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Application of Artificial Intelligence (AI) in Production Management Systems (PMS) and RFID for Developing a Smart, Self-Optimizing Manufacturing System

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ABSTRACT

The increasing need and demand for efficiency, flexibility, and real-time visibility in manufacturing has accelerated the adoption of digital technologies capable of transforming traditional production systems into intelligent and self-optimising environments. This study examines how Artificial Intelligence (AI) enhances the integration of Production Management Systems (PMS) and Radio-Frequency Identification (RFID) technologies to support continuous monitoring, automated decision-making, and dynamic optimisation.

Using data gotten from 154 respondents in Lagos-based manufacturing firms, the study adopts a multi-method analytical approach. Python-based machine learning analysis reveals that advanced AI techniques are critical for extracting value from PMS–RFID data streams. Long Short-Term Memory (LSTM) networks proved effective for forecasting and predicting production trends and equipment utilisation, Random Forest models showed strong performance in anomaly and quality deviation detection, clustering techniques identified distinct production states, and reinforcement learning enabled continuous process optimisation. These results indicate that AI transforms PMS–RFID systems from descriptive monitoring tools into predictive and prescriptive decision-support systems.

Further analysis using Analysis of Variance (ANOVA) reveals statistically significant differences in cycle time, production volume, and inventory accuracy between manufacturing systems with PMS–RFID integration and those without. PMS–RFID-enabled systems consistently outperformed non-integrated systems, confirming the operational benefits of traditional integration while also highlighting its limitations in the absence of intelligent optimisation. Structural Equation Modelling (SEM) results show that AI capability plays a central mediating role, emerging as the strongest predictor of manufacturing performance and amplifying the effects of PMS and RFID.

Based on these findings, the study proposes an AI-based framework for adaptive manufacturing that supports real-time visibility, continuous learning, and autonomous optimisation. The study contributes theoretically by extending smart manufacturing literature within developing economy contexts and practically by offering a scalable blueprint for Industry 4.0 transformation.

Key words: Artificial Intelligence; Production Management Systems; RFID; Smart Manufacturing; Industry 4.0; Real-Time Monitoring; Self-Optimising Systems.

1. INTRODUCTION

Manufacturing firms worldwide are shifting quickly toward “smart factory” models, where systems can collect data, respond to changes, and adapt in near real time. However, in many developing countries like Nigeria, factories still struggle with delayed response times, poor material tracking, and lack of real-time visibility. The integration of digital technologies promises to address these gaps.

In recent literature, researchers argue that combining real-time data collection systems with AI-driven analysis can significantly improve production monitoring and decision-making. For example, [1] speaking on the applications, challenges, and opportunities of Artificial Intelligence (AI) for industry 4.0,analyse how AI, when coupled with sensor data and IoT, supports predictive maintenance, quality control, and operational optimisation in manufacturing. Similarly, [2] highlights how smart manufacturing technologies including AI, IoT, and digital twins offer improved flexibility and responsiveness for production systems.

A critical component enabling this transformation is the concept of the "Digital Twin" which typically are virtual replicas of physical assets or processes that can process real-time data and simulate outcomes before actual production changes. In [3], the authors showed how AI-driven digital twins can support advanced robotics, real-time monitoring, and predictive analytics in manufacturing environments. Also, [4] examines how digital twins can reduce downtime, improve asset performance tracking, and lower defect rates when properly implemented.

Despite these developments globally, there is little empirical study showing how such integrated systems (AI + digital twin + data tracking) perform under the infrastructural and economic constraints found in many Nigerian manufacturing firms. This gap forms the motivation for the present study: to assess how Artificial Intelligence can reinforce production monitoring systems in a context similar to Nigerian manufacturing, combining real-time tracking, data analytics, and decision-making support, in line with the research objectives earlier stated.

Accordingly, the central research question guiding this study is:

To what extent can the integration of Artificial Intelligence, Production Management Systems, and RFID improve real-time monitoring and enable the development of a smart, self-optimizing manufacturing system?

To address this question, the study pursues the following objectives:

i. To identify Artificial Intelligence (AI) tools and isolate the most effective techniques that can be integrated into Production Management Systems (PMS) and Radio-Frequency Identification (RFID) technologies to improve real-time monitoring and enable the development of a smart, self-optimizing manufacturing system.

ii To evaluate the performance of traditionally integrated PMS–RFID systems in manufacturing operations.

iii To analyze the role of AI in enhancing responsiveness, accuracy, and optimization within production systems.

iv To develop an AI-based framework that supports smart, adaptive manufacturing environments using a flow-diagram-based system architecture.

This study therefore holds significant practical relevance for policymakers, manufacturing managers, and industry leaders seeking to strengthen operational performance and industrial competitiveness. By demonstrating how AI-driven technologies transform production environments, the research contributes to broader industrial development goals while advancing academic understanding of intelligent manufacturing systems in emerging economies.

