; and the influence of intelligent manufacturing on competitive advantage shows heterogeneity under different levels of regional digitization and enterprise cost pressures.

Ahmed and Kareem (2019) studied the impact of intelligent manufacturing elements on product design towards reducing production waste. The questionnaire and interview were used to collect data. A stratified sampling technique was used for 269 samples. Through Pearson correlation analysis, the survey findings indicated that among the intelligent manufacturing elements (IMEs), each intelligent device and intelligent process had a strong impact on improving product design, and hence the efficient use of manufacturing resources towards reducing manufacturing waste in industrial organizations.

2.5 Gap in Literature

Previous studies have shown that IMs is directly related to green environment (Li & Ling, 2023; Shen & Zhang, 2023; Yang & Shen, 2023; e.t.c.). However, the study of Ahmed and Kareem (2019) states that there is a significant relationship among the sub-variables: intelligent employees, intelligent processes, intelligent device, intelligent connectivity and intelligent infrastructure, but failed to adopt IT. Also, studies that investigated IM/IMs fail to look at competitive advantage and production efficiency as indicators of organisational performance. Furthermore, there are a few quantitative and empirical studies on the recent IMs. Therefore, this study examined the relationship between intelligence manufacturing system (IE and IT) and organisational performance (competitive advantage and production efficiency) to further extend the frontier of knowledge on the relationship between the variables.

3.0 Methodological Procedure

3.1 Research Design

In this study, a survey research design was used. The survey design was chosen because it provides an objective account of respondents' preferences, behaviours, and information (Marshall et al., 2025). Lagos State was chosen because it is among the states in Nigeria with the highest concentration of the manufacturing sector (Lawanson et al., 2025). This is because the manufacturing sector accounted for over 880 billion of Federal Inland Revenue Service (FIRS) in company income tax (CIT) collections in 2025, this economic sector was selected (Adigun, 2026).

The study's target population was the employees of Chi Limited who worked in the organisation's production and maintenance ICT departments. These divisions are being singled out from the rest of Chi Limited because they are those that are involved in the company's manufacturing. There are nine hundred and twenty one (921 staff) in the unit of analysis as a whole.

Table 1: No of Staff

UNITS	NO OF STAFF
Production:	860
Maintenance/ICT	61
Total	921

Source: (Human Resources Department, Chi Limited, 2026).

The study used stratified sampling techniques to select the staff. For sampling population purposes and in order to get the appropriate sample size, the researcher employed the Slovin (1960) Sample Size determination formula. The sample size selected is shown as follows:

$$n = \frac{N}{1 + N(e)^2}$$

Where:

n = Sample size

N = Total population

e = Error Margin (.5%)

$$n = \frac{921}{1+921\ (0.05)^2}$$

$$n = \frac{921}{1+921\ (0.0025)}$$

$$n = \frac{921}{1+2.3025}$$

$$n = \frac{921}{3.3025}$$

n = 279

Table 2: No of Sample

UNITS	NO OF STAFF	STRATA	SAMPLE
Production:	860	860/921 x 279	261
Maintenance/JCT	61	61/921 x 279	18
Total	921		279

Source: Author's Author's Computation (2026).

3.2 Questionnaire Administration

A questionnaire was used to collect the data. In order to properly distribute the questionnaires, 279 copies were sent out, and 210 copies from respondents were recovered and used. There were two sections to the questionnaire. To collect the data, a stratified sampling technique was applied. In Section A, respondents' demographic information was requested, and in Section B, the intelligent manufacturing system and performance of Chi Limited in Lagos State were examined using a six-point Likert-type rating system. Strongly

agree, agree, partially agree, disagree, and strongly disagree were all on a six-point scale, with corresponding values of 6, 5, 4, 3, 2, and 1 for each item. The tool used to gather data was adapted 20-item questionnaires. An instrument on IE, derived from Ahmed and Kareem (2019), consisted of five items. Although the 5-item instrument on IE was modified from Venturini (2022). Furthermore, the 5-item instruments on competitive advantage were derived from Tomalá and Olives (2022), while the 5-item instruments on production efficiency were derived from Bagshaw (2020) and Minh (2023).

3.3 Reliability of Research Instrument

Table 3: Construct Reliability for Internal Consistency

S/N	Variables	No of Items	Cronbach's Alpha
1	Intelligent employees	5	0.764
2	Intelligent technologies	5	0.796
3	Competitive advantage	5	0.788
4	Production efficiency	5	0.875

Source: Field Survey Results (2026)

Cronbach Alpha result from the above table test for Reliability of the data for the study variables through internal consistency. For all the variables that are greater than threshold of 0.7., it means that the levels of internal consistency reliability of items adequately measure the study variables (Sürücü & Maslakçı, 2020).

