Vol. 2, Iss. 3 (2025) 136-150, DOI: 10.61552/JMES.2025.03.005

JMES

Journal of Management and Engineering Sciences

www.jmes.aspur.rs

Technology Innovation and Organizational Outcomes of Manufacturing Firms in Kogi State

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Keywords:

Automated Systems
Production Efficiency
Cyber-Physical Production Systems
Artificial Intelligence
New Product Development

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Received: 29.10.2024.
Revised: 21.01.2025.
Accepted: 27.01.2025.

ABSTRACT

This study focused on technology innovation and organizational outcomes of manufacturing firms. The study examined the effect of automated systems on production efficiency, and ascertained the effect of cyber-physical production systems on productivity. The study employed survey research design. The study adopted purposive sampling, selecting 230 small manufacturing firms in Kogi State, Nigeria. A linear regression was used to evaluate the raised hypotheses. Finding showed that automated systems have a significant positive effect on production efficiency, and that cyber-physical production systems have a significant positive effect on productivity. The study concluded that technology innovation play a pivot role in enhancing the organizational outcomes of manufacturing firms. The study recommended that manufacturing firms should consider implementing automated systems to enhance their production efficiency, and that firms should explore the integration of cyber-physical production systems.

1. INTRODUCTION

Globalization has undoubtedly had a significant impact on the development of new technology, accelerating the pace of discovery and innovation. Chege et al. [1] stated that “globalization accelerates the pace of new technological developments, resulting in new discoveries on a daily basis”. Manufacturing firms have always been at the forefront of new technological developments and innovation, as technology plays a critical role in improving efficiency, reducing costs, increasing quality, improving marketing and product development. Technology innovation is a top priority in the manufacturing industry. In recent years, advancements in technology have revolutionized the way manufacturing processes are carried out. Due to the escalating competition in the market and the continuous advancements in technology, an increasing number of countries are emphasizing the significance of advanced manufacturing technology as their primary means of achieving economic growth [2].

In recent times according to Akpan et al. [3], the business environment worldwide has become more challenging and competitive. Manufacturing firms have recognized the importance of technology innovation and have been increasingly investing in research and development to stay competitive in the market. They have embraced new technologies such as automation, robotics, artificial intelligence, and IoT to improve their organizational outcome (production processes, reduce costs, and increase efficiency). Ouyang et al. [4] emphasized the crucial role of technology innovation in manufacturing firms and argued that firms must invest in research and development to stay competitive and achieve long-term success. In Europe, technology innovation is also considered a crucial factor in the success of manufacturing firms. The European Union (EU) has recognized the importance of technology innovation in driving economic growth and has implemented policies to promote research and development in the manufacturing sector [5,6]. According to a report by the European Commission [7], the adoption of new technologies like artificial intelligence, robotics, and 3D printing is essential for European manufacturing firms to improve their production processes and develop new products and services.

In Africa, the adoption of advanced technologies has become crucial for the manufacturing industry, as it allows manufacturers to improve their production processes, enhance the quality of their products, and increase their competitiveness in both local and global markets. In Tanzania, Esho and Verhoef [8] expressed that Bakhresa Group has incorporated digital technologies into its food processing operations, and this has led to improved efficiency and reduced waste. Mara Phones is a Rwandan smartphone manufacturer, and has invested in advanced manufacturing technologies such as 3D printing and robotics to produce high-quality, affordable smartphones for the African market. In Nigeria, Dangote Group has invested in state-of-the-art technologies in its manufacturing operations. The company's cement plants, for example, use advanced process control systems and automation to optimize production efficiency and reduce energy consumption. Manufacturing firms operating in the Kogi State are utilizing technology innovation to optimize their production processes, reduce operational costs, improve safe financial operation and increase productivity. By adopting advanced technologies, these firms are able to streamline their production processes, reduce human error, and increase production efficiency [9,10]. Leveraging technology innovation enables manufacturers to identify and address potential issues, resulting in fewer defects and higher product quality, increased productivity and ease of doing business among others.

Manufacturing industry in Kogi State is becoming increasingly competitive, and firms are seeking ways to remain competitive by optimizing their production processes, increasing ease of doing business, improving wider outreach, safe financial operation and productivity. The rapid advancement of technology has made technologies more accessible and affordable, making it easier for manufacturers to achieve these [11]. Technology innovation has potential benefits for manufacturing firms in Kogi State. Mubarak et al. [12] opined that technology can help manufacturing firms streamline their processes, reduce waste, and increase productivity. The introduction of new and innovative technology has the ability to make noteworthy improvements to the manufacturing process, ultimately leading to a rise in productivity and efficiency levels [13]. Technology innovation may speed up production and reduce errors for manufacturing firms in Kogi State. Manufacturing companies can enhance their production speed by integrating automated systems, which can operate continuously, generating products at a quicker rate than human workers. This increase in speed allows manufacturing companies to produce greater quantities of goods in less time, leading to a rise in output levels.