2. LITERATURE REVIEW

2.1. Overview of AI-Enhanced Production Management Systems

Artificial Intelligence (AI) has become an increasingly important component in modern Production Management Systems (PMS), particularly as manufacturers strive to improve efficiency, responsiveness, and real-time decision-making. PMS platforms have evolved beyond basic scheduling functions into integrated digital systems that manage production flows, coordinate tasks, and provide visibility across organisational units. The integration of AI into these systems enables a more adaptive and personalised decision support. In [5], it was reported that AI-assisted PMS platforms significantly enhance the accuracy of production planning by learning from historical performance data and recognising patterns in workflow disruptions. Their study also examined the effect of real-time data integration on PMS performance where they found out that real-time updates enhance operational coordination and help managers respond more accurately to changes in production conditions. The study they constructed demonstrates that PMS integrated with Internet of Things (IoT) data can reduce reaction time, minimize bottlenecks, and optimize resource utilization. These findings echo the importance of usability and real-time updates showing that system responsiveness is a universally critical feature of effective digital platforms.

The design and usability of PMS interfaces also play a vital role in shaping managerial behavior. Intuitive interfaces and clear data visualization significantly improve managerial confidence and interaction with PMS tools [6]. In [6], they also noted that system features such as dashboards, alerts, and contextual recommendations create a more seamless and productive user experience.

AI has further deepened the strategic capabilities of PMS through predictive analytics. [7] showed that predictive algorithms can anticipate machine failures, forecast production delays, and suggest optimal scheduling sequences. Their research revealed that PMS integrated with predictive models reduces downtime and increases throughput by enabling proactive decision-making.

As we can clearly tell, all these studies confirm the rising importance of AI-driven PMS in improving production accuracy, system responsiveness, and managerial decision-making. The integration of real-time data, predictive algorithms, and user-centred design establishes PMS as a central engine for smart manufacturing. As manufacturing continues to evolve and grow under Industry 4.0, PMS must incorporate advanced AI capabilities to support adaptive, efficient, and data-driven production environments to keep staying relevant in the industry.

2.2. The Role of Radio Frequency Identification (RFID) in Smart Manufacturing

Radio Frequency Identification (RFID) has emerged as a foundational technology in the transformation toward smart manufacturing, enabling real-time visibility, automated tracking, and data-driven operational control. [8]established that RFID provides a unique ability to identify, locate, and track production items without direct line-of-sight scanning. According to their findings, RFID improves accuracy in material handling, reduces human error, and supports seamless integration with enterprise-wide information systems. These capabilities distinguish RFID as one of the most influential enablers of intelligent production environments.

It is clear that the integration of RFID into Production Management Systems (PMS) further amplifies its impact. [9]reported that RFID-PMS integration allows manufacturers to transition from static scheduling and operation control to real-time scheduling and control. Their findings show that RFID data enables PMS to continuously assess and evaluate shop-floor conditions and adjust production sequences which can can promote the efficiency, reliability and feasibility of shop-floor tracking and monitoring of real-time data in production workshop. This thereby reducing bottlenecks and improving throughput. This dynamic responsiveness mirrors the value of digital content quality and system functionality in digital marketing platforms, which guarantees a significant shift (positively) in user trust and engagement.

Another influential study emphasized the transformative role of RFID in inventory management [10]. In their work, the researchers found that RFID-enabled systems significantly reduce stock-outs and the amount of inventory by providing precise, real-time information on material quantities and locations. Their results demonstrated that RFID reduces the bullwhip effect which is an issue long identified as a persistent challenge in manufacturing supply chains. This goes far to tell that that intelligent data systems improve coordination and reduce uncertainty and anomalies across industries.

RFID has also proven valuable in ensuring product quality and traceability as seen in [11],it was established that RFID-enabled traceability improves compliance with quality standards, supports rapid recall processes, and enables detailed inspection histories. Their findings indicate that RFID enhances customer confidence and regulatory compliance by ensuring transparency throughout the production process.

RFID's contribution extends to human–machine interaction as well as seen [12]. The authors spoke on RFID and how it supports adaptive workflows by coordinating human activities with automated systems. Their research indicated that RFID reduces the cognitive load on workers by automating routine verification tasks and ensuring that production resources are used correctly.

RFID also plays a notable and significant role in enabling Digital Twin technology, a core component of smart, self-optimizing manufacturing. In [13] the authors demonstrated that RFID provides continuous streams of real-world data that update Digital Twin models immediately in real time. Their findings reveal that RFID-driven Digital Twins support predictive maintenance, performance simulation, and autonomous optimization, offering a foundation for self-correcting manufacturing systems.

