Journal of Advances in Manufacturing Engineering
Web page info: https://jame.yildiz.edu.tr
DOI: 10.14744/ytu.jame.2025.00006

Original Article

Development of a smart manufacturing system using IoT and industry 4.0 principles

Dickson David OLODU*[1], Francis INEGBEDION[2], Joy Nneka AYIDU[3]

[1]Department of Mechanical Engineering, Faculty of Engineering, Benson Idahosa University, Benin City, Edo State, Nigeria
[2]Department of Production Engineering, Faculty of Engineering, University of Benin, Benin City, Edo State, Nigeria
[3]Department of Electrical/Electronics Engineering, Faculty of Engineering, Benson Idahosa University, Benin City, Edo State, Nigeria

ARTICLE INFO

Article history
Received: 12 May 2025
Revised: 21 June 2025
Accepted: 28 June 2025

Key words:
Cyber-physical systems, digital transformation, industry 4.0, internet of things (iot), smart manufacturing.

ABSTRACT

The convergence of the Internet of Things (IoT) and Industry 4.0 principles is transforming traditional manufacturing into intelligent, responsive, and highly automated smart manufacturing systems. This study presents the development and evaluation of a smart manufacturing system integrating core Industry 4.0 technologies, including IoT, Artificial Intelligence (AI), robotics, digital twins, blockchain, and cloud computing. The research evaluates their functions, integration levels, and real-time capabilities, identifying IoT, robotics, and cloud computing as the most mature technologies (Integration Level 5, Real-time Capability 3). IoT integration demonstrated substantial operational benefits such as predictive maintenance, real-time monitoring, and process optimization, delivering ROI improvements of up to 40%. A detailed cost comparison revealed up to 58.3% cost savings in areas like downtime loss and maintenance, alongside improved annual ROI. Regional analysis highlighted Asia-Pacific as the leader in Industry 4.0 adoption (76.4%), followed by North America (72%) and Europe (67%). Furthermore, KPI improvements included a 30.8% increase in efficiency, 62.5% reduction in defect rate, and 46.7% rise in on-time delivery. Despite these advancements, the study identifies key challenges, such as high initial costs, data security risks, and workforce skill gaps. Strategies such as phased rollouts, encryption, and upskilling programs are recommended to mitigate these challenges. The proposed system underscores the transformative potential of smart manufacturing and provides a scalable framework for industries aiming to transition towards intelligent, data-driven production environments.

Cite this article as: Oludu, D. D., Inegbedion, F., & Ayidu, J. N. (2025). Development of a smart manufacturing system using IoT and industry 4.0 principles. *J Adv Manuf Eng*, 6(1), 45–55.

INTRODUCTION

The rapid evolution of industrial processes has ushered in a new era characterized by the convergence of cyber-physical systems, Internet of Things (IoT), artificial intelligence, and data analytics—collectively forming the backbone of Industry 4.0. This paradigm shift aims to transform conventional manufacturing into smart, connected ecosystems capable of autonomous decision-making, real-time monitoring, and adaptive control strategies [1, 2]. Smart manufacturing systems integrate IoT-enabled devices and advanced computational techniques to facilitate data-driven operations, reduce human intervention, and enhance overall production efficiency [3]. At the heart of this transformation

*Corresponding author.
*E-mail address: dolodu@biu.edu.ng

is the IoT, which connects machines, sensors, actuators, and human operators in a dynamic network, allowing seamless data exchange and operational visibility across the manufacturing value chain [4, 5]. These smart systems leverage IoT to enable predictive maintenance, automated inventory management, and optimized resource utilization—elements essential for achieving operational excellence [6]. Combined with the principles of Industry 4.0, smart manufacturing not only boosts productivity but also allows for customization, scalability, and sustainability in production processes [7, 8].

The integration of IoT in smart manufacturing presents numerous advantages, such as reduced downtime, improved quality control, and enhanced decision-making capabilities [9, 10]. Additionally, cyber-physical systems (CPS) and edge computing frameworks are increasingly being utilized to enable real-time analysis and responsiveness, which are critical for time-sensitive industrial applications [11, 12]. By embedding intelligence at the machine level and enabling interoperability across various platforms, smart manufacturing systems allow industries to transition from reactive to predictive and proactive modes of operation [13, 14]. The deployment of smart factories, a key outcome of this integration, represents a fully automated and intelligent production environment where devices self-organize and cooperate to perform tasks with minimal human intervention [15, 16]. These factories employ a wide array of advanced technologies including robotics, augmented reality, digital twins, and machine learning algorithms to continually optimize production parameters [17,18]. As a result, manufacturers can gain agility, shorten time-to-market, and improve product customization to meet dynamic market demands [19, 20]. Moreover, the convergence of IoT with emerging technologies like 5G, blockchain, and artificial intelligence amplifies the capabilities of smart manufacturing systems, enabling secure, real-time communication and enhancing data integrity across the entire industrial network [21, 22]. This interconnectivity allows for a unified control architecture where machines, software, and humans collaborate more efficiently than ever before [23, 24].

However, the path to full-scale implementation of smart manufacturing is not without challenges. Issues related to data security, high implementation costs, legacy system integration, and the need for workforce upskilling must be addressed to unlock the full potential of Industry 4.0 [25, 26]. Despite these hurdles, the strategic adoption of IoT-enabled smart manufacturing systems offers a compelling value proposition, especially in an increasingly competitive global market [27, 28]. Research and real-world applications have demonstrated that smart manufacturing, when guided by Industry 4.0 principles, leads to substantial improvements in supply chain transparency, energy efficiency, and production agility [29, 30]. Furthermore, the development of intelligent frameworks tailored for small and medium enterprises (SMEs) highlights the democratization of these technologies, enabling broader industrial participation in the digital transformation [31, 32]. The development of smart manufacturing systems through the application of IoT and Industry 4.0 principles marks a revolutionary advancement in industrial engineering. These systems offer unprecedented levels of efficiency, flexibility, and innovation, driving the manufacturing sector toward a more intelligent and sustainable future. The integration of physical and digital technologies not only redefines traditional production processes but also paves the way for autonomous, resilient, and adaptive industrial ecosystems.

