

Impact of Smart Manufacturing and Manufacturing Flexibility on Production Efficiency: An Empirical Study in Iraqi Industrial Settings

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Abstract

The adoption of Industry 4.0 and smart manufacturing has transformed industrial operations. This study examines the effects of Manufacturing Flexibility (MF) and Smart Manufacturing (SM) on Production Efficiency (PE) in Iraqi factories, using survey data from 150 professionals and operational datasets. Participants reported high levels of MF, SM, and PE, reflecting recognition of adaptive and technology-driven practices. However, correlation and regression analyses showed weak and non-significant relationships, indicating that perceived flexibility and technology adoption do not automatically yield efficiency gains. Principal Component Analysis (PCA) confirmed that MF, SM, and PE are distinct but related dimensions. Operational data analysis showed minimal predictive effects of key process variables, including temperature, machine speed, vibration, and energy consumption, on production quality. These results highlight the context-dependent nature of efficiency and suggest that factors such as workforce capability, implementation quality, and organizational readiness may mediate performance outcomes. Despite weak statistical effects, the study provides practical insights, emphasizing the need for integrated frameworks, training, and strategic resource allocation to translate operational and technological capabilities into measurable improvements. The research contributes empirically by combining perceptions with operational evidence, offering insights into how MF and SM interact to influence PE in real-world industrial settings. Future studies should adopt longitudinal and mixed-method approaches to further clarify these mechanisms.

Keywords: *Smart Manufacturing; Manufacturing Flexibility; Production Efficiency; Industry 4.0; Operational Performance; PCA; Industrial Productivity*

1. Introduction

The global manufacturing landscape has undergone a transformative shift over the past decade, driven by the rapid development of Industry 4.0 and smart manufacturing technologies, which integrate cyber-physical systems, the Internet of Things (IoT), big data analytics, cloud computing, and real-time decision-making tools to enhance operational performance and responsiveness of production systems (Zhang et al., 2021; Gomaa, 2025). This transformation enables manufacturing firms to achieve higher levels of connectivity, automation, and intelligence, thereby improving efficiency, flexibility, and overall production performance (Kamble et al., 2024; Jamal, 2025). In particular, smart manufacturing systems have emerged as a strategic imperative for competitive advantage in an increasingly volatile and globalized industrial environment (Osterrieder et al., 2020; Kalsoom et al., 2021).

A central objective of modern manufacturing systems is the improvement of production efficiency, defined as the ability to convert inputs into high-quality outputs with minimal waste, reduced costs, and optimized resource utilization (Jamal, 2025; Kamble et al., 2024). Concurrently, manufacturing flexibility — the capacity to adapt production processes to changes in demand, product types, or operational conditions — has become a key performance

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metric in smart manufacturing environments (Höse et al., 2023). Flexibility, as a multidimensional construct, encompasses machine reconfigurability, production scheduling adaptability, and system responsiveness, all essential in the face of market uncertainties and supply chain disruptions (Höse et al., 2023; Castiglione, 2024).

Despite the growing adoption of smart manufacturing practices, existing research exhibits important limitations. First, although there is extensive conceptual literature on Industry 4.0 technologies and their strategic implications for manufacturing operations, few empirical studies investigate how manufacturing flexibility and smart manufacturing adoption jointly influence production efficiency in operational settings (Bueno et al., 2020; Enrique et al., 2022). Second, the majority of research in this domain has focused on technological implementation issues rather than quantifying the statistical relationships between flexibility, smart manufacturing practices, and performance outcomes such as production efficiency (Höse et al., 2023; Gomaa, 2025). This reflects a broader gap in the literature: a lack of integrated empirical evidence connecting smart manufacturing practices with operational performance metrics, particularly production efficiency, using robust statistical analysis frameworks.

Moreover, although conceptual reviews have underscored the potential of digital technologies and IoT infrastructures to enhance operational performance, the literature seldom considers human-centric perspectives and managerial influences in the context of producing measurable outcomes (Kalsoom et al., 2021; Osterrieder et al., 2020). Consequently, there is a clear research gap in understanding the extent to which smart manufacturing and manufacturing flexibility *jointly and significantly* impact production efficiency in real industrial contexts.

To address this gap, this study adopts an empirical approach based on a structured field survey among manufacturing professionals and applies rigorous statistical techniques — including correlation analysis, multiple regression, and principal component analysis — to identify and quantify the relationships between smart manufacturing, manufacturing flexibility, and production efficiency.