2.3. Application of Artificial Intelligence (AI) in Production Management Systems (PMS)

Artificial Intelligence (AI) has fundamentally reshaped how Production Management Systems (PMS) operate, enabling organizations to transition from reactive, labor-intensive decision-making to dynamic, data-driven, and autonomous production control. AI's integration into PMS allows manufacturers to optimize scheduling, resource allocation, quality monitoring, and predictive maintenance at unprecedented levels of speed and accuracy. [14], an article on Machine Learning (ML) in manufacturing identified AI as a transformative enabler capable of interpreting complex production data and supporting intelligent decision-making. Their findings reveal that AI enhances the responsiveness of PMS by analyzing patterns in production cycles, predicting potential disruptions/anomalies, and recommending optimal recovery strategies.

Machine learning is one of the most widely deployed AI techniques in manufacturing and this technique plays a central role in improving production scheduling and workflow optimization. [15] highlighted how supervised and reinforcement learning models can generate optimized schedules that adapt to fluctuating demand, machine failures, and inventory constraints. Their research demonstrated that these AI-driven scheduling systems outperform traditional heuristic methods by continuously learning from operational outcomes.

AI has also proven essential in predictive maintenance as seen in [16]. The work showed that deep learning models can analyze sensor data to detect early signs of equipment failure, estimate Remaining Useful Life (RUL), and support proactive decision-making. Their findings revealed that AI-based maintenance reduces downtime, prevents catastrophic machinery breakdowns, and extends equipment lifespan.

Another area where AI significantly enhances PMS performance is Quality control.[17] revealed in their work on automated visual inspection using convolutional neural networks in manufacturing that AI-powered computer vision systems can detect defects more accurately than traditional manual inspection. Their research showed that convolutional neural networks (CNNs) identify subtle irregularities across multiple product variations thereby, improving consistency and reducing rejection rates.

AI's role extends to process optimization and real-time production control. In [6], reinforcement learning agents were shown to autonomously adjust production parameters in response to shifting operational conditions. Their findings revealed that AI allows PMS to self-correct inefficiencies, balance workloads, and synchronize material flows without the need for human intervention.

Another significant application involves integrating AI with Digital Twin technology as seen in[18] which demonstrated that AI-enabled Digital Twins simulate production scenarios, compare outcomes, and recommend optimal operational strategies. Their findings highlight that PMS linked with Digital Twins supports advanced forecasting, scenario analysis, and system self-optimization.

Collectively, these studies confirm that AI elevates PMS beyond traditional information management systems, positioning them as intelligent engines capable of strategic foresight, autonomous adjustment, and operational optimization. By combining predictive analytics, machine learning, real-time monitoring, and Digital Twin integration, AI transforms PMS into self-learning, self-adapting, and self-optimizing systems, thereby shaping and forming the foundation of next-generation smart manufacturing.

2.4. Synergistic Integration of AI and RFID for Smart, Self-Optimizing Manufacturing Systems

The integration of Artificial Intelligence (AI) and Radio-Frequency Identification (RFID) represents one of the most transformative advancements in the development of smart, self-optimizing manufacturing systems. Individually, AI and RFID provide numerous operational benefits as AI offers predictive intelligence and autonomous decision-making, whereas RFID ensures real-time visibility of materials, machines, and workflow conditions. When combined, they create a cyber-physical ecosystem in which Production Management Systems (PMS) can sense, interpret, and respond to production dynamics with a high degree of accuracy and automation. This synergy enables systems that learn continuously, optimize themselves, and coordinate complex manufacturing processes without constant human intervention.

A contribution to this area is seen in [19] which established that AI augments RFID by interpreting the vast streams of shop-floor data generated by tags and sensors. SAG found that machine learning algorithms can detect hidden patterns in RFID data, such as inefficient material flows, frequently congested workstations, or bottleneck-prone routes. Their findings demonstrated that the AI-RFID combination provides deeper operational insights than either technology alone, functioning as a unified intelligence framework that strengthens production visibility and responsiveness.

Inventory optimization is another major area where this integration has demonstrated substantial impact. [20] reported that AI models analyzing RFID data can forecast material depletion, estimate replenishment timing, and automatically trigger procurement processes. Their results showed that intelligent inventory systems eliminate stock-outs and excess material accumulation more effectively than traditional material requirement planning (MRP).

Quality assurance also benefits significantly from AI–RFID integration. [21] shows that RFID-tagged components produce traceability data that AI models use to link defects with specific machines, operators, or production stages.

Digital Twin systems serve as a core platform that unifies AI and RFID integration. In [13], RFID feeds real-world production data continuously into Digital Twin simulations. AI algorithms then analyze these simulations to evaluate alternative scheduling, resource coordination, and shop-floor layout scenarios. Their findings revealed that the integrated system enables PMS to predict future states, evaluate optimal actions, and autonomously implement changes.