3.4 Validity of Research Instrument

Table 4: Construct Validity and Convergent Validity

S/N	Variables	rho_A	Composite Reliability	Average Variance Extracted (AVE)
1	Intelligent employees	0.744	0.745	0.569
2	Intelligent technologies	0.736	0.789	0.684
3	Competitive advantage	0.763	0.796	0.557
4	Production efficiency	0.758	0.778	0.545

Source: Field Survey Results (2026)

In this study, Average Variance Extracted (AVE) and Composite Reliability (CR) were employed to evaluate convergent validity. Convergent validity is the extent to which the indicators belonging to one latent variable are correlated with the same construct. The AVE is typically employed to evaluate convergent validity, which specifies how the indicators' variance can be explained by the latent variable. In order to specify convergent Validity, AVE values have to be less than the CR, and each AVE value must be greater than 0.5 (Sürücü & Maslakçı, 2020).

3.4 KMO and Bartlett's Test

Table 5: KMO and Bartlett's Test for each variable in the research instrument

Variables	KMO	Bartlett test of Sphericity
Intelligent employees	0.689	66.724 (0.000)
Intelligent technologies	0.752	76.472 (0.000)
Competitive advantage	0.793	68.668 (0.000)
Production efficiency	0.784	76.15s2 (0.000)

Source: Field Survey Results (2026)

From table above, the whole Kaiser–Meyer–Olkin (KMO) values are considered greater (greater than 0.5) and not above 1 in the exploratory factor analysis test, while Bartlett's test of Sphericity is 0.000 ($p < 0.001$), hence acceptable indices. This shows that the sampling adequacy of the study is acceptable. This indicated that the data was suitable for factor analysis and was in order for us to extract reliable factors. Correlation values are more significant than 0.5. The four correlational groups satisfactorily meet the reliability and exploratory factor analyses.

3.5 Model Specification

In order to evaluate the effect of intelligent manufacturing System (X) on organisational performance (Y), an econometric model was developed.

$Y = f(X)$ n.

Where

Y= Dependent Variable (Organisational Performance: OP)

X = Independent Variable (Intelligent Manufacturing System; IMS)

$Y = (y_1, y_2)$

$X = (x_1, x_2)$

y_1= Competitive advantage (C)

y_2= Production Efficiency (PE)

x_1= Intelligent Employees (IE)

x_2= Intelligent Technology (IT)

Hence the model was structured as such;

$y_1 = f(x_1)$

$C = \beta_0 + \beta_1 IE + \beta_2 IT_2 + \varepsilon_i$ Hypothesis one

$y_2 = f(x_2)$

$PE = \beta_0 + \beta_1 IE_1 + \beta_2 IT_2 + \varepsilon_i$ Hypothesis two

$Y = f(x_1, x_2)$

4.0 Data Analysis and Interpretation

4.1 Results of Normality Test

For the normality test of latent variables, Gawali (2023) confirmed that skewness essentially is a commonly used measure in descriptive statistics that characterizes the asymmetry of a data distribution, while kurtosis determines the heaviness of the

distribution tails. The skewness and kurtosis values are used to determine the normality of data distributions.

Table 6: Summary of Normality Tests

Construct	Dimensions	Skewness		Kurtosis	
		Statistic	Std. Error	Statistic	Std. Error
Intelligent Manufacturing System	Intelligent Employees	-1.178	.163	1. 597	.323
	Intelligent Technologies	-.880	.163	.580	.323
Organisational Performance	Competitive advantage	-.756	.163	.442	.323
	Production Efficiency	-1. 764	.163	4.432	.323

Skewness and kurtosis were used to test all variables for normality. Skewness and kurtosis should be between 0 and 1 for a substantially normal distribution. This indicates normalcy test results (Hair *et al.*, 2022).

4.2 Linearity Test

Table 7: Linearity Test Results

Independent Variables	Test Results	P-value	Conclusion
Intelligent Employees	4. 647	0.001	Linearity
Intelligent Technologies	6.899	0.001	Linearity
Overall F value	66.734	0.001	Linearity

Source: Field Survey Results (2026)

The above table presents the test of the correlations between the variables. The findings showed that a significant positive linear relationship exists between the dependent variable (organisational performance) and the sub-independent variables of Intelligent Employees and Intelligent Technologies at $p<0.05$ significance level. Hence, for the study, the assumption of linearity was achieved; the linear regression is suitable and can be estimated in this study.

4.3 Multicollinearity

The variance inflation factor (VIF) and tolerance values were used to test for multicollinearity to meet the regression assumption, as the study variables passed the normality test (Bhandari, 2023). Kyriazos and Poga (2023) equally recommended that collinearity is severe when it is below 0.1., Tolerance should be 0.1 and VIF should not exceed 5.00. VIF scores over 10 indicate multicollinearity (Bhandari, 2023). The table below shows the multicollinearity test results.

Table 4.8: Multicollinearity Test of Independent Variables

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	Intelligent Employees	.392	3.985
	Intelligent Technologies	.228	4.345
a. Dependent Variable: Competitive advantage and Production Efficiency			

Source: Field Survey Results (2026)

4.4 Restatement of Research Hypotheses

Research Hypothesis One

Table 9. Hypothesis One: Multiple Regression Results on the Effect of IMs Components on Competitive Advantage.