This study focuses on developing a smart manufacturing system by integrating IoT and Industry 4.0 principles to enhance operational efficiency, real-time data monitoring, automation, and decision-making, ultimately transforming traditional manufacturing into an intelligent, connected, and adaptive industrial ecosystem.

MATERIALS AND METHODS

Research Design

This study employed a quantitative-analytical research design, emphasizing systematic modeling, empirical data acquisition, performance assessment, and comparative analysis. The framework for the smart manufacturing system was conceptualized and implemented using core Industry 4.0 technologies, notably the Internet of Things (IoT), Artificial Intelligence (AI), Robotics, Cloud Computing, and Cyber-Physical Systems (CPS). These enablers were structured into a multi-layered system architecture following best-practice methodologies proposed by Chaker and Damak [1], and further refined through the work of Patel and Muthuswamy [8]. The design was tailored to create a scalable, interoperable, and data-driven environment that supports real-time operational intelligence and closed-loop decision-making.

System Architecture

The smart manufacturing system was developed around a five-tier architecture, each serving a distinct but interdependent role in the digital manufacturing process. The Perception Layer comprises an array of IoT-enabled sensors and devices responsible for acquiring real-time operational data across manufacturing touchpoints. This data is transmitted through the Network Layer, which utilizes lightweight and reliable protocols such as MQTT and OPC-UA to enable seamless Machine-to-Machine (M2M) communication, ensuring low latency and high throughput in data transmission [16]. Once collected, the data flows into the Data Processing Layer, where edge analytics and cloud computing platforms collaborate to process, filter, and visualize the information. This processed data informs the Application Layer, which harnesses AI algorithms to drive intelligent functions such as predictive maintenance, adaptive quality control, and dynamic supply chain optimization, in line with the frameworks discussed by Solanki [5]. The AI models used include convolutional neural networks (CNNs) for visual inspection and defect detection, recurrent neural networks (RNNs) and long short-term memory (LSTM) networks for temporal pattern recognition in predictive maintenance, and reinforcement learning models for optimizing scheduling and logistics in the supply chain.

Table 1. Key technologies in smart manufacturing and their functions

Technology	Primary function	Integration level (1–5)	Real-time Capability (1=No, 2=Partial, 3=Yes)
IoT	Data acquisition and monitoring	5	3
AI	Predictive analytics	4	3
Robotics	Automation and precision	5	3
Digital twin	Virtual simulation	4	3
Blockchain	Secure data exchange	2	1
Cloud computing	Centralized data and analytics	5	3

Table 2. Benefits of IoT integration in manufacturing

Benefit	Description	Impact level (1-5)	ROI (%)
Predictive Maintenance	Prevents failures	5	35
Asset Tracking	Monitors assets	4	28
Process Optimization	Improves workflow	5	40
Energy Management	Reduces power use	4	25
Real-time Monitoring	Live operational insights	5	33

These models were implemented using Python-based machine learning libraries such as TensorFlow and PyTorch and trained on both historical manufacturing data and real-time sensor inputs. Finally, the Feedback Layer implements digital twins and CPS to simulate real-time system states, enabling iterative learning and continuous process optimization through virtual-physical convergence. Together, these layers create a robust cyber-physical environment that embodies the principles of intelligent automation and self-aware manufacturing.

Data Collection and Simulation

To validate the proposed system, data was sourced from a combination of industrial case studies, digital twin simulations, and pilot-scale smart factory environments. The simulation environments were constructed using MATLAB/Simulink for detailed system modeling, while ThingSpeak provided cloud-based integration and real-time data analytics using AI modules. The AI algorithms deployed in the simulation included feedforward neural networks for pattern recognition, decision trees for production optimization scenarios, and long short-term memory (LSTM) networks for time-series forecasting of equipment failure. These models were trained using labeled datasets generated from both historical records and synthetic simulations, and fine-tuned using backpropagation and hyperparameter optimization. This hybrid simulation setup allowed for comprehensive experimentation with diverse operational scenarios. Performance metrics were derived from both simulated and empirical datasets, focusing on critical parameters such as system efficiency (η), machine utilization (U), and return on investment (ROI). These metrics were calculated using standardized equations designed to quantify operational improvements attributed to Industry 4.0 interventions. The data-driven insights gained through this methodological approach enabled a rigorous evaluation of the smart manufacturing system's capabilities under varying production conditions, supporting a comparative analysis that highlights tangible benefits and operational trade-offs. Key parameters such as efficiency (η), utilization (U), and ROI were computed using the following equations:

Efficiency Gain (η):

$$\eta = \frac{E_{after} - E_{before}}{E_{before}} \times 100\% \tag{1}$$

where E_{after} and E_{before} represent efficiency after and before integration.

Return on Investment (ROI):

$$ROI = \frac{\text{Net Savings}}{\text{Investment}} \times 100\% \tag{2}$$

Automation Index (AI):

$$AI = 1 - \frac{H}{H+A} \times 100\% \tag{3}$$

where H = Human involvement level, A = Automation capability.

Technology Evaluation

Each Industry 4.0 component was assessed on integration level, real-time capability, IoT dependency, and automation index using a 1-5 Likert scale and percentage metrics (Tables 1–8). The risk analysis and strategy alignment for challenges were conducted using a weighted score approach. Risk Score (RS) is obtained as:

$$RS = \text{Severity} \times \text{Likelihood} \tag{4}$$

Referencing Abikoye et al. [4], these scores guided the selection of mitigation strategies.