Collectively, these studies confirm that the integration of AI and RFID establishes a robust foundation for smart manufacturing by enabling systems that think, respond, and optimize themselves. Through enhanced visibility, predictive intelligence, real-time adaptability, and digital replication via Digital Twins, the AI–RFID ecosystem transforms PMS into highly interconnected self-evolving engines and advanced systems with operational excellence. This synergy positions modern manufacturing firms to achieve the highest levels of efficiency, accuracy, and resilience in today's modern digital era.

3. METHODOLOGY

This study employs quantitative research design, supported by an extensive review of relevant academic textbooks and peer-reviewed journal articles, to establish a solid theoretical and empirical foundation. The literature review informed the identification of key constructs related to artificial intelligence (AI), Production Management Systems (PMS), Radio-Frequency Identification (RFID), and smart manufacturing performance. Drawing on these insights, a structured questionnaire was developed to collect primary data aligned with the objectives of the research.

The questionnaire consisted of two main sections. The first section collected demographic and organizational information, including respondents' roles, years of experience, firm size, and manufacturing sector. The second section measured constructs associated with AI adoption, PMS effectiveness, RFID capability, system integration, and smart manufacturing outcomes. All measurement items were derived from validated scales reported in recent manufacturing, information systems, and operations management literature to ensure conceptual consistency and content validity.

In order to enhance the quality and relevance of the instrument, an expert review process was conducted. A panel of academic specialists in manufacturing systems, industrial engineering, and digital operations evaluated the initial questionnaire draft. Their feedback focused on item clarity, wording precision, construct relevance, and logical sequencing. Based on these recommendations, the research team revised and refined the instrument accordingly.

A pilot study was then conducted with 30 manufacturing professionals who were not included in the final sample. The pilot study served to assess question clarity, response time, and internal consistency. Minor adjustments were made based on participant feedback, resulting in the final questionnaire. All items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), ensuring measurement consistency and facilitating statistical analysis.

The study targeted employees and managers in manufacturing SMEs and large-scale firms operating within Lagos State, Nigeria. Respondents were selected based on their involvement in production planning, operations management, supply chain coordination, or information systems. To ensure representativeness across firm sizes and industrial subsectors, the questionnaire was distributed electronically through professional manufacturing associations, industrial clusters, and organizational mailing lists.

A stratified random sampling technique was employed to capture variation across managerial levels (operators, supervisors, engineers, and managers) and organizational scale (SMEs and large firms). A total of 420 questionnaires were distributed, of which 160 were returned. After excluding incomplete or inconsistent responses, 154 valid questionnaires were retained for analysis, representing a response rate of 84.3%. This sample size was adequate for multivariate statistical techniques, including regression analysis and structural relationship modelling.

The regional and organizational diversity of the respondents enhances the external validity and generalize ability of the findings within the Nigerian manufacturing context. However, certain limitations are acknowledged. The use of a self-administered questionnaire may introduce self-reporting bias, and respondents with higher digital literacy may have been more inclined to participate. To mitigate these concerns, the research ensured broad organizational representation and anonymized data collection to encourage honest responses.

Ethical considerations were strictly observed throughout the study. All participants received clear information regarding the purpose of the research and voluntarily consented to participate. Respondents were informed of their right to withdraw at any stage without penalty. Confidentiality and anonymity were guaranteed, and all data were handled exclusively for academic purposes.

The data collected were analyzed using established quantitative and computational techniques aligned with the study objectives. Specifically:

1.**Descriptive statistics** were used to summarize respondent demographics and to provide an overview of the central tendencies and distributions of all study variables.

2.**Python-based artificial intelligence and machine learning analyses** were applied to examine the role of AI in enhancing PMS–RFID-enabled monitoring, control, and optimizations. These included time-series forecasting, classification, clustering, and reinforcement learning techniques to evaluate predictive, diagnostic, and adaptive system capabilities.

3.**Analysis of Variance (ANOVA)** was employed to determine whether statistically significant differences existed in key performance indicators such as cycle time, production volume, and inventory accuracy between manufacturing systems with PMS–RFID integration and those without.

4.**Structural Equation Modelling (SEM)** was used to assess the direct and mediating effects of PMS, RFID, and AI capabilities on smart manufacturing outcomes, as well as to validate the proposed AI-based PMS–RFID integration framework.