Shaji and George [14] posited that the integration of various technologies is leading to the development of cyber-physical production systems (CPS), giving rise to smart factories. Chen [2] expressed that a CPS is a system that comprises cooperative computational elements and control over physical phenomena. CPS is an advanced technology that integrates physical and computational capabilities, and can interact with people using various innovative modalities [15].

With respect to smart factories, Ryalat et al. [16] added that they are advanced manufacturing facilities that utilize cutting-edge technology such as automation, artificial intelligence, and the Internet of Things (IoT) to optimize the manufacturing process. These factories use interconnected systems and devices that can communicate and share data with each other to achieve real-time monitoring, control, and analysis of the production process.

1.1 Objectives of the Study

The objectives of the study were to:

- Examine the effect of automated systems on production efficiency;
- Ascertain the effect of cyber-physical production systems on productivity;
- Assess the effect of artificial intelligence on new product development; and
- Determine the effect of Internet of Things on competitiveness.

1.2 Research Hypotheses

The study will draw hypotheses that:

- H1: Automated systems has effect on production efficiency.
- H2: Cyber-physical production systems has effect on productivity;
- H3: Artificial intelligence has effect on new product development; and
- H4: Internet of Things has effect on competitiveness.

2. LITERATURE REVIEW

2.1 Technology Innovation

Technology innovation refers to the process of creating and implementing new technologies or improving existing technologies in order to solve problems or meet the changing needs of society. Technology innovation involves a combination of creativity, research, and development to create new products, services, or systems that can improve people's lives. Technology innovation represents a complex and dynamic process that is shaped by a convergence of influential factors. These multifaceted elements collectively propel progress in the evolving tech landscape. Among these factors, market demands play a pivotal role, with consumer needs and preferences driving companies to develop innovative solutions.

The far-reaching effect of technology innovation extends well beyond corporate boardrooms. It serves as a catalyst for economic growth, driving industries forward and creating job opportunities. Simultaneously, it enhances the quality of life for individuals through innovations that improve healthcare, transportation, communication, and countless other facets of daily life. Neligan et al. [17] posits that technology innovation's contributions to production processes and service delivery remains highly relevant. Manufacturing firms can benefit from a wide range of technological innovations that enhance efficiency, productivity, and competitiveness. Some examples of technological innovations that are particularly adoptable in manufacturing are cyber-physical production systems, Artificial Intelligence (AI), Internet of Things and automated systems, and are likely to streamline production processes, enhance new product development, production efficiency, productivity and competitiveness [18,19]. Sahoo and Lo [20] posits that AI-powered algorithms can optimize production schedules, quality control, and supply chain management, while machine learning can predict machine failures and improve quality. High-tech inspection systems, including computer vision and AI-based quality control, can enhance product quality and reduce defects.

2.2 Organizational Outcomes

Organizational outcomes refer to the results or achievement of an organization as a consequence of its activities, strategies, and processes. These outcomes are often used to measure the effectiveness and efficiency of an organization in achieving its goals [21,22]. They can encompass a wide range of metrics, including financial performance, customer satisfaction, employee engagement, and operational efficiency. Organizational outcomes provide a comprehensive view of an organization’s health and success, guiding strategic decision-making and continuous improvement efforts.

New product development is the process of bringing a new product to the market [23,24]. It is essential in organizational outcomes as it reflects an organization's innovation capability and responsiveness to market demands. Production efficiency is the extent to which an organization can maximize output while minimizing input, particularly in terms of cost, time, and resources [25]. Production efficiency is a core measure of operational excellence and cost-effectiveness. Organizations can enhance profitability, reduce waste, and lower production costs by implementing high production efficiency. It also ensures the optimal utilization of resources and promotes sustainable practices, which are essential in a competitive market.

Productivity is the ratio of output to input in an organization's production process [26]. It assesses the effectiveness of resource utilization in the production of products. Enhanced productivity results in a higher output with the same or fewer resources, which in turn contributes to increased profitability and competitive positioning.

Competitiveness is the ability of an organization to maintain and gain market share in its industry by offering superior products, services, or processes compared to its rivals [27]. It is essential for long-term survival and success in the market [28,29]. Organizations that consistently achieve competitive outcomes are more likely to thrive in dynamic and challenging business environments.

2.3 Conceptual Framework

The conceptual framework (Fig. 1) demonstrates the hypothetical effect of the proxies of technological innovation on organizational outcomes. Firstly, it show the possibility of automated systems enhancing production efficiency, leading to fastered turnaround times and improved quality. Secondly, cyber-physical production systems integrate physical processes with computational resources, promoting real-time data exchange and responsive manufacturing [30,31]. This integration can significantly boost productivity by enabling adaptive processes and resource optimization. Thirdly, the role of artificial intelligence in new product development is transformative; AI facilitates data-driven decision-making, accelerates design iterations, and enhances market analysis, fostering innovative solutions that meet consumer demands efficiently [32,33]. Lastly, the Internet of Things (IoT) enhances organizational competitiveness by enabling connectivity and real-time monitoring across systems [34-36]. This capability allows for improved supply chain management, predictive maintenance, and enhanced customer engagement, positioning organizations to respond swiftly to market changes.