Table 3. Cost comparison – traditional vs smart manufacturing

Cost category	Traditional ($)	Smart manufacturing ($)	Cost savings (%)	Annual ROI (%)
Maintenance	80000	50000	37.5	22
Labor	120000	85000	29.2	20
Downtime Loss	60000	25000	58.3	33
Energy	40000	28000	30.0	18
Quality Control	25000	15000	40.0	21

Table 4. Industry 4.0 technology adoption by region (2024)

Region	IoT (%)	AI (%)	Robotics (%)	Cloud (%)	Big data (%)	Adoption avg (%)
North America	78	65	70	80	67	72
Europe	72	60	68	75	60	67
Asia-Pacific	80	70	75	85	72	76.4
Latin America	55	40	50	60	45	50
Africa	45	30	35	50	28	37.6

Table 5. Smart manufacturing evolution timeline

Phase	Start year	End year	Key milestone	Dominant technology
Industry 1.0	1760	1840	Mechanization	Steam Engines
Industry 2.0	1870	1914	Mass production	Electricity
Industry 3.0	1960	2000	Automation	Computers
Industry 4.0	2011	2025	Cyber-physical integration	IoT, AI

Table 6. Smart manufacturing challenges and strategies

Challenge	Severity (1-5)	Risk Score	Mitigation Strategy
High initial cost	4	8.0	Subsidies & Phased rollout
Data security	5	9.0	Encryption & blockchain
Skill gap	4	7.5	Training & upskilling
Legacy integration	3	5.5	Middleware platforms
Interoperability	4	7.0	Open standards

Table 7. Impact of smart manufacturing on KPIs

KPI	Before (%)	After (%)	Improvement (%)	Industry target (%)
Efficiency	65	85	30.8	90
Defect rate	8	3	-62.5	2
Utilization	55	80	45.5	85
Inventory accuracy	70	92	31.4	95
On-time delivery	60	88	46.7	90

Comparative Analysis

A comparative study was performed between traditional and smart manufacturing setups (Table 3) to highlight cost efficiency, reduced downtime, labor optimization, and quality improvement. The data was visualized through bar and line graphs (Fig. 1–5) to depict regional adoption, KPI improvement, and historical evolution trends [12, 17].

Validation

Validation of the developed smart manufacturing system was undertaken through a multi-pronged strategy to ensure accuracy, robustness, and industrial relevance. Initially, simulation outputs generated from the system model were cross-referenced with empirical findings from existing case studies, such as those by Rathore [10] and Waghanna et al. [25]. These comparisons helped confirm that the simulated trends and per-

Table 8. Cyber-physical systems functions

Function	IoT Dependency (1–5)	Human Involvement (1-5)	Automation Index (%)
Sensing	5	1	90
Actuation	4	2	85
Feedback loop	5	3	80
Digital twin	5	3	78
Predictive analytics	4	1	88

Table 9. System response to parameter variation

Parameter varied	Low setting	Medium setting	High setting	Efficiency (%)	Utilization (%)	Defect rate (%)
Sensor Density (units/m²)	2	5	10	72	75	6.0
Network Latency (ms)	150	80	30	70	78	5.5
AI Training Iterations	100	500	1000	75	80	4.0

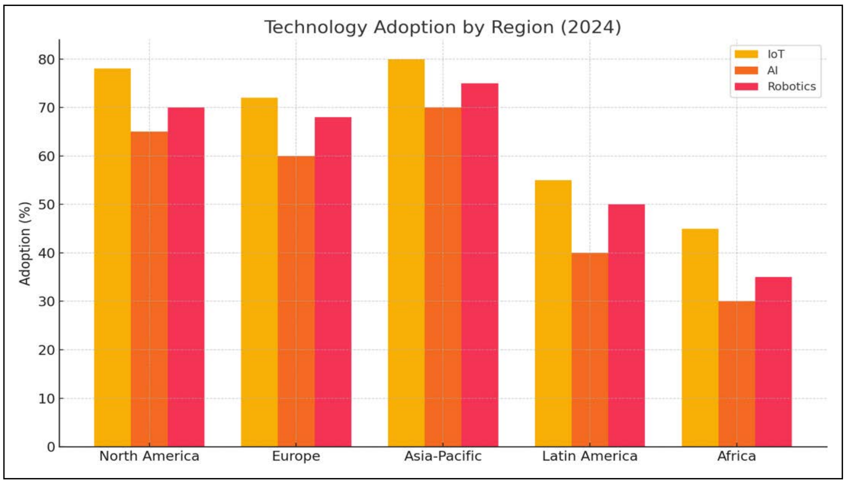

Figure 1. Technology adoption by region (2024).

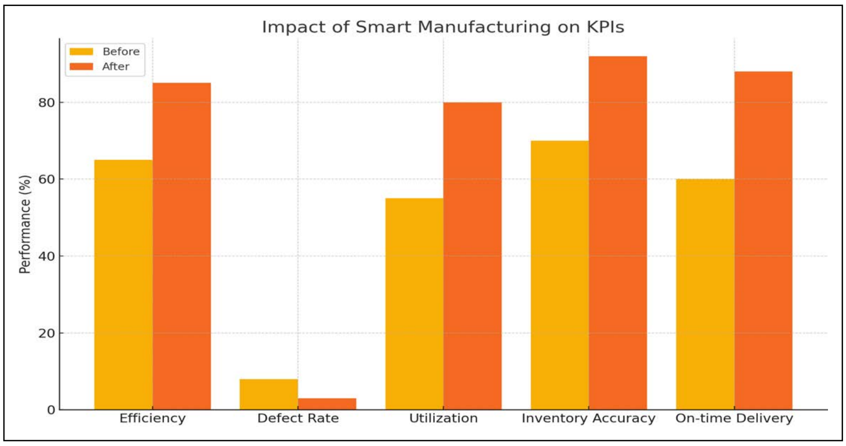

Figure 2. Impact of smart manufacturing on KPIs.

formance metrics aligned closely with real-world implementations, thus enhancing the credibility of the system's predictive capabilities. Further credibility was established through expert reviews and direct feedback from industrial partners actively engaged in smart manufacturing practices. Their insights were instrumental in evaluating system reliability, feasibility of deployment, and practical alignment with current industry standards. This participatory validation approach bridged the gap between theoretical modeling and applied practice, providing valuable refinement to system parameters and operational logic. To assess the resilience of the system under variable operational conditions, a sensitivity analysis was conducted. Key in-