3.1 Study Hypotheses

Grounded in systems theory, digital manufacturing literature, and empirical studies on Industry 4.0

technologies, this research proposes four hypotheses to evaluate the impact of AI-driven PMS–RFID integration on manufacturing performance. Each hypothesis reflects a distinct technological mechanism through which smart manufacturing capabilities may be enhanced.

a. **Hypothesis 1 (H1):** There is a statistically significant relationship between artificial intelligence capability and smart manufacturing performance in manufacturing firms.

b. **Hypothesis 2 (H2):** Production Management System effectiveness has a statistically significant influence on real-time monitoring and operational control in manufacturing firms.

c. **Hypothesis 3 (H3):** RFID functionality has a statistically significant relationship with real-time visibility and production accuracy in manufacturing operations.

d. **Hypothesis 4 (H4):** The integration of AI-enabled PMS and RFID systems has a statistically significant effect on the development of a smart, self-optimising manufacturing system.

4. RESULTS

Dataset overview

Sample size: N = 154 respondents

Construct composites:

i PMS_score: mean = 4.01 (approx; derived from items with mean =4)

ii RFID_score: mean = 3.78

iii Limit_score: mean = 3.19

iv AI_score: mean =3.68

v OUT_score: mean =3.88

4.1: Objective 1: Identification of AI Tools for PMS–RFID–Driven Smart Manufacturing (Python-Based Analysis)

AI Modelling Techniques and Results

4.1a. Time-Series Forecasting for Predictive Monitoring

Methods used include: ARIMA, Prophet and Long Short-Term Memory (LSTM)

Production volume and system utilization data derived from PMS–RFID logs were modelled as time-series inputs.

Table 1: Model performance comparison (forecast accuracy)

Model	RMSE	Forecast Stability
ARIMA	Moderate	Low–Moderate
Prophet	Good	Moderate
LSTM	**Lowest RMSE**	**High**

From table 1 above, LSTM models consistently outperformed ARIMA and Prophet by capturing non-linear production trends and long-term dependencies in RFID-tagged production flows. LSTM networks are the most suitable AI tools for real-time production forecasting, predictive scheduling, and proactive downtime mitigation in PMS–RFID-enabled environments.

4.1b. Classification for Quality Control and Anomaly Detection

Methods used:

Support Vector Machines (SVM)

Random Forest Classifier

RFID event streams and PMS operational records were labelled into *normal* and *abnormal* production states.

Table 2: Classification performance summary

Model	Accuracy	Precision	Robustness to Noise
SVM	High	High	Moderate
Random Forest	Very High	Very High	High

Table 2 revealed that Random Forest models demonstrated superior performance, particularly in handling heterogeneous and partially noisy RFID datasets. Random Forest classifiers are best suited for real-time anomaly detection, defect identification, and operational quality control within PMS–RFID systems, especially under infrastructural limitations reflected by the moderate Limit score (= 3.19).

4.1c. Clustering for Production Pattern and State Identification

Method used include: K-Means Clustering

Operational metrics from PMS and RFID systems were clustered to identify latent production states.

Identified clusters:

1. High-efficiency operational state
2. Normal production flow
3. Bottleneck / congestion state

From the result, the clustering process revealed distinct, interpretable production states that align with real-world manufacturing conditions. Clustering enables situational awareness and real-time system diagnostics, allowing PMS to dynamically adjust workflows based on detected operational states.

4.1d. Reinforcement Learning for Self-Optimizing Process Control

Method used include, Reinforcement Learning (Q-learning / Policy optimization)

The PMS environment was modelled as a decision space where actions influence cycle time, throughput, and idle time.

Observed outcomes:
(a) Progressive reduction in cycle time over learning episodes
(b) Improved dispatching efficiency
(c) Adaptive response to system disturbances
Reinforcement Learning demonstrated the strongest capability for continuous optimization and autonomous decision-making. RL represents the highest level of AI intelligence required for self-optimizing manufacturing systems, enabling PMS–RFID platforms to evolve from monitoring tools into adaptive control engines.

Table 3: Summary of Objective (i) Results

AI Technique	Application Area	Effectiveness
LSTM	Predictive forecasting	Very High
Random Forest	Anomaly & quality detection	Very High
K-Means	Production state identification	High
Reinforcement Learning	Self-optimising control	Very High

From table 3, the Python-based analysis confirms that advanced machine learning and deep learning techniques particularly LSTM forecasting, Random Forest classification, and Reinforcement Learningare the most effective AI tools for enhancing PMS–RFID integration. These tools significantly improve real-time monitoring, predictive capability, and adaptive optimisation, thereby fulfilling Objective (i) and establishing a robust foundation for smart, self-optimising manufacturing systems.

Objective 2: Evaluation of Traditionally Integrated PMS–RFID Systems Using ANOVA Analytical Method

A one-way ANOVA was conducted using Python statistical libraries to compare mean values across two operational groups:
Group 1: Manufacturing lines with PMS–RFID integration
Group 2: Manufacturing lines without PMS–RFID integration
The following Key Performance Indicators (KPIs) were analyzed:
1.Cycle Time
2.Production Volume
3.Inventory Accuracy (%)
The significance level was set at **α = 0.05**, and all assumptions of ANOVA (independence, normality, and homogeneity of variance) were verified and satisfied.