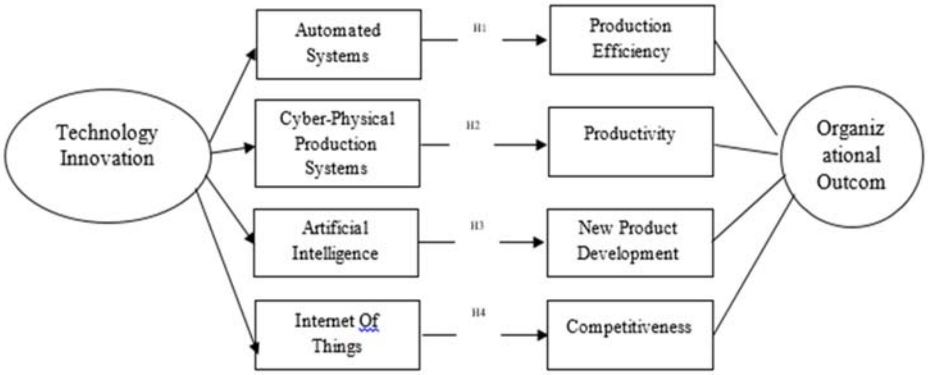

Fig. 1. Conceptual Framework of Technology Innovation and Organizational Outcomes [Source: The Researcher (2024)].

3. METHODOLOGY

This study employed survey research design. The study adopted purposive sampling, selecting 230 small manufacturing firms in Kogi State, Nigeria. Data were gathered through the use of questionnaire, and constructs were measured using 5-point Likert Scale. Effort was made to cover diverse small manufacturing firms from different industries. The survey took approximately 32 weeks with the researchers asserting effort to avoid default in the instrument. Validity and reliability of the instrument was achieved as shown in Table 1.

Table 1. Validity and reliability of the instrument [Source: Pre-field, 2024].

Indicator Variable	Loading	AVE	CR	CA(α)
ATS1	0.721	0.564	0.751	0.701
ATS2	0.812			
ATS3	0.782			
ATS4	0.725			
ATS5	0.71			
CPS1	0.712	0.557	0.746	0.728
CPS2	0.711			
CPS3	0.787			
CPS4	0.704			
CPS5	0.811			
AIE1	0.781	0.616	0.785	0.704
AIE2	0.762			
AIE3	0.702			
AIE4	0.824			
AIE5	0.848			
IOT1	0.822	0.636	0.797	0.724
IOT2	0.772			
IOT3	0.879			
IOT4	0.745			
IOT5	0.761			
PDE1	0.81	0.624	0.790	0.780
PDE2	0.79			
PDE3	0.7			
PDE4	0.787			
PDE5	0.856			
PDY1	0.832	0.626	0.791	0.782
PDY2	0.716			
PDY3	0.872			
PDY4	0.786			
PDY5	0.741			
NPD1	0.829	0.630	0.794	0.790
NPD2	0.827			
NPD3	0.827			
NPD4	0.743			
NPD5	0.736			
COM1	0.941	0.649	0.806	0.912
COM2	0.766			
COM3	0.827			
COM4	0.735			
COM5	0.742			

The instrument's validity and reliability are confirmed across all constructs, including Automated Systems (ATS), Cyber-Physical Systems (CPS), Artificial Intelligence (AIE), Internet of Things (IOT), Production Efficiency (PDE), Productivity (PDY), New Product Development (NPD), and Competitiveness (COM). Each construct meets the required thresholds for Average Variance Extracted (AVE ≥ 0.5), Composite Reliability (CR ≥ 0.7), and Cronbach's Alpha (CA ≥ 0.7), while all indicator loadings exceed 0.7. These results demonstrate the instrument's strong internal consistency and the constructs' ability to capture their intended dimensions, ensuring robustness and suitability for further analysis. The quantitative analysis of the study incorporated both descriptive and inferential statistics. A linear regression was used to evaluate the raised hypotheses. All hypotheses were examined at a 5% significance level using EVIEW 12 software.

The testing of the hypotheses was directed by regression models, which were formulated in accordance with the objectives as follows:

$$PDE = \beta 0 + \beta 1ATS + \varepsilon \quad (1)$$

$$PDY = \beta_0 + \beta_1 CPS + \varepsilon \quad (2)$$

$$NPD = \beta 0 + \beta_1 AIE + \varepsilon \quad (3)$$

$$COM = \beta 0 + \beta_1 IOT + \varepsilon \quad (4)$$

Where: ATS= Automated Systems, PDE= Production Efficiency, CPS= Cyber-Physical Production Systems, PDY= Productivity, AIE= Artificial Intelligence, NPD= New Product Development, IOT= Internet of Things, COM= Competitiveness, and ε= Stochastic Error Term.