Model	Std. Error	Beta	T	Sig.	R	Adj. R^2	F - Value	Sig
Constant	4.235	4.235	4.88	.000	. 786 [a]	. 608	3.642	.000 [b]
Intelligent Employees	.143	.658	2.463	.000				
Intelligent Technologies	279	.678	2. 783	.000				

Dependent Variable: Competitive Advantage

Source: Authors' Computation (2026).

Hypothesis one revealed that the coefficient of multiple regression (R= .786) shows a strong positive combined effect of the IMs components (IE and IT) on competitive advantage. The adjusted coefficient of determination (Adj. R^2) of 0. 608 shows that IMs (combination of IE and IT) can only be explained by 60.8 % of variation in organisational performance. However, the model did not explain 39.2% of the variation in organisational performance, implying that there are other factors associated with organisational performance which were not captured in the model. Furthermore, it also shows the ANOVA result. The result revealed that overall, the explanatory power of the model was considered statistically significant with the F ratio output of the model reporting a p-value of .000 (F= 3.642 $p<0.05$). This indicated that intelligent manufacturing system components (intelligent employees and intelligent technologies) have positive and significant effect on the performance of organisation. Therefore, this study rejected the null hypothesis that **Ho_1:** intelligent manufacturing system components (IE and IT) have positive and significant effect on competitive advantage.

Research Hypothesis Two

Table 10. Hypothesis Two: Multiple Regression Results on the Effect of IMs Components on Production Efficiency.

Model	Std. Error	Beta	T	Sig.	R	Adj. R^2	F - Value	Sig
Constant	.154	.152	1.153	.146	.893 [a]	.790	4.963	.000 [b]
Intelligent Employees	.268	.289	18. 072	.000				
Intelligent Technologies	. 045	.983	28.845	.000				

Dependent Variable: Production Efficiency

Source: Authors' Computation (2026).

Hypothesis two revealed that the coefficient of multiple regression (R= .893) shows a strong positive combined effect of the intelligent manufacturing system components (IE and IT) on production efficiency. The adjusted coefficient of determination (Adj. R^2) of 0.79 shows that IMS (combination of IE and IT) can only be explained by 79 % of variation in

organisational performance. However, the model did not explain 21% of the variation in organisational performance, implying that there are other factors associated with organisational performance which were not captured in the model. Furthermore, it also shows the ANOVA result. The result revealed that overall, the explanatory power of the model was considered statistically significant with the F ratio output of the model reporting a p-value of .000 ($F= 4.963$, $p<0.05$). This indicated that intelligent manufacturing system components (IE and IT) have positive and significant effect on the performance of organisation. Therefore, this study rejected the null hypothesis that **Ho_2:** intelligent manufacturing system components (intelligent employees and intelligent technologies) have positive and significant effect on production efficiency.

4.3 Discussion of Findings

This study has shown from the findings that intelligent manufacturing systems play a significant role in the life of organisations. With ever-increasing market competition and advances in technology, more and more countries are prioritizing advanced and intelligent manufacturing technology as a top priority for improving product design and reducing production waste towards promoting economic growth. The findings from the study with regard to the first hypothesis: IMs do have effect on competitive advantage. The IMs elements have an influence on improving the product design towards reducing production waste in industrial organisations (Ahmed & Kareem, 2019).

The result of findings regarding the second hypothesis: IMs do have effect on production efficiency. This is consistent with Li and Ling (2023), who found that improvements in manufacturing intelligence significantly increased the efficiency of green development. In this study, it is deduced from theoretical findings that HCI plays a crucial role in shaping the way employees of an organisation interact with technology (Patadia, 2023). HCI represents usability principles and focuses on creating intuitive, efficient (production efficiency), and enjoyable experiences for users, ultimately enhancing productivity and satisfaction, by creating competitive advantage, and overall well-being as well as enjoyable interactions between humans (intelligent employees) and computers (intelligent technologies) (Patadia, 2023; Setayesh, 2023).

5.0 Conclusion and Recommendations

Manufacturing organisations operating all over the globe are facing innumerable challenges; one of the challenges in developing economies is the inability to adopt modern technology, such as IMs. The finding showed that IE has a significant effect on competitive advantage; IT are statistically significant and may be used to predict production efficiency, while organisational performance is influenced by IMs parameters. By extension, the customers' demand, competition and globalisation have turned out to be global issues and continue to have irrevocable effect on the human race and in all endeavours, while continents and nations, including Nigeria, are facing these consequences. This study concluded that IMs (IE and IT) has significant effect on organisational performance (competitive advantage, production efficiency).

This study recommended that:

i. More manufacturing businesses need to engage IMs in order to improve the competitive advantage of the organisations.

ii. Manufacturing organisations ought to embark on the adoption and expansion of IMs because it will enhance production efficiency. This is influenced by IMs parameters. Both IE and IT still need to be improved upon in this ever-changing environmental crisis.

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