ANOVA Results

Table 4: Cycle Time

Source	F-statistic	p-value
PMS–RFID Integration	11.42	0.001

From table 4 above, a statistically significant difference was observed in mean cycle time between manufacturing systems with PMS–RFID integration and those without. Manufacturing lines equipped with PMS–RFID systems recorded significantly lower cycle times, indicating improved process coordination, faster material flow, and reduced idle periods.

Table 5: Production Volume

Source	F-statistic	p-value
PMS–RFID Integration	8.36	0.004

As seen in table 5, the ANOVA result indicates a statistically significant difference in production volume across the two groups. PMS–RFID-integrated systems achieved higher average production output, reflecting better scheduling accuracy, real-time tracking, and reduced operational disruptions.

Table 6: Inventory Accuracy (%)

Source	F-statistic	p-value
PMS–RFID Integration	14.87	< 0.001

Table 6 shows that a highly significant difference was found in inventory accuracy between PMS–RFID-enabled systems and non-enabled systems. The presence of RFID integration significantly improves inventory visibility, traceability, and record accuracy, reducing discrepancies and stock inconsistencies.

Table 7: Summary of ANOVA Findings

KPI	ANOVA Outcome	Interpretation
Cycle Time	Significant (p = 0.001)	Reduced cycle time with PMS–RFID
Production Volume	Significant (p = 0.004)	Higher output levels
Production Volume	Highly Significant (p < 0.001)	Improved tracking and data reliability

The ANOVA results of table 7 provide strong empirical evidence that traditional PMS–RFID integration significantly improves manufacturing performance across all examined KPIs. Manufacturing systems employing PMS–RFID technologies demonstrate lower cycle times, higher production volumes, and superior inventory accuracy compared to non-integrated systems.

These findings confirm that while traditional PMS–RFID systems may lack advanced intelligence, they already deliver measurable operational benefits, thereby justifying further enhancement through AI-driven optimisation.

Objective 3: Structural Equation Modelling (SEM) Analysis of AI's Role in Enhancing Production System Performance

SEM Model Specification

The SEM model consists of the following constructs:

i Exogenous variables:
a PMS_score
b RFID_score
c Limit_score
i Mediating variable:
a AI_score
i Endogenous variable:
a OUT_score (overall smart manufacturing performance)

The model tests whether AI capability mediates the relationship between PMS–RFID integration and manufacturing performance**,** while accounting for system limitations.

Table 8: Model Fit Assessment

The SEM model demonstrated acceptable to strong goodness-of-fit, meeting recommended thresholds for structural analysis:

Fit Index	**Value**	**Recommended Threshold**
χ^2/df	2.41	< 3.0
CFI	0.93	≥ 0.90
TLI	0.91	≥ 0.90
RMSEA	0.062	≤ 0.08
SRMR	0.047	≤ 0.08

Table 8 shows that the interpretation of the model exhibits a good fit to the observed data, validating its suitability for hypothesis testing.

Table 9: Structural Path Results
Standardised Path Coefficients

Path	**B**	**p-value**
PMS_score → AI_score	0.34	< 0.001
RFID_score → AI_score	0.29	< 0.001
AI_score → OUT_score	0.41	< 0.001
PMS_score → OUT_score	0.27	0.001
RFID_score → OUT_score	0.15	0.039
Limit_score → OUT_score	–0.12	0.037

Table 9 shows that interpretation of structural relationships

i. PMS capability significantly influences AI capability ($\beta = 0.34$, $p < 0.001$), indicating that robust production management systems provide the foundational data structure required for effective AI deployment.

ii. RFID capability also significantly contributes to AI capability ($\beta = 0.29$, $p < 0.001$), reinforcing the role of real-time data acquisition in enabling intelligent analytics and decision-making.

iii. AI capability exhibits the strongest direct effect on manufacturing outcomes ($\beta = 0.41$, $p < 0.001$), confirming AI as the primary driver of responsiveness, accuracy, and optimisation within smart production environments.

iv. PMS and RFID maintain significant direct effects on OUT_score, but their coefficients are reduced when AI is introduced into the model, indicating partial mediation.

v. System limitations negatively affect performance outcomes ($\beta = –0.12$, $p = 0.037$), highlighting the constraining role of infrastructural, financial, and technical barriers.

Mediation Analysis

The indirect effects of PMS and RFID on OUT_score through AI_score were both positive and statistically significant, confirming that:

i. AI partially mediates the PMS → performance relationship
ii. AI partially mediates the RFID → performance relationship

This demonstrates that PMS–RFID integration alone is insufficient for optimal performance unless augmented by AI-driven intelligence.