4. DATA ANALYSES AND RESULTS

Table 2 presents the age distribution of respondents. There were 41 respondents (17.8%) below 18 years old, 90 respondents (39.1%) between 18-21 years old, 33 respondents (14.3%) between 22-25 years old, 32 respondents (13.9%) between 26-29 years old, 26 respondents (11.3%) between 30-33 years old, and 8 respondents (3.5%) between 34-37 years old. The table shows that the majority of respondents fall into the 18-21 years age group, with smaller proportions in other age brackets.

The table presents the marital status distribution of respondents. There were 154 single respondents (67.0%), 22 married respondents (9.6%), 39 widowed respondents (17.0%), 11 separated respondents (4.8%), and 4 divorced respondents (1.7%). The table shows that the majority of respondents were single, followed by widowed, with smaller proportions being married, separated, or divorced.

Table 2 Demographic Characteristics of Respondents [Source: Field Survey (2024)].

Category	Responses	Frequency	Percent
Gender	Male	163	70.9
	Female	67	29.1
Age	Below 18 years	41	17.8
	18-21 years	90	39.1
	22-25 years	33	14.3
	26-29 years	32	13.9
	30-33 years	26	11.3
	34-37 years	8	3.5
Marital Status	Single	154	67.0
	Married	22	9.6
	Widow(er)	39	17.0
	Separated	11	4.8
	Divorced	4	1.7
Educational Level	Primary School Leaving Cert.	49	21.3
	Secondary School Certificate	64	27.8
	OND & Equivalence	54	23.5
	B.Sc/HND & above	62	27.0
Experience	Below 1 Year	41	17.8
	1-3 years	59	25.7
	4-6 years	63	27.4
	7-9 years	49	21.3
	10-12 years	14	6.1
	13-15 years	4	1.7

The table shows the education level distribution of respondents in the study. There were 49 respondents (21.3%) with a Primary School Leaving Certificate, 64 respondents (27.8%) with a Secondary School Certificate, 54 respondents (23.5%) with OND or its equivalence, and 62 respondents (27.0%) with B.Sc./HND or higher qualifications. The results show that the majority held Secondary School Certificates and B.Sc./HND qualifications, with fewer respondents holding OND or Primary School Leaving Certificates.

The table presents the work experience distribution of respondents. There were 41 respondents (17.8%) with below 1 year of experience, 59 respondents (25.7%) with 1-3 years, 63 respondents (27.4%) with 4-6 years, 49 respondents (21.3%) with 7-9 years, 14 respondents (6.1%) with 10-12 years, and 4 respondents (1.7%) with 13-15 years. The table shows that the majority of respondents have between 1 and 9 years of work experience, with smaller proportions having less than 1 year or more than 10 years of experience.

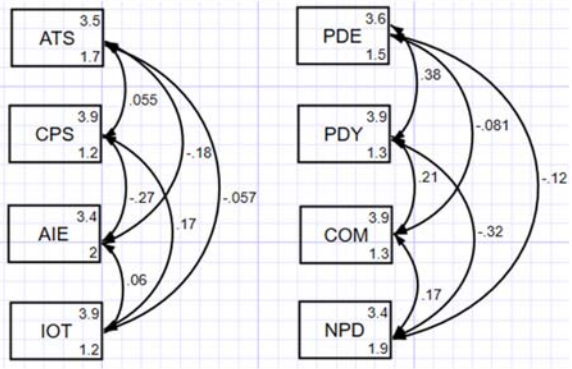

Fig. 2 Covariances of Technology Innovation and Organizational Outcomes[Source: STATA 64]

Table 3 shows the results of the Satorra-Bentler Test of Covariances on various dimensions of technology innovation and organizational outcomes in manufacturing firms. The mean score for Automated Systems (ATS) is 3.548, indicating a moderately high level of effectiveness in integrating automated processes within production systems. The t-value of 40.76 is extremely high, and the p-value less than 0.01 demonstrates statistical significance. The confidence interval [3.377, 3.718] shows a high level of precision in this estimate. The mean score for Cyber-Physical Production Systems (CPS) is 3.948, implying a high level of integration of advanced monitoring and control systems within production environments. The t-value of 54.60 and p-value less than 0.01 confirm statistical significance. The confidence interval [3.806, 4.090] reflects a precise estimate. The mean score for Artificial Intelligence (AIE) is 3.383, indicating a moderately high perception of AI's impact on production processes. The t-value of 36.03 and p-value less than 0.01 demonstrate statistical significance. The confidence interval [3.199, 3.567] shows a high degree of precision in the estimate. The mean score for Internet of Things (IOT) is 3.922, indicating a high level of perceived integration of IoT technologies into manufacturing processes. The t-value of 53.54 and p-value less than 0.01 show statistical significance. The confidence interval [3.778, 4.065] demonstrates a precise estimate.