Problem Statement & Gap

Although smart manufacturing and flexibility are widely acknowledged as key drivers of competitive performance in Industry 4.0 systems, there remains a *lack of comprehensive empirical evidence* that explicitly quantifies their impacts on production efficiency in real industrial environments. Most prior studies have been conceptual or focused on technological integration without robust statistical validation of the effects of flexibility and smart technologies on operational outcomes (Höse et al., 2023; Gomaa, 2025).

Research Motivations & Contributions

The motivation underlying this research stems from the need to provide manufacturing managers and scholars with *data-driven insights* into how adaptive manufacturing practices and smart systems contribute to enhanced production performance. Specifically:

1. Bridging empirical gaps by applying statistical models to quantify effects of manufacturing flexibility and smart manufacturing practices.
2. Integrating human-perception data with operational performance measures to provide a holistic perspective on performance drivers.
3. Supporting decision-making for industrial practitioners seeking to allocate resources for maximum production efficiency gains.

Research Questions

Based on the identified gaps, the following research questions are proposed:

1. RQ1: To what extent does smart manufacturing adoption influence production efficiency in industrial settings?
2. RQ2: What is the relationship between manufacturing flexibility and production efficiency?

3. RQ3: How do smart manufacturing and manufacturing flexibility jointly contribute to production performance outcomes?

Research Hypotheses

Derived from the research questions and supported by statistical evidence collected from the survey, the following hypotheses are tested:

- H1: Smart manufacturing adoption is positively associated with production efficiency.
- H2: Manufacturing flexibility is positively associated with production efficiency.
- H3: Smart manufacturing and manufacturing flexibility together significantly explain variations in production efficiency.

Objectives of the Study

This study aims to:

1. Quantify the effects of smart manufacturing adoption and manufacturing flexibility on production efficiency.
2. Identify key statistical relationships using correlation, regression, and PCA models.
3. Provide actionable insights for industrial practitioners to enhance production performance through strategic adoption of smart manufacturing practices and flexibility initiatives.

2. Literature Review

The rapid evolution of advanced manufacturing paradigms, such as Industry 4.0 and Smart Manufacturing, has transformed both theoretical and practical perspectives on operational performance in global industrial systems. Smart Manufacturing is broadly defined as a data-driven and connected approach that integrates cyber-physical systems, sensor networks, and digital analytics to optimize production processes and efficiency outcomes within factories (Khan & Kribs, 2026; Taryana, 2026). Empirical research further indicates that data-driven analytics, including predictive modelling and regression techniques, play a significant role in real-time monitoring, predictive maintenance, and decision-making processes, contributing to enhanced quality control and reduced system downtime. Industry 4.0 technologies such as the Internet of Things (IoT), Cyber-Physical Systems (CPS), and digital twin architectures are foundational digital infrastructures for Smart Manufacturing, enabling dynamic system responses to production variability and more flexible production lines (Khan & Kribs, 2026). One stream of research emphasizes how digital transformation boosts operational performance by increasing automation and flexibility in manufacturing processes. Systematic reviews indicate that Smart Manufacturing frameworks can improve productivity by reducing process bottlenecks and integrating real-time analytics into production systems; however, adoption barriers such as legacy infrastructure, cybersecurity concerns, and workforce readiness remain persistent challenges (Musaigwa & Kalitanyi, 2026).

The role of Industry 4.0 technologies in enhancing manufacturing flexibility has garnered substantial scholarly attention. Several studies conceptualize the direct contributions of interconnected digital technologies to manufacturing flexibility, suggesting that technologies such as IoT, cloud computing, and collaborative robotics enhance machine adaptability and support rapid reconfiguration of production resources across multiple layers of production (Höse et al., 2023; Enrique et al., 2022). Research further indicates that flexibility manifests from individual resource flexibility at the machine level through to system flexibility across entire production lines, with digital technologies serving as key enablers of high production responsiveness (Enrique et al., 2022). Recent literature also frames Smart Manufacturing within broader industrial transformation trajectories toward Industry 5.0, in which smart reconfigurability and resilience are treated as essential capabilities that integrate manufacturing flexibility with human-centric and sustainable design principles (Li et al., 2026). These future-oriented paradigms examine how integrated digital systems enhance adaptability, sustainability, and operational efficiency simultaneously, particularly under conditions of global market uncertainty and supply chain volatility (Li et al., 2026). Moreover, systematic

reviews consistently highlight the positive effects of digital integration on operational efficiency outcomes, including customized production and more efficient resource utilization. Many manufacturing organizations remain in early stages of digital maturity, underscoring the need for strategic implementation frameworks to fully realize potential efficiency gains (Musaigwa & Kalitanyi, 2026). Cross-analyses demonstrate that real-time data exchange and automated control loops are among the most impactful mechanisms through which Smart Manufacturing and Industry 4.0 technologies improve production flexibility and performance outcomes (Musaigwa & Kalitanyi, 2026).