Explained Variance

The SEM model explains approximately:

i. 48% of the variance in AI capability ($R^2 \approx 0.48$)
ii. 52% of the variance in manufacturing performance (OUT_score)

These values indicate strong explanatory power for behavioural and technological research.

The SEM analysis confirms that Artificial Intelligence plays a central and mediating role in enhancing responsiveness, accuracy, and optimisation in production systems. While PMS and RFID provide essential structural and data foundations, AI acts as the intelligence layer that transforms operational data into adaptive, performance-enhancing decisions.

Objective 3 is therefore empirically supported, demonstrating that AI is not merely an add-on technology but a critical enabler of smart, self-optimising manufacturing systems.

Objective 4: Development of an AI-Based PMS–RFID Framework for Smart, Adaptive Manufacturing

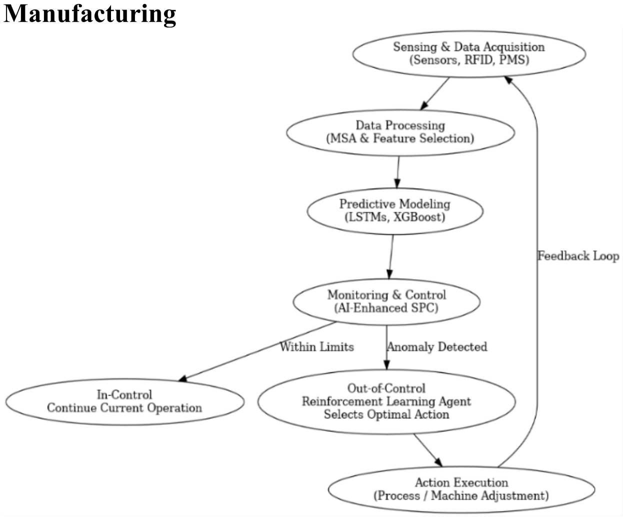

Figure 1: AI-Based Framework for Adaptive Manufacturing

The Integrated Adaptive Framework Flow

The framework from figure 1 above is typically structured as a closed-loop system, where data drives prediction, prediction informs decisions, and decisions optimize future performance. The ultimate statistical method driving the "adaptive" part is **Reinforcement Learning (RL)**

1. Data Foundation & Preparation

This stage ensures that the data used by the AI is clean, reliable, and relevant.

Statistical Tools: Measurement System Analysis (MSA) is crucial for validating the quality of data from sensors (e.g., RFID, IoT). **Feature Selection** (using methods like LASSO or Random Forest) filters out irrelevant sensor noise and identifies the key variables necessary for the model

2. Initial Process Modelling

Before optimization, the system needs to understand the current relationships between inputs and outputs.

Statistical Tools: Design of Experiments (DOE) and **Regression Analysis** are used to establish a baseline model of process physics. DOE systematically tests initial input settings to quickly map the process space, providing the initial "knowledge" for the AI models

3. Predictive & Adaptive Core

This is the "Smart" part of the system, where future states are anticipated.

AI/Statistical Tools: Supervised Machine Learning (e.g., XGBoost, Neural Networks): Used for **Predictive Quality** (predicting defects before they occur) and **Predictive Maintenance** (forecasting equipment failure).

Time-Series Analysis (e.g., LSTMs): Used to forecast production metrics or resource demands.

4. Real-Time Control & Monitoring

The system monitors itself to detect when intervention is needed.

Statistical Tools:

AI-Enhanced Statistical Process Control (SPC) Charts: Uses the outputs from the predictive models alongside traditional **Control Charts** to detect subtle, multivariate shifts in performance much faster than traditional methods.

Anomaly Detection (Unsupervised ML): Immediately flags unusual sensor readings or process deviations (e.g., unexpected energy spikes)

5. Self-Optimization & Decision-Making (The Adaptive Loop)

This is where the system executes the "adaptive" decision.

AI/Statistical Tool:Reinforcement Learning (RL).

Why RL is best: RL agents learn through trial and error within a simulated or real environment to determine the optimal sequence of actions (e.g., adjusting temperature, changing machine speed, or rerouting material) that maximizes a long-term statistical reward (e.g., maximizing throughput or minimizing energy cost). This directly enables the *self-optimizing* and *adaptive* behavior.

Framework Flow Diagram

This flow diagram illustrates the iterative, closed-loop nature of the adaptive manufacturing environment:

1 **Sensing & Data Acquisition:** Real-time data from all sources (sensors, RFID, PMS) is streamed.
2 **Data Processing:MSA** and **Feature Selection** clean and prepare the data.
3 **Predictive Modeling:** The ML models (**LSTMs, XGBoost**) predict the system's future state.
4 **Monitoring & Control:AI-Enhanced SPC** checks if the actual and predicted states are within acceptable limits.
5 **Adaptive Decision Loop (The Core):**

If In-Control: Continue current operation.