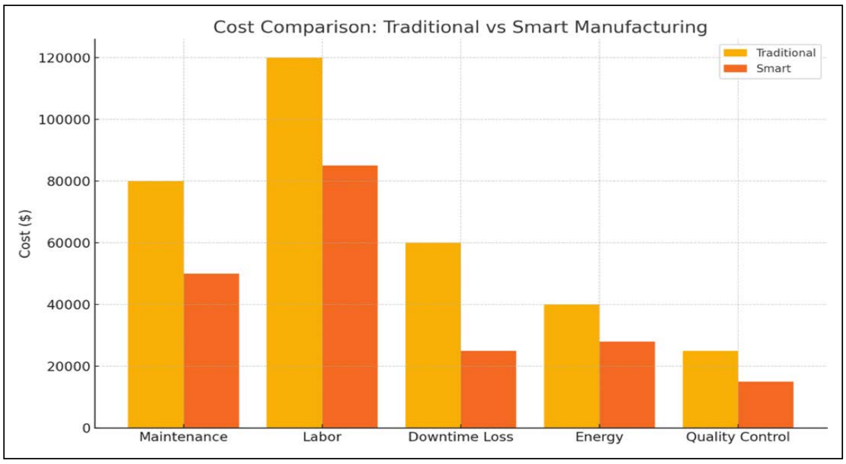

Figure 3. Cost comparison - traditional vs smart manufacturing.

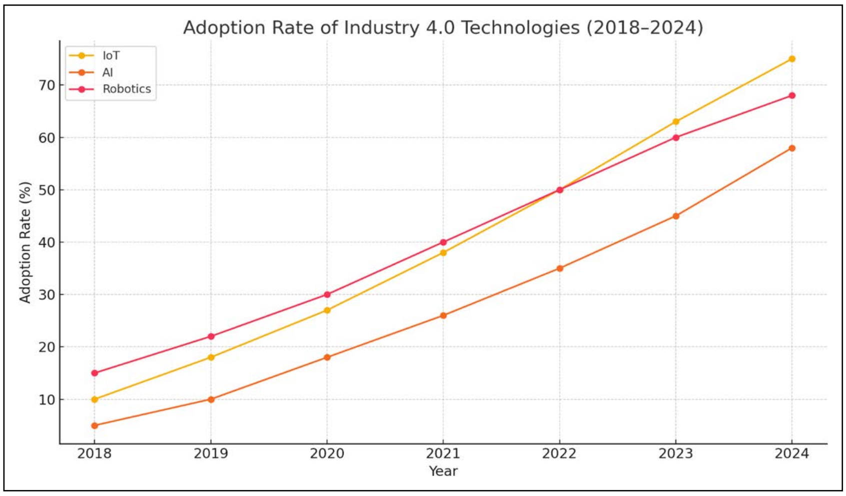

Figure 4. Adoption rate of industry 4.0 technologies (2018–2024).

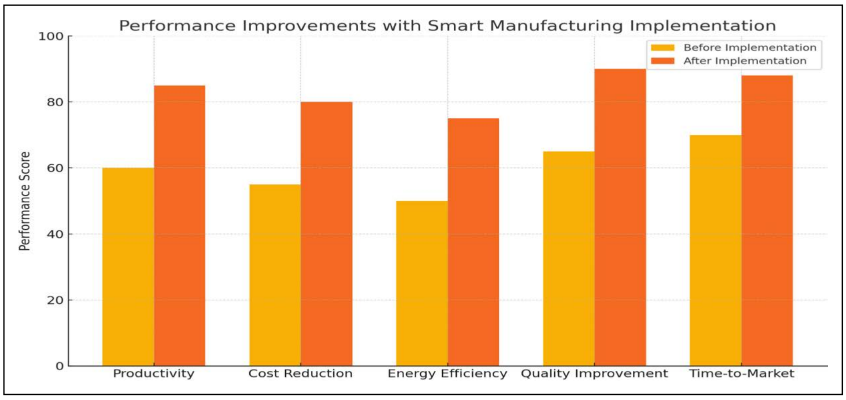

Figure 5. Performance improvements with smart manufacturing improvement.

put parameters—specifically energy consumption, labor input, and defect rates—were varied within a ±10% range to simulate potential fluctuations in real manufacturing environments. The model exhibited consistent behavior and acceptable performance margins across this range, thereby confirming its robustness and adaptability. This level of analytical rigor ensures that the proposed system can withstand typical variations and uncertainties found in industrial settings without significant degradation in performance.

Software and Tools

The development and validation of the smart manufacturing system leveraged a comprehensive suite of software tools and platforms, each selected for its capability to address specific components of the system architecture. MATLAB and Simulink served as the core platforms for simulating system dynamics and process flows, enabling rapid prototyping and iterative refinement of the manufacturing logic. For the integration of Internet