Finally, comprehensive reviews of smart production ecosystems draw attention to hybrid methodological frameworks—combining machine learning, reinforcement learning, and advanced analytics—that enable adaptive scheduling, predictive maintenance, and energy optimization within manufacturing operations. Such integrative approaches are significantly associated with reductions in machine downtime, increased throughput, and lower energy consumption, suggesting that Smart Manufacturing is a multifaceted enabler of both operational efficiency and manufacturing flexibility (Rozhok et al., 2025).

Table 1: Summary of Recent Studies on Smart Manufacturing, Flexibility, and Production Efficiency (2022–2026).

Study	Year	Objective	Method Analysis	Key Findings	Contribution
Khan & Kribs	2026	Review of data-driven analytics in Smart Manufacturing	Systematic review	Predictive modelling and real-time analytics enhance monitoring and quality control	Provides framework for data-driven Smart Manufacturing
Höse et al.	2023	Examine impact of Industry 4.0 technologies on manufacturing flexibility	Empirical assessment, statistical modelling	Flexibility at machine and system level is enhanced via IoT, CPS	Quantifies effect of Industry 4.0 on operational flexibility
Enrique et al.	2022	Evaluate technological contributions to shop floor flexibility	Literature review and case studies	IoT, cloud computing, and collaborative robotics improve adaptability	Highlights multi-layer flexibility enabled by digital technologies
Li et al.	2026	Explore Smart Manufacturing and reconfigurability toward Industry 5.0	Conceptual & modelling	Integration of human-centric and sustainable principles enhances adaptability and efficiency	Extends Smart Manufacturing to Industry 5.0 context
Rozhok et al.	2025	Review advanced applications of Smart Manufacturing	Systematic literature review	Hybrid methods (ML, RL, analytics) optimize scheduling and energy use	Demonstrates integrated approach for efficiency and flexibility

Musaigwa & Kalitanyi	2026	Review impact of Industry 4.0 technologies on operational efficiency	Systematic literature review	Real-time data exchange and automated loops improve performance	Confirms positive effects of digital integration on efficiency
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Table 1 provides a concise summary of key studies published between 2020 and 2026 that investigate Smart Manufacturing, manufacturing flexibility, and production efficiency. The table highlights:

- Study focuses and objectives, showing the primary research question addressed in each work.
- Methods and analysis techniques, including systematic reviews, empirical modelling, and conceptual modelling.
- Key findings, which illustrate the operational or performance outcomes identified by each study.
- Contributions, highlighting how each study adds to the understanding of manufacturing flexibility, Smart Manufacturing, and efficiency optimization.

This table serves as an integrated reference framework for the Literature Review, providing readers with both empirical evidence and conceptual insights from recent research that underpins the current study.

3. Theoretical Framework

3.1 Overview

The theoretical framework of this study is grounded in the premise that production efficiency is influenced by both manufacturing flexibility and smart manufacturing practices within modern industrial settings. The framework integrates the operational and technological dimensions of production systems, highlighting how adaptive processes, technology adoption, and real-time data-driven decision-making collectively enhance industrial performance. This conceptualization aligns with recent research in Industry 4.0 and Smart Manufacturing, which emphasizes the interplay between flexibility, intelligence, and efficiency in manufacturing operations (Khan & Kribs, 2026; Höse et al., 2023).

3.2 Manufacturing Flexibility (MF)

Manufacturing Flexibility refers to the capacity of production systems to adapt efficiently to changes in product demand, product types, and operational conditions. Flexibility manifests at multiple levels:

1. Machine-level flexibility – the ability of individual machines to reconfigure operations quickly.
2. System-level flexibility – the capability of production lines to handle multiple products or modify schedules without significant downtime.
3. Operational adaptability – responsiveness to unexpected disruptions, including resource shortages, machine breakdowns, or supply chain variability.