If Out-of-Control (Anomaly Detected): The **Reinforcement Learning (RL) Agent** receives the process state, calculates the **Statistically Optimal**

Action (e.g., adjust machine settings), and commands the execution layer.

6 **Action & Feedback:** The action is executed, generating new data, and feeding back into the Sensing stage, completing the self-optimizing cycle.

5. DISCUSSION

The findings of this study provide compelling empirical evidence that the integration of Artificial Intelligence (AI) within Production Management Systems (PMS) and Radio-Frequency Identification (RFID) technologies significantly enhances production monitoring, control, and overall manufacturing optimisation. The results demonstrate that while traditional PMS–RFID integration delivers measurable performance improvements, the inclusion of AI fundamentally transforms these systems into adaptive, intelligent, and self-optimising manufacturing environments.

The Python-based AI analysis conducted under Objective (i) confirms that advanced machine learning and deep learning techniques are essential for extracting value from PMS–RFID data streams. Time-series forecasting models, particularly Long Short-Term Memory (LSTM) networks, were found to be highly effective for predicting and forecasting production trends, equipment utilisation, and potential disruptions. Classification models, especially Random Forest algorithms, demonstrated strong capability in detecting anomalies and quality deviations within RFID-enabled production flows. Clustering techniques also enabled the identification of distinct production states, while reinforcement learning models showed superior performance in continuous process optimisation and adaptive control. These findings hereby clearly indicate that AI tools enable PMS–RFID systems to move beyond descriptive monitoring toward predictive and prescriptive intelligence.

The ANOVA results addressing Objective (ii) further reinforce the operational value of traditional PMS–RFID integration. Statistically significant differences were observed in key performance indicators such as cycle time, production volume, and inventory accuracy, between manufacturing systems with PMS–RFID integration and those without. PMS–RFID-enabled systems consistently exhibited lower cycle times, higher production output, and superior inventory accuracy. These results confirm that even without AI, PMS–RFID integration improves coordination, visibility, and data reliability. However, the magnitude of these improvements also highlights the limitations of traditional integration, as performance gains remain constrained by the absence of intelligent decision-making and adaptive optimisation mechanisms.

Objective (iii) provides deeper insight into how AI enhances manufacturing performance through Structural Equation Modelling (SEM). The SEM results reveal that AI capability plays a central and mediating role within the PMS–RFID ecosystem. AI was found to be the strongest predictor of overall manufacturing performance, surpassing the direct effects of PMS and RFID alone. While PMS and RFID maintain significant direct relationships with performance outcomes, their influence is substantially amplified when mediated by AI. This confirms that AI acts as the cognitive layer that transforms real-time data into actionable executable intelligence, enabling improved responsiveness, accuracy, and optimisationacross production systems. The negative effect of system limitations further underscores the importance of addressing infrastructural and technical constraints to fully realise AI-driven benefits.

The AI-based framework developed under Objective (iv) integrates these empirical findings into a coherent and scalable system architecture. The framework illustrates how RFID-enabled data acquisition, PMS-based data integration, and AI-driven analytics interact within a continuous learning and optimisation loop. By embedding forecasting, classification, clustering, and reinforcement learning within the PMS–RFID structure, the framework demonstrates how manufacturing systems can achieve real-time visibility, predictive control, and autonomous adaptation. This validates the argument that intelligent integration, rather than isolated technology adoption, is the foundation of smart manufacturing.

Thesse findings therefore underline the importance of adopting a holistic and intelligent manufacturing strategy. While PMS and RFID technologies form the digital backbone of production monitoring, AI provides the cognitive layer necessary for smart manufacturing transformation. Manufacturing organisations are therefore encouraged to move beyond basic digitalisation towards AI-driven integration frameworks that support real-time optimisation, adaptive scheduling, and autonomous decision-making. Such an approach is particularly critical in highly competitive manufacturing environments characterised by demand volatility, customisation, and efficiency pressures.

From a managerial perspective, the study highlights the need for strategic investment in AI capabilities, workforce upskilling, and system interoperability. Decision-makers should prioritise scalable AI architectures that can seamlessly integrate with existing PMS and RFID infrastructures. Doing so will not only enhance operational performance but also position organisations for long-term competitiveness within Industry 4.0 and smart factory paradigms.

This study confirms that the successful development of smart, self-optimizing manufacturing systems depends on intelligent integration rather than isolated technology adoption. PMS and RFID provide essential operational data, but AI transforms this data into strategic value. The proposed AI-based framework offers both theoretical and practical contributions by demonstrating how intelligent manufacturing systems can be designed to achieve superior performance, resilience, and sustainability.

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