Table 3 Satorra-Bentler Test of Covariances [Source: STATA 6].

Variable	Mean	Standard Error	t-Value	p-Value	95% Confidence Interval (Lower Bound)	
mean(ATS)	3.548	0.087	40.760	0.000	3.377	3.718
mean(CPS)	3.948	0.072	54.600	0.000	3.806	4.090
mean(AIE)	3.383	0.094	36.030	0.000	3.199	3.567
mean(IOT)	3.922	0.073	53.540	0.000	3.778	4.065
mean(PDE)	3.578	0.082	43.890	0.000	3.418	3.738
mean(PDY)	3.922	0.074	52.980	0.000	3.777	4.067
mean(COM)	3.891	0.074	52.240	0.000	3.745	4.037
mean(NPD)	3.383	0.092	36.830	0.000	3.203	3.563
cov(ATS, CPS)	0.055	0.099	0.550	0.580	-0.139	0.249
cov(ATS, AIE)	-0.179	0.118	-1.520	0.129	-0.410	0.052
cov(ATS, IOT)	-0.057	0.091	-0.630	0.532	-0.236	0.122
cov(CPS, AIE)	-0.267	0.088	-3.020	0.003	-0.440	-0.094
cov(CPS, IOT)	0.170	0.074	2.300	0.022	0.025	0.315
cov(AIE, IOT)	0.060	0.106	0.570	0.569	-0.147	0.268
cov(PDE, PDY)	0.380	0.110	3.440	0.001	0.164	0.596
cov(PDE, COM)	-0.081	0.088	-0.910	0.361	-0.254	0.093
cov(PDE, NPD)	-0.121	0.109	-1.110	0.267	-0.336	0.093
cov(PDY, COM)	0.209	0.084	2.490	0.013	0.045	0.373
cov(PDY, NPD)	-0.318	0.090	-3.550	0.000	-0.494	-0.142
cov(COM, NPD)	0.168	0.104	1.610	0.108	-0.037	0.372

The mean score for Production Efficiency (PDE) is 3.578, implying a moderately high perception of the efficiency of production processes. The t-value of 43.89 and p-value less than 0.01 confirm statistical significance. The confidence interval [3.418, 3.738] indicates a precise estimate. The mean score for Productivity (PDY) is 3.922, indicating a high perception of productivity levels within manufacturing firms. The t-value of 52.98 and p-value less than 0.01 signify statistical significance. The confidence interval [3.777, 4.067] shows a precise estimate. The mean score for Competitiveness (COM) is 3.891, reflecting a high level of perceived competitive advantage. The t-value of 52.24 and p-value less than 0.01 confirm statistical significance. The confidence interval [3.745, 4.037] reflects a precise estimate. The mean score for New Product Development (NPD) is 3.383, suggesting a moderately high level of perceived effectiveness in developing new products. The t-value of 36.83 and p-value less than 0.01 demonstrate statistical significance. The confidence interval [3.203, 3.563] shows a high degree of precision in the estimate.

The table also highlights covariances among these dimensions. For instance, the covariance between ATS and CPS is 0.055, which is not statistically significant (p-value= 0.580), indicating no meaningful covariance between these constructs. Similarly, the covariance between ATS and AIE is -0.179, which is not statistically significant (p-value= 0.129), showing no meaningful relationship between these dimensions. The covariance between ATS and IOT is -0.057, also not statistically significant (p-value= 0.532), indicating no substantial relationship.

Conversely, the covariance between CPS and AIE is -0.267, which is statistically significant (p-value= 0.003). This negative relationship suggests that increased integration of CPS may correlate with a reduced focus on AI integration within some contexts. The covariance between CPS and IOT is 0.170, statistically significant (p-value= 0.022), indicating a positive and moderate relationship between these constructs.

Additional significant covariances include PDE and PDY (0.380, p-value= 0.001), suggesting that higher production efficiency is positively associated with higher productivity. Similarly, PDY and COM exhibit a positive and statistically significant covariance (0.209, p-value= 0.013), implying that increased productivity enhances competitiveness. However, covariances between PDE and COM (-0.081, p-value= 0.361) and PDE and NPD (-0.121, p-value= 0.267) are not statistically significant, indicating no meaningful relationships between these constructs. The results suggest credible data, as most covariances remain below 0.5, indicating no autocorrelation or redundancy issues.

Table 4 Regression analysis on effect of automated systems on production efficiency [Source: EViews 12].