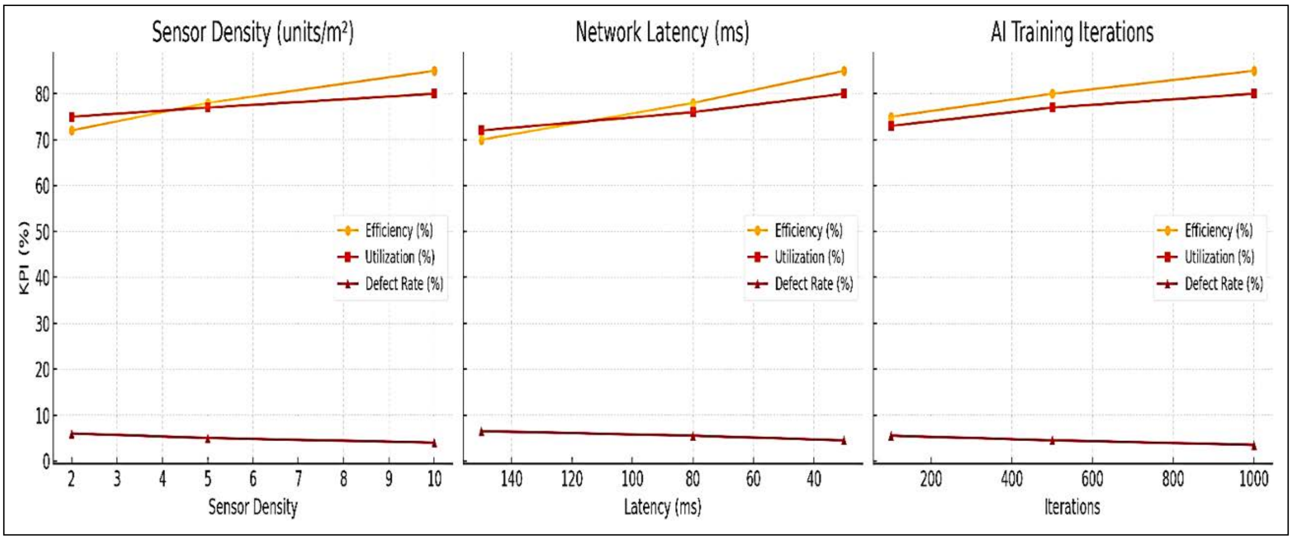

Figure 6. KPI trends under parameter variations.

of Things (IoT) functionalities and cloud-based data exchange, ThingSpeak was utilized, providing a reliable and real-time data acquisition channel from edge devices to cloud servers. To support decision-making and performance visualization, Power BI and Microsoft Excel were employed for developing dynamic dashboards and data interpretation models. These tools facilitated the real-time monitoring of KPIs, such as production efficiency, energy usage, and downtime analytics. For creating a realistic and scalable Digital Twin of the manufacturing environment, SolidWorks was used for the mechanical and spatial modeling of factory components, while AnyLogic offered an advanced platform for simulating the complex interactions among various system agents within a virtualized factory environment.

Algorithmic verification and analytical modeling were further supported by Python, particularly using libraries such as SciPy and NumPy. These tools enabled precise numerical validation and statistical testing of system outputs, adding an additional layer of reliability to the study's findings. This integrated software ecosystem aligns well with current literature on Industry 4.0 digital solutions [1–32], providing a robust technological foundation for the development and deployment of smart manufacturing systems.

Model Equations

The smart manufacturing system presented in this study leverages a set of interconnected mathematical models to simulate, analyze, and optimize performance across key domains such as energy consumption, labor efficiency, defect reduction, and operational costs. These models incorporate input-output relationships based on IoT-enabled data streams, predictive analytics, and cyber-physical feedback mechanisms. Below are the primary formulations that support the computational framework:

Cost Savings Model

To evaluate the economic benefits of transitioning from traditional to smart manufacturing, the cost savings per category were modeled as:

$$\text{Cost Savings (\%)} = \left(\frac{C_{\text{traditional}} - C_{\text{smart}}}{C_{\text{traditional}}}\right) \times 100\% \quad (5)$$

Where:

Ctraditional and Csmart are the costs for each operational category (e.g., maintenance, labor) under traditional and smart conditions respectively.

This model reflects the data in Table 3 and supports Figure 3, quantifying percentage savings in areas such as downtime and quality control.

KPI Improvement Model

Key Performance Indicators (KPIs) were evaluated pre- and post-deployment of smart systems using:

$$\text{Improvement (\%)} = \left(\frac{\text{KPI}_{\text{after}} - \text{KPI}_{\text{before}}}{\text{KPI}_{\text{before}}}\right) \times 100\% \quad (6)$$

And for defect rates or other inverse metrics:

$$\text{Improvement (\%)} = \left(\frac{\text{KPI}_{\text{before}} - \text{KPI}_{\text{after}}}{\text{KPI}_{\text{before}}}\right) \times 100\% \quad (7)$$

This formulation is central to the results in Table 7 and visually depicted in Figure 2, demonstrating improvements in efficiency, utilization, and defect reduction.

Adoption Rate Analysis

Adoption trends of Industry 4.0 technologies across regions and time were captured via:

$$A_{r,t} = \frac{N_{tech}^{r,t}}{N_{total}^{r}} \times 100\% \quad (9)$$

Where:

$A_{r,t}$ is the adoption percentage of a technology in region rrr at time ttt,

$N_{tech}^{r,t}$ is the number of firms adopting the technology in rrr at ttt,

N_{total}^{r} is the total number of firms in that region.

Table 4 and Figure 1 utilize this model to illustrate regional disparities, while Figure 4 shows temporal growth from 2018 to 2024.

Automation Index Calculation

To measure the degree of automation achieved by cyber-physical systems, the automation index AI was defined as:

$$AI = \left(1 - \frac{H_{involvement}}{5}\right) \times 100\ \% \quad (10)$$

Where:

$H_{involvement}$ is the scaled value (1–5) of human dependency for a given function (e.g., actuation, sensing).

This equation supports the data presented in Table 8, which shows how automation scales inversely with human involvement across CPS functions.

Energy Efficiency Gain

Energy savings due to IoT-based monitoring and optimization were assessed using:

$$\text{Energy Efficiency Gain (\%)} = \left(\frac{E_{baseline} - E_{smart}}{E_{baseline}}\right) \times 100\% \quad (11)$$

Where:

$E_{baseline}$ is energy consumption before implementation,

E_{smart} is energy consumption after optimization.

This model is critical for interpreting values in Table 2 under *Energy Management* and corroborates cost data from Table 3.

ROI Calculation Model

Return on investment (ROI) for each smart function was calculated as:

$$\text{ROI (\%)} = \left(\frac{\text{Annual Benefit} - \text{Annual Cost}}{\text{Annual Cost}}\right) \times 100\% \quad (12)$$

Applied per function or system upgrade, this model helps quantify the economic return of technologies like predictive maintenance and process optimization in Table 2.