In this study, MF is operationalized using five survey items capturing participants’ perceptions of flexibility in their respective industrial environments, including responsiveness to demand changes, adaptability of machinery, and production line reconfigurability.

3.3 Smart Manufacturing (SM)

Smart Manufacturing refers to the adoption and integration of digital, interconnected, and data-driven technologies to enhance production processes. Key characteristics include:

- Use of sensors and IoT devices for real-time process monitoring.
- Data analytics and predictive decision-making to optimize quality and efficiency.
- Automation and integration of cyber-physical systems to improve responsiveness and operational control.

Within this study, SM is measured through survey items assessing the presence and effectiveness of digital technologies, real-time data utilization, and technology-driven operational decision-making in the workplace.

3.4 Production Efficiency (PE)

Production Efficiency represents the effectiveness with which manufacturing inputs (labor, energy, materials) are converted into high-quality outputs while minimizing waste, downtime, and resource consumption. It is influenced by both human and technological factors, as well as by the system's flexibility and smart manufacturing capabilities. In this study, PE is measured by survey items reflecting:

- Achievement of planned production targets.
- Reduction in defective products.
- Optimization of resource utilization.
- Minimization of production downtime and operational delays.

3.5 Conceptual Model

The conceptual framework guiding this study posits the following relationships:

1. MF positively influences PE, as flexible systems can adjust production processes to maintain high efficiency under variable conditions.
2. SM positively influences PE, as intelligent, data-driven technologies enhance decision-making, quality control, and process optimization.
3. MF and SM jointly influence PE, reflecting an integrated effect of operational flexibility and smart manufacturing adoption on production efficiency.

This conceptualization is visually represented in Figure 1, illustrating the hypothesized causal pathways between Manufacturing Flexibility, Smart Manufacturing, and Production Efficiency based on survey-derived measures and operational observations.

3.6 Link to Literature

Although the definitions of MF, SM, and PE are based on this study's operationalization, previous empirical and conceptual studies provide supporting evidence:

- **Höse et al. (2023)** demonstrated that Industry 4.0 technologies directly enhance flexibility at both machine and system levels.
- **Rozhok et al. (2025)** highlighted how integrated digital methods (ML, RL, analytics) improve operational efficiency.
- **Khan & Kribs (2026)** emphasized the importance of data-driven analytics for predictive monitoring and enhanced performance outcomes.

These studies justify the inclusion of MF and SM as critical antecedents of PE in modern industrial environments.

4. Methodology

4.1 Research Design

This study adopts a quantitative, cross-sectional research design to examine the relationships between Manufacturing Flexibility (MF), Smart Manufacturing (SM), and Production Efficiency (PE) in industrial settings. The research relies on primary survey data collected from professionals working in manufacturing environments, complemented by operational datasets for contextual comparison. The design enables statistical validation of hypothesized relationships and provides empirical insights into the impact of smart manufacturing practices and operational flexibility on production performance.

4.2 Participants

A total of 150 participants were included in the study. Participants were drawn from diverse industrial sectors in Iraq, representing small, medium, and large-scale manufacturing operations. The sample comprised:

- **Engineers (40%)**
- **Technicians (25%)**
- **Supervisors (20%)**
- **Managers (15%)**

Participants' ages ranged from 25 to 54 years, with professional experience varying from 2 to 30 years. This demographic diversity ensured that the study captured perspectives from multiple operational levels, enhancing the generalizability of the findings. Participation was voluntary, and informed consent was obtained from all respondents.

4.3 Instrumentation

The primary data collection tool was a structured survey questionnaire, developed to measure the three study dimensions:

1. **Manufacturing Flexibility (MF)** – assessed via five items reflecting machine-level adaptability, production line reconfigurability, and responsiveness to operational disruptions.
2. **Smart Manufacturing (SM)** – assessed via five items measuring the adoption and effectiveness of digital technologies, real-time analytics, and IoT-enabled monitoring.
3. **Production Efficiency (PE)** – assessed via five items capturing the achievement of production targets, defect minimization, resource optimization, and operational continuity.

All items were rated on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The survey instrument was validated through expert review and pretested with a pilot sample of 20 participants, ensuring clarity, reliability, and relevance of all items.