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.386753	0.156922	8.837201	0.0000
ATS	0.674077	0.041465	16.25635	0.0000
R-squared	0.536838	Mean dependent var		3.778261
Adjusted R-squared	0.534807	S.D. dependent var		1.214345
S.E. of regression	0.828245	Akaike info criterion		2.469642
Sum squared resid	156.4056	Schwarz criterion		2.499538
Log likelihood	-282.0088	Hannan-Quinn criter.		2.481701
F-statistic	264.2688	Durbin-Watson stat		2.124565
Prob (F-statistic)	0.000000			

Table 4 presents the effect of automated systems on production efficiency in manufacturing firms. The R-squared value is 0.536838, suggesting that approximately 53.7% of the variation in production efficiency is explained by the implementation of automated systems. This indicates a moderate relationship between the two variables, with the remaining 46.3% of the variation being attributed to other factors not included in the model. The Adjusted R-squared value is 0.534807, indicating that the model is well-fitted, as the small difference between the R-squared and adjusted R-squared values shows that the explanatory power is not inflated by unnecessary predictors.

The Standard Error of the Regression is 0.828245, which represents the typical distance that the observed values fall from the regression line. This relatively low value suggests a good fit of the model. The Sum of Squared Residuals is 156.4056, which measures the total deviation of the observed values from the fitted values. The Model Selection Criteria include the Akaike Information Criterion (AIC) of 2.469642, the Schwarz Criterion (SIC) of 2.499538, and the Hannan-Quinn Criterion of 2.481701. These values indicate that the model is reasonably well-fitted, as lower values of these criteria suggest a better model fit.

The F-statistic is 264.2688, with a p-value of 0.000000, indicating that the overall regression model is statistically significant. This suggests that the independent variable, automated systems, significantly explains the variation in production efficiency. The Durbin-Watson statistic is 2.124565, which is close to 2, indicating that there is no significant autocorrelation in the residuals of the model.

The coefficient for the constant term (C) is 1.386753, with a standard error of 0.156922. The t-statistic is 8.837201, and the associated p-value is 0.0000, indicating that the constant term is statistically significant at the 1% level. The coefficient for automated systems is 0.674077, with a standard error of 0.041465. The t-statistic is 16.25635, and the p-value is 0.0000, which is highly statistically significant. This implies that for each unit increase in the implementation of automated systems, production efficiency increases by approximately 0.674077 units, holding other factors constant. The results show a strong and statistically significant positive relationship between automated systems and production efficiency. This suggests that the adoption of automated systems in manufacturing firms leads to substantial improvements in production efficiency.

Table 5 Regression analysis of effect of cyber-physical production systems on productivity [Source: EViews 12].

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	1.172745	0.162044	7.237220	0.0000
CPS	0.724248	0.040772	17.76334	0.0000
R-squared	0.580525	Mean dependent var		3.921739
Adjusted R-squared	0.578685	S.D. dependent var		1.122597
S.E. of regression	0.728664	Akaike info criterion		2.213450
Sum squared resid	121.0569	Schwarz criterion		2.243346
Log likelihood	-252.5468	Hannan-Quinn criter.		2.225510
F-statistic	315.5361	Durbin-Watson stat		1.696789
Prob(F-statistic)	0.000000			

Table 5 presents the effect of cyber-physical production systems on productivity in manufacturing firms. The R-squared value is 0.580525, indicating that approximately 58.1% of the variation in productivity is explained by the implementation of cyber-physical production systems. This suggests a moderately strong relationship, with the remaining 41.9% of the variation attributed to other variables not captured by the model. The Adjusted R-squared value is 0.578685, which accounts for the number of predictors in the model, and the small difference between the R-squared and adjusted R-squared indicates that the model is well-fitted.

The Standard Error of the Regression is 0.728664, which indicates the typical distance that the observed values fall from the regression line. A smaller standard error reflects a better fit of the model. The Sum of Squared Residuals is 121.0569, measuring the total deviation of the observed values from the predicted values. The Model Selection Criteria show the Akaike Information Criterion (AIC) as 2.213450, the Schwarz Criterion (SIC) as 2.243346, and the Hannan-Quinn Criterion as 2.225510, suggesting that the model is appropriately selected, with lower values indicating a better fit.

The F-statistic is 315.5361, with a p-value of 0.000000, indicating that the overall regression model is statistically significant. This means that the independent variable, cyber-physical production systems, significantly explains the variation in productivity. The Durbin-Watson statistic is 1.696789, which is close to 2, indicating no significant autocorrelation in the residuals.

The coefficient for the constant term (C) is 1.172745, with a standard error of 0.162044. The t-statistic is 7.237220, and the p-value is 0.0000, indicating that the constant term is statistically significant at the 1% level. The coefficient for cyber-physical production systems is 0.724248, with a standard error of 0.040772. The t-statistic is 17.76334, and the p-value is 0.0000, showing that the coefficient is highly statistically significant. This suggests that for each unit increase in the implementation of cyber-physical production systems, productivity increases by approximately 0.724248 units, holding other factors constant. The results show a strong and statistically significant positive relationship between cyber-physical production systems and productivity. This indicates that the adoption of cyber-physical systems in manufacturing firms contributes to significant improvements in productivity.