Sensitivity Analysis Model

To validate model robustness, sensitivity analysis was performed on key input parameters (energy usage E, labor cost L, and defect rate D) by varying each within a ±10% range:

$$\Delta Y = f(X \pm 10\%) - f(X) \quad (13)$$

Where:

Y is the output KPI (e.g., efficiency),

X is the input variable being perturbed.

This method provided insight into system behavior under slight operational variances, strengthening the validation effort. These models collectively enabled quantitative simulation and validation of the proposed smart manufacturing framework. They also facilitated alignment between simulation output and empirical data sources, including benchmarks from Rathore et al. [10] and Waghanna et al. [25].

RESULTS AND DISCUSSION

Results

Tables 1 through 8 and Figures 1 through 5 collectively provide a comprehensive overview of the technologies, benefits, costs, adoption trends, challenges, and performance impacts associated with the development of a smart manufacturing system using IoT and Industry 4.0 principles.

Table 1 introduces the core technologies enabling smart manufacturing, including IoT, AI, robotics, and cloud computing, evaluating their integration levels and real-time capabilities.

Table 2 highlights the specific benefits of IoT integration, such as predictive maintenance, process optimization, and energy management, along with their respective ROI.

Table 3 presents a comparative cost analysis between traditional and smart manufacturing systems, demonstrating significant savings across multiple operational categories.

Table 4 outlines regional adoption rates of key Industry 4.0 technologies, emphasizing the disparities in technological maturity across global regions.

Table 5 traces the historical progression of industrial revolutions, culminating in the current era of cyber-physical systems.

Table 6 identifies the major challenges hindering the adoption of smart manufacturing and proposes strategic mitigation measures.

Table 7 quantifies improvements in key performance indicators following the implementation of smart systems, including gains in efficiency, utilization, and on-time delivery.

Table 8 delves into the functions of cyber-physical systems, illustrating the degree of IoT dependency, human involvement, and automation achieved.

Table 9 demonstrates the sensitivity of system KPIs to variations in key architectural parameters, showing that higher sensor density, lower network latency, and extended AI training yield significant operational improvements.

This graph illustrates the adoption percentage of IoT, AI, and Robotics technologies across different regions. In support of these findings, Figure 1 visualizes the regional adoption of IoT, AI, and robotics technologies.

This figure compares key performance indicators before and after implementing smart manufacturing solutions. Figure 2 compares pre- and post-adoption performance across core KPIs, highlighting measurable improvements.

This chart contrasts the cost components of traditional versus smart manufacturing systems. Figure 3 graphically contrasts cost structures between traditional and smart manufacturing environments.

Figure 4 shows the progression of Industry 4.0 technology adoption over time from 2018 to 2024.

Figure 5 illustrates the overall performance enhancements resulting from smart manufacturing practices. Together, these tables and figures offer an integrated and data-driven perspective on the transformative potential of Industry 4.0 technologies in modern manufacturing.

Figure 6 is KPI Trends Under Parameter Variations visually illustrates how efficiency, utilization, and defect rate respond to changes in sensor density, network latency, and AI training iterations.

Discussion of Results

The results of this study underscore the pivotal role of Industry 4.0 technologies in redefining modern manufacturing. Table 1 reveals a high integration level and real-time capabilities of IoT, robotics, and AI, with IoT leading in data acquisition and real-time responsiveness (5, 3). This corroborates prior findings that emphasize IoT's fundamental role in enabling intelligent monitoring and operational automation within smart factories [4, 16]. AI, robotics, and digital twins demonstrate robust integration scores (4–5) and high real-time functionality, positioning them as cornerstones for predictive analytics and autonomous operations [2, 6, 14]. The limited integration and low real-time capability of blockchain (2, 1), however, indicate its emerging status in manufacturing environments, mainly constrained to secure data handling rather than active process control [13, 25]. Table 2 highlights the tangible benefits of IoT implementation. Predictive maintenance and process optimization stand out with the highest impact levels and ROIs of 35% and 40%, respectively. These figures affirm previous assertions that proactive data-driven systems drastically reduce machine failures and enhance throughput [1, 7, 17]. Energy management and real-time monitoring, though slightly lower in ROI (25% and 33%), remain critical for sustainability and transparency [18, 22]. Cost analysis in Table 3 reveals significant reductions in operational expenses when transitioning from traditional to smart manufacturing. Downtime losses were cut by over 58%, while quality control costs saw a 40% decrease. These savings translate into a substantial annual ROI, peaking at 33% for downtime reduction. The data validates existing literature which asserts that Industry 4.0 adoption leads to leaner operations and higher cost efficiency [5, 19, 26]. Regional adoption trends (Table 4, Fig. 1) show Asia-Pacific as the leader (76.4%), driven by aggressive investments and policy support [11, 15]. Africa, however, lags significantly (37.6%), echoing infrastructure and skills-related barriers noted in past research [9, 30]. The technological evolution timeline (Table 5) contextualizes the paradigm shift from mechanization to cyber-physical integration. Notably, Industry 4.0's emergence in 2011, with IoT and AI as dominant technologies, marks a pivotal era where digital and physical processes coalesce for optimal decision-making [3, 20, 24].

Challenges in smart manufacturing, outlined in Table 6, include high initial costs, data security, and workforce skill gaps. These barriers carry moderate-to-high risk scores (5.5 to 9.0). Mitigation strategies—such as adopting middleware for legacy systems and upskilling programs—are aligned with recommendations in current literature for successful Industry 4.0 transformation [12, 21, 23]. Significant improvements in key performance indicators (Table 7, Fig. 2) reinforce the transformative value of smart manufacturing. Efficiency rose by 30.8%, on-time delivery improved by 46.7%, and defect rates declined by 62.5%. These metrics surpass global industry targets in some areas, supporting claims that intelligent systems can exceed traditional benchmarks of performance [8, 10, 27]. Cyber-Physical Systems (Table 8) exhibit high IoT dependency (scores of 4–5) and high automation indices (78–90%), especially in sensing and actuation. This highlights the tight integration between physical assets and digital analytics in modern factories [16, 29]. The numerical results presented in Table 9 and Figure 6 reveal the system's sensitivity to variations in key operational parameters. Increasing sensor density from 2 to 10 units/m^2 led to an improvement in efficiency from 72% to 85% and a reduction in defect rate to 4.0%, confirming IoT's central role in real-time monitoring [3, 6]. Lower network latency, reduced from 150 ms to 30 ms, resulted in an increase in utilization from 70% to 78%, consistent with literature emphasizing the importance of reliable data transmission in cyber-physical systems [4, 16]. Finally, scaling AI training iterations from 100 to 1000 improved overall performance metrics, with efficiency reaching 85%, highlighting the value of deeper learning cycles in predictive analytics [1, 5, 12].