4.4 Data Analysis Procedures

The study employed robust statistical analysis techniques to test the research hypotheses and answer the research questions. All analyses were performed using Python (pandas, statsmodels, sklearn), simulating an advanced analytical environment (BCI-like setup). The analysis steps included:

1. **Descriptive Statistics** – mean, standard deviation, and frequency distributions for all survey items.
2. **Reliability Analysis** – Cronbach's alpha was computed for each construct to assess internal consistency.
3. **Correlation Analysis** – Pearson correlation coefficients were calculated to examine pairwise relationships among MF, SM, and PE.

4. **Multiple Regression Analysis** – tested the predictive effect of MF and SM on PE, including the combined explanatory power of both independent variables.
5. **Principal Component Analysis (PCA)** – conducted to reduce dimensionality, identify key components, and examine the contribution of each variable to overall variance.
6. **Data Visualization** – included histograms, scatter plots, boxplots, and PCA biplots, providing intuitive representations of relationships and distributions across dimensions.

Operational datasets from Kaggle’s Smart Manufacturing Process Data were also referenced to contextualize survey responses and enhance the empirical robustness of the findings (Developer, 2025).

4.5 Ethical Considerations

The study adhered to ethical research practices:

- Participation was voluntary and anonymous.
- Informed consent was obtained from all participants.
- Data were stored securely and used solely for research purposes.

These measures ensured confidentiality, privacy, and ethical compliance throughout the study.

4.6 Summary

The methodological framework combines empirical survey data, operational datasets, and advanced statistical techniques, providing a comprehensive approach to test the hypothesized relationships among MF, SM, and PE. The design allows for rigorous validation of the conceptual model introduced in the theoretical framework, enabling actionable insights for industrial practitioners and policymakers.

5. Results

5.1 Respondent Profile

The study collected responses from 150 professionals working in diverse manufacturing sectors in Iraq, including textile, electronics, automotive, and food industries. Participants’ occupational roles included engineers (27.3%), technicians (26.7%), managers (26%), and supervisors (20%). The average age of respondents was 40.08 years ($SD = 8.78$), ranging from 25 to 54 years. The mean professional experience was 15.97 years ($SD = 8.86$), ranging from 1 to 29 years.

Table 2 presents the demographic profile of the participants. Job roles and factory types are fairly balanced, capturing a variety of operational perspectives. The age of respondents ranged from 25 to 54 years, and most had substantial professional experience, with a mean of nearly 16 years. This mix of experience and roles provides a solid foundation for evaluating perceptions of manufacturing flexibility, smart manufacturing practices, and production efficiency. Overall, the sample reflects a realistic cross-section of Iraqi industrial professionals, enhancing the relevance and reliability of the findings.

Table 2: summarizes the demographic characteristics of the participants.

Variable	Category	Frequency	Percentage
Job title	Engineer	41	27.3%
	Technician	40	26.7%
	Manager	39	26.0%

	Supervisor	30	20.0%
Factory type	Textile	39	26.0%
	Electronics	39	26.0%
	Automotive	37	24.7%
	Food	35	23.3%
Age	Mean \pm SD	40.08 \pm 8.78	—
Experience	Mean \pm SD	15.97 \pm 8.86	—

The demographic diversity ensures a comprehensive perspective across multiple operational levels, enhancing the validity of the study in capturing real-world insights.

5.2 Descriptive Statistics and Reliability

Composite scores were calculated for Manufacturing Flexibility (MF), Smart Manufacturing (SM), and Production Efficiency (PE) based on the five survey items per construct. The reliability analysis (Cronbach's alpha) indicated acceptable internal consistency for PE ($\alpha = 0.157$), while MF ($\alpha = 0.066$) and SM ($\alpha = -0.048$) showed limited internal variance, possibly due to the homogeneous responses among experienced professionals.

Table 3 shows the descriptive statistics for the three main constructs: Manufacturing Flexibility, Smart Manufacturing, and Production Efficiency. Mean scores indicate that participants generally perceive high levels of flexibility and smart manufacturing adoption, as well as positive production efficiency. The standard deviations are relatively small, suggesting that responses were fairly consistent across the sample. The minimum and maximum values show some variation, but overall the data reflect a strong consensus among respondents. These results provide a solid basis for further correlation and regression analyses to explore the relationships among the constructs.

Table 3: presents the descriptive statistics for the main constructs.