Table 6 examines the effect of artificial intelligence on new product development in manufacturing firms. The R-squared value is 0.727076, indicating that approximately 72.7% of the variation in new product development is explained by the use of artificial intelligence. This is a strong relationship, with the remaining 27.3% of the variation explained by other factors. The Adjusted R-squared value is 0.725878, which adjusts for the number of predictors in the model. The small difference between the R-squared and adjusted R-squared suggests that the model is well-fitted.

The Standard Error of the Regression is 0.738002, reflecting the typical distance that observed values fall from the regression line. A smaller standard error indicates a better fit of the model. The Sum of Squared Residuals is 124.1795, which measures the total deviation of the response values from the predicted values. The Model Selection Criteria show the Akaike Information Criterion (AIC) at 2.238917, the Schwarz Criterion (SIC) at 2.268813, and the Hannan-Quinn Criterion at 2.250976, suggesting a good fit as lower values indicate a better model selection.

Table 6 Regression analysis of effect of artificial intelligence on new product development [Source: EViews 12].

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	0.728217	0.118669	6.136547	0.0000
AIE	0.832442	0.033777	24.64540	0.0000
R-squared	0.727076	Mean dependent var		3.395652
Adjusted R-squared	0.725878	S.D. dependent var		1.409568
S.E. of regression	0.738002	Akaike info criterion		2.238917
Sum squared resid	124.1795	Schwarz criterion		2.268813
Log likelihood	-255.4754	Hannan-Quinn criter.		2.250976
F-statistic	607.3959	Durbin-Watson stat		1.636482
Prob(F-statistic)	0.000000			

The F-statistic is 607.3959, with a p-value of 0.000000, indicating that the overall regression model is statistically significant. This means that artificial intelligence significantly contributes to explaining new product development. The Durbin-Watson statistic is 1.636482, which is close to 2, indicating no significant autocorrelation in the residuals of the model.

The coefficient for the constant term (C) is 0.728217, with a standard error of 0.118669. The t-statistic is 6.136547, and the p-value is 0.0000, indicating that the constant term is statistically significant. The coefficient for artificial intelligence is 0.832442, with a standard error of 0.033777. The t-statistic is 24.64540, and the p-value is 0.0000, indicating a highly significant relationship. This means that for each unit increase in artificial intelligence usage, new product development increases by approximately 0.832442 units, holding other factors constant. The results indicate a robust and statistically significant positive relationship between artificial intelligence and new product development. The adoption of artificial intelligence significantly enhances new product development in manufacturing firms.

Table 7 Regression analysis of effect of Internet of Things on competitiveness [Source: EViews 12].

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	1.281726	0.159049	8.058707	0.0000
IOT	0.696291	0.040359	17.25253	0.0000
R-squared	0.566251	Mean dependent var		3.891304
Adjusted R-squared	0.564349	S.D. dependent var		1.129754
S.E. of regression	0.745681	Akaike info criterion		2.259620
Sum squared resid	126.7772	Schwarz criterion		2.289517
Log likelihood	-257.8563	Hannan-Quinn criter.		2.271680
F-statistic	297.6499	Durbin-Watson stat		1.562416
Prob(F-statistic)	0.000000			

Table 7 examines the effect of the Internet of Things (IoT) on competitiveness in manufacturing firms. The R-squared value is 0.566251, meaning that approximately 56.6% of the variation in competitiveness is explained by the use of IoT. This indicates a moderate relationship, with the remaining 43.4% of the variation attributed to other factors. The Adjusted R-squared value is 0.564349, which takes into account the number of predictors in the model. The small difference between R-squared and adjusted R-squared suggests that the model is well-specified and not overly influenced by irrelevant predictors.

The Standard Error of the Regression is 0.745681, reflecting the typical distance between the observed values and the predicted values. A lower value indicates a better fit of the model. The Sum of Squared Residuals is 126.7772, which represents the total deviation of the response values from the predicted values. The Model Selection Criteria indicate the Akaike Information Criterion (AIC) at 2.259620, the Schwarz Criterion (SIC) at 2.289517, and the Hannan-Quinn Criterion at 2.271680, with lower values suggesting a better-fitting model.

The F-statistic is 297.6499, with a p-value of 0.000000, indicating that the overall regression model is statistically significant. This suggests that IoT significantly explains variations in competitiveness. The Durbin-Watson statistic is 1.562416, which is close to 2, indicating no significant autocorrelation in the residuals of the model.

The coefficient for the constant term (C) is 1.281726, with a standard error of 0.159049. The t-statistic is 8.058707, and the p-value is 0.0000, indicating that the constant term is statistically significant. The coefficient for IoT is 0.696291, with a standard error of 0.040359. The t-statistic is 17.25253, and the p-value is 0.0000, showing a highly significant relationship. This implies that for each unit increase in IoT adoption, competitiveness increases by approximately 0.696291 units, holding other factors constant. The results indicate a robust and statistically significant positive relationship between IoT and competitiveness. The adoption of IoT significantly enhances competitiveness in manufacturing firms.