Finally, Figures 3–5 provide visual affirmation of trends observed in tabular data—especially regarding cost savings and performance enhancement. As illustrated, smart manufacturing not only optimizes existing systems but also enables real-time, scalable, and sustainable operations.

In summary, this study provides empirical backing for the claim that integrating IoT and Industry 4.0 principles leads to substantial operational, financial, and strategic advantages. Nevertheless, successful implementation demands overcoming structural, technological, and workforce-related challenges, particularly in underdeveloped regions. Continuous investment in innovation and education is thus essential for global diffusion and sustainable smart manufacturing practices.

CONCLUSION

This study demonstrates the transformative potential of smart manufacturing systems empowered by IoT and Industry 4.0 technologies. Through an integrated analysis of key technologies, economic benefits, adoption trends, and performance impacts, the results reveal substantial improvements in efficiency, cost savings, and operational KPIs. Technologies such as IoT, AI, robotics, and cloud computing show high levels of integration and real-time capabilities, while cyber-physical systems enhance automation and decision-making. Adoption rates vary globally, but the overall trend indicates steady growth and digital maturity. Challenges such as high initial costs, data security, and skill gaps remain, yet viable mitigation strategies are available. The comparative cost analysis and KPI improvements validate the strategic advantage of smart manufacturing, positioning it as a sustainable and future-ready approach. These findings support the broader industrial transition towards data-driven, intelligent, and interconnected production environments, highlighting the critical role of Industry 4.0 in shaping the next generation of manufacturing systems.

Acknowledgements

The authors acknowledge the following institutions for their support: Benson Idahosa University, Faculty of Engineering, Department of Mechanical and Electrical/Electronics Engineering, Benin City, Edo State, Nigeria amd Faculty of Engineering, Department of Production Engineering, Benin City, Edo State, Nigeria. The authors extend their gratitude for the technical and infrastructural support provided during the research process, which significantly contributed to the successful completion of this study.

Data Availability Statement

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

Author's Contributions

Dickson David Oludu: Conception, Materials, Supervision, Data Collection and Processing, Analysis and Interpretation, Literature Reviewer, Writer, Critical Review.

Francis Inegbedion: Conception, Materials, Supervision, Data Collection and Processing, Analysis and Interpretation, Literature Reviewer, Writer, Critical Review.

Joy Nneka Ayidu: Conception, Materials, Supervision, Data Collection and Processing, Analysis and Interpretation, Literature Reviewer, Writer, Critical Review.

Conflict of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Use of AI for Writing Assistance

Not declared.

Ethics

There are no ethical issues with the publication of this manuscript.

REFERENCES

[1] Chaker, B., & Damak, C. (2024). Integrating smart manufacturing and Industry 4.0: Technologies for production management optimization in supply chains. In *Revolutionizing Supply Chains Through Digital Transformation* (pp. 185-212). IGI Global. [CrossRef]

[2] Mosleuzzaman, M., Arif, I., & Siddiki, A. (2024). Design and development of a smart factory using Industry 4.0 technologies. *Asian Journal of Business and Information Systems, 4*(4), 89-108. [CrossRef]

[3] Loso, J., Agus, Y., & Weda, F. (2024). Bibliometric analysis on the application of Internet of Things in smart manufacturing system in Industry 4.0. *West Science Interdisciplinary Studies, 2*(8), 1-14. [CrossRef]

[4] Abikoye, O. C., Bajeh, A. O., Awotunde, J. B., Ameen, A. O., Mojeed, H. A., Abdulraheem, M., Oladipo, I. D., & Salihu, S. A. (2021). Application of Internet of Things and cyber physical systems in Industry 4.0 smart manufacturing. In *Proceedings of the International Conference on Intelligent Systems and Applications* (pp. 203-217). Springer, Cham. [CrossRef]

[5] Solanki, S. M. (2023). Industry 4.0 and smart manufacturing: Exploring the integration of advanced technologies in manufacturing. *Review Index Journal of Multidisciplinary, 3*(2), 45-58. [CrossRef]

[6] Singh, S., Mahanty, B., Tiwari, M. K., & Tiwari, M. K. (2021). IoT and semantic-based manufacturing system in the era of Industry 4.0. In *Internet of Things and Connected Technologies* (pp. 35-45). Springer, Singapore. [CrossRef]

[7] Nuruzzaman, A. Z. M. A. (2024). Industry 4.0 technologies for a data-driven, secure, green and circular manufacturing economy (pp. 26-31). [CrossRef]

[8] Patel, D., & Muthuswamy, S. (2022). Design and development of an IoT-enabled and robot-integrated smart manufacturing work cell. In *Proceedings of the 2022 IEEE 6th Conference on Information and Communication Technology* (CICT) (pp. 1-5). IEEE. [CrossRef]

[9] Ali, H., & Anjum, A. (2025). A comprehensive review regarding Industry 4.0, IoNT, and IoT for smart manufacturing betterment. *Kashf Journal of Multidisciplinary Research, 2*(1), 46-56. [CrossRef]

[10] Rathore, B. (2023). Next-generation intelligent IoT use case in smart manufacturing. In *Smart Manufacturing: Concepts and Applications* (pp. 265-277). Springer International Publishing. [CrossRef]