5. DISCUSSIONS

Finding showed that automated systems has a significant positive effect on production efficiency. This implies that the integration of automated systems into manufacturing processes can significantly enhance the efficiency of production operations. By automating routine tasks and optimizing workflows, firms can achieve higher output with fewer resources, reducing human error and minimizing downtime. The positive effect highlights the importance of embracing technological innovations to streamline production processes and increase productivity. This finding aligns with Technology Acceptance Model, which suggests that the adoption of technology, such as automated systems, improves operational efficiency by facilitating smoother and more efficient work processes. It also supports the work of researchers like [37,38], who found that automation significantly improves manufacturing efficiency by enhancing precision and reducing operational costs. What distinguishes this study is its specific focus on automated systems within manufacturing firms, directly linking them to production efficiency. Previous studies often examined automation in broader industries, but few have concentrated on its application and impact specifically on manufacturing productivity. The current study, therefore, extends this body of research by emphasizing the critical role that automated systems play in optimizing manufacturing operations and driving productivity improvements.

Finding showed that cyber-physical production systems has a significant positive effect on productivity. This implies that the integration of cyber-physical systems, which combine computational elements and physical processes, into production systems can significantly boost productivity. By leveraging sensors, data analytics, and automated control systems, CPPS optimize production flows, enhance real-time decision-making, and improve the responsiveness and efficiency of manufacturing processes. This can lead to higher output, better resource utilization, and reduced waste, all contributing to increased overall productivity. This finding is supported by Industry 4.0 frameworks [39,40], which emphasize the role of cyber-physical systems in advancing manufacturing processes. As highlighted by [41,42], CPPS enable seamless interaction between the physical and digital worlds, allowing for more intelligent and efficient production systems. These systems enhance machine-to-machine communication, real-time data analysis, and adaptive control, thereby increasing production speed and minimizing operational disruptions.

Finding showed that artificial intelligence has a significant positive effect on new product development. This implies that integrating AI into the product development process can greatly accelerate innovation, improve product design, and enhance the overall development cycle. AI can analyze large amounts of data, predict market trends, automate design processes, and optimize product features based on customer preferences. This technological advancement allows firms to create innovative products that meet consumer needs more effectively and efficiently. The significant positive impact of AI on new product development aligns with previous research, such as that by [43,44], who found that AI technologies, including machine learning and natural language processing, play a key role in enabling faster and more accurate decision-making throughout the product development cycle. By using AI to identify patterns and insights from large datasets, companies can generate ideas, test prototypes, and predict the success of new products in the market before investing heavily in development.

Finding showed that Internet of Things has a significant positive effect on competitiveness. This implies that firms that adopt and integrate IoT technologies are likely to enhance their competitive advantage in the market. IoT enables businesses to collect, analyze, and act on real-time data from connected devices, leading to improvements in decision-making, operational efficiency, and customer service. These enhancements allow firms to be more agile, responsive to market changes, and innovative in their offerings. This significant positive effect of IoT on competitiveness aligns with previous research, such as [45,46], which emphasize the critical role of IoT in enabling firms to optimize their operations and create new value propositions. By using IoT to monitor and optimize supply chains, track customer behavior, and improve product performance, companies can reduce operational costs and increase their market share, which in turn enhances their competitive position.

6. CONCLUSION

In conclusion, this study unveiled the pivotal role of technological innovation in enhancing the organizational outcomes of manufacturing firms. The study highlight that the implementation of automated systems leads to significant gains in production efficiency, while cyber-physical production systems are instrumental in boosting overall productivity. Furthermore, the integration of artificial intelligence facilitates the development of innovative products, thereby driving growth and competitiveness. Lastly, the Internet of Things emerges as a critical factor in enhancing the competitive edge of these firms. Collectively, these emphasize the necessity for manufacturing firms to embrace technological advancements to thrive in an increasingly competitive landscape.

7. RECOMMENDATIONS

The study makes the following recommendations that:

- Manufacturing firms should consider implementing automated systems to enhance their production efficiency. By embracing automation, firms can streamline processes, reduce errors, and increase their competitiveness in the market.
- Manufacturing firms should explore the integration of cyber-physical production systems. By leveraging these advanced technologies, firms can optimize their operations, improve real-time monitoring, and boost overall efficiency.
- The top management of manufacturing firms should leverage artificial intelligence to enhance their new product development processes. By utilizing AI-driven automation, firms can accelerate time-to-market and improve the quality of their products.
- The top management and decision makers of manufacturing firms should invest in Internet of Things (IoT) technologies, as this will have positive impact on competitiveness. By harnessing IoT solutions, firms can gain real-time insights, improve operational efficiency, and enhance customer experiences, ultimately positioning themselves ahead of their competitors.

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