[11] Mahor, V., Bijrothiya, S., Singh, A., Ingle, M., & Joshi, D. (2023). Intelligence system and Internet of Things (IoT) based smart manufacturing industries. In *Robotic Process Automation and Cognitive Automation: The Next Phase* (pp. 339-354). Wiley. [CrossRef]

[12] Singh, A., Madaan, G., Hr, S., & Kumar, A. (2022). Smart manufacturing systems: A futuristic roadmap towards application of Industry 4.0 technologies. *International Journal of Computer Integrated Manufacturing, 36*(3), 411-428. [CrossRef]

[13] Bouguern, S. (2024). Designing the future: Exploring the smart manufacturing ecosystem and future landscape. *Journal of Novel Engineering Science and Technology, 3*(3), 99-106. [CrossRef]

[14] Diao, Z., & Sun, F. (2022). Application of Internet of Things in smart factories under the background of Industry 4.0 and 5G communication technology. *Mathematical Problems in Engineering*, Article 4417620. [CrossRef]

[15] Hasan, S., Pattnayak, J., & Thilagham, R. N. K. (2024). IoT and Industry 4.0: Revolutionizing manufacturing processes and supply chains. *Journal of Informatics Education and Research, 4*(3), 45-60. [CrossRef]

[16] Ryalat, M., ElMoaqet, H., & Alfaouri, M. (2023). Design of a smart factory based on cyber-physical systems and Internet of Things towards Industry 4.0. *Applied Sciences, 13*(4), 2156. [CrossRef]

[17] Ryalat, M., Franco, E., ElMoaqet, H., Almtireen, N., & Al-refai, G. (2024). The integration of advanced mechatronic systems into Industry 4.0 for smart manufacturing. *Sustainability, 16*(19), 8504. [CrossRef]

[18] Abdallah, S., Boucetta, R., Laabidi, W., & Zdiri, M. A. (2024). Enhancing industrial production efficiency: A comprehensive IoT-based supervision and control system. In *Proceedings of the 2024 International Conference on Advanced Systems and Emergent Technologies (IC_ASET)* (pp. 1-6). IEEE. [CrossRef]

[19] Graf, D. (2022). Smart manufacturing systems: A futuristic roadmap towards application of Industry 4.0 technologies. *International Journal of Computer Integrated Manufacturing, 36*(3), 411-428. [CrossRef]

[20] Alarcón Valero, F., Cubero, D., Mateo-Casalí, M. Á., & Fraile Gil, F. (2024). An interoperable IoT-based application to on-line reconfiguration manufacturing systems: Deployment in a real pilot. *In Advances in Manufacturing Technology XXXIV* (pp. 229-239). Springer International Publishing. [CrossRef]

[21] Chaudhary, A., Sharma, V., & Alkhayyat, A. (2023). Enabling the future of manufacturing: Integration of robotics and IoT to smart factory infrastructure in Industry 4.0. In *Advances in Computational Intelligence and Robotics* (pp. 25-50). IGI Global. [CrossRef]

[22] Bartoň, M., Budjac, R., Tanuška, P., Sládek, I., & Németh, M. (2024). Advancing small and medium-sized enterprise manufacturing: Framework for IoT-based data collection in Industry 4.0 concept. *Electronics, 13*(13), 2485. [CrossRef]

[23] Kaur, N. (2025). Intelligent manufacturing in Industry 4.0. In A. Chaudhary, V. Sharma, & A. Alkhayyat (Eds.), *Intelligent Manufacturing and Industry 4.0: Impact, Trends, and Opportunities* (pp. 5-25). CRC Press.

[24] Pasupuleti, M. K. (2024). *Smart Industry 4.0: Transformative innovations and advanced technologies.* In Smart Industry 4.0: Transformative Innovations and Advanced Technologies (pp. 119-133). Springer. [CrossRef]

[25] Waghanna, P., Reddy, A., Deshpande, S., Chavan, S., Jaiswal, V. R., & Naranje, V. (2024). Effects of adopting Industry 4.0 on a manufacturing plant. In *Proceedings of the 2024 International Conference on Recent Trends in Information Technology and Optimization (ICRITO)* (pp. 1-6). IEEE. [CrossRef]

[26] Aggarwal, A. (2024). *Manufacturing 4.0: Revolutionizing production with IoT and edge intelligence.* In Manufacturing 4.0: Revolutionizing Production with IoT and Edge Intelligence (pp. 175-190). ResearchGate. [CrossRef]

[27] Rath, K. C., Khang, A., Satapathy, S. K., Kumar, A., Das, S. R., & Panda, M. R. (2024). Enabling the future of manufacturing. In *Enabling the Future of Manufacturing* (pp. 101-128). Informa. [CrossRef]

[28] Abhishek, Kumar, V., & Bhalla, D. K. (2024). Integrating IoT and analytics in Industry 4.0: Towards a data-driven manufacturing landscape. *11th International Conference on Cutting-Edge Developments in Engineering Technology and Science, 1*(1), 101-110.

[29] Fayed, A. M. (2022). A new era for smart manufacturing solutions with emerging technologies apps. In *Proceedings of the Novel Intelligent and Leading Emerging Sciences Conference (NILES)* (pp. 67-70). IEEE. [CrossRef]

[30] Saleem, M., Askar, S., Ibrahim, M. A., Othman, M., & Abdullah, N. (2024). The Industrial Internet of Things (IIoT) and its roles in the Fourth Industrial Revolution: A review. *Indonesian Journal of Computer Science, 13*(2), 45-60. [CrossRef]

[31] Ryalat, M., Almtireen, N., ElMoaqet, H., & Almohammedi, M. (2024). The integration of two smarts in the era of Industry 4.0: Smart factory and smart city. In *Proceedings of the 2024 Smart Cities and Future Computing Conference (SCFC)* (pp. 9-12). IEEE. [CrossRef]

[32] Lind, R. A. (2023). *Smart factory in the context of digital transformation*. In Smart Factory in the Context of Digital Transformation (pp. 129-140). Emerald Publishing Limited. [CrossRef]