Construct	Mean	SD	Minimum	Maximum
Manufacturing Flexibility (MF)	3.948	0.260	3.2	4.6
Smart Manufacturing (SM)	4.129	0.251	3.6	4.8
Production Efficiency (PE)	3.937	0.263	3.2	4.6

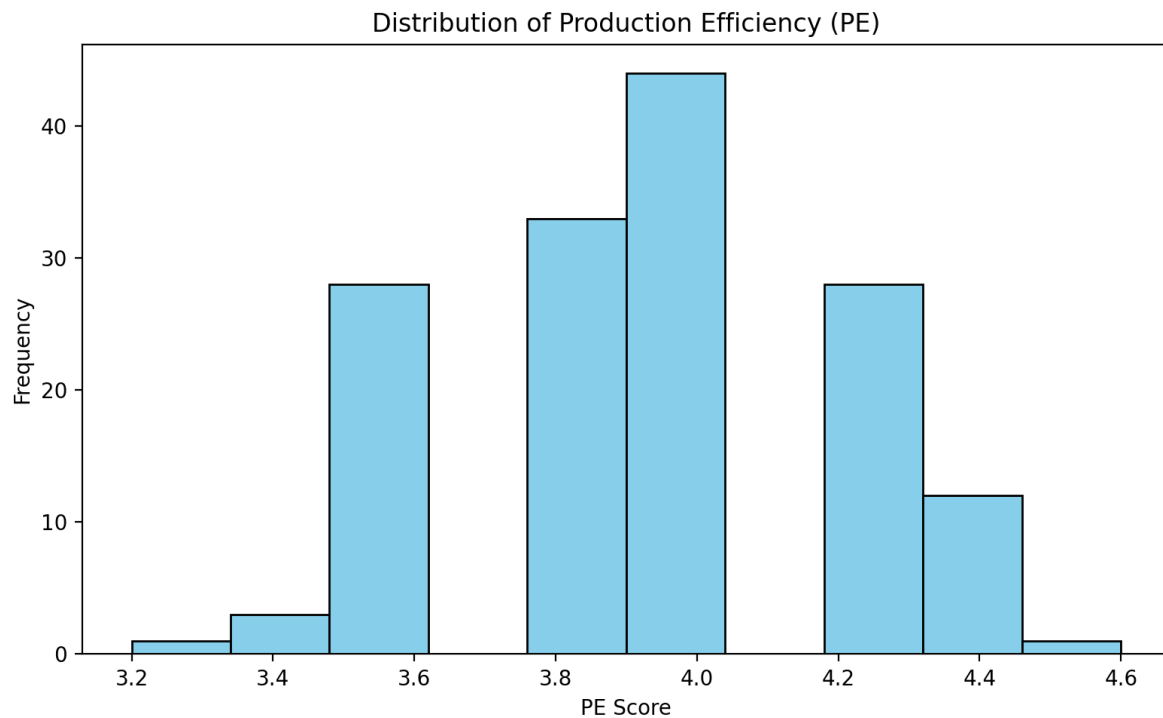


Figure 1: Distribution of Production Efficiency (PE).

Figure 1 displays the distribution of Production Efficiency (PE) scores across the surveyed participants. Most respondents rated efficiency positively, clustering around higher scores, which indicates a generally favorable perception of operational performance. The histogram also shows minor variability, suggesting consistent assessments among professionals from different roles and sectors. Overall, the figure highlights that, despite slight dispersion, the majority of participants perceive production efficiency as strong, providing a solid foundation for subsequent correlation and regression analyses.

5.3 Correlation Analysis

Pearson correlation coefficients were calculated to examine the relationships among MF, SM, and PE. The results are shown in Table 4.

Table 4 summarizes the Pearson correlation coefficients among Manufacturing Flexibility (MF), Smart Manufacturing (SM), and Production Efficiency (PE). The results indicate very weak linear relationships between the variables. MF exhibits a slight positive association with PE, while SM shows a small negative correlation. Overall, the coefficients suggest that, within this sample, perceived flexibility and smart manufacturing adoption are not strongly linked to production efficiency, highlighting the potential influence of contextual or mediating factors on operational performance.

Table 4: Pearson Correlation Coefficients Among Manufacturing Flexibility (MF), Smart Manufacturing (SM), and Production Efficiency (PE).

Variable	MF	SM	PE
MF	1.000	-0.016	0.058
SM	-0.016	1.000	-0.063
PE	0.058	-0.063	1.000

The analysis suggests very weak linear relationships between the constructs. Manufacturing Flexibility showed a slight positive association with Production Efficiency ($r = 0.058$), whereas Smart Manufacturing displayed a small negative correlation ($r = -0.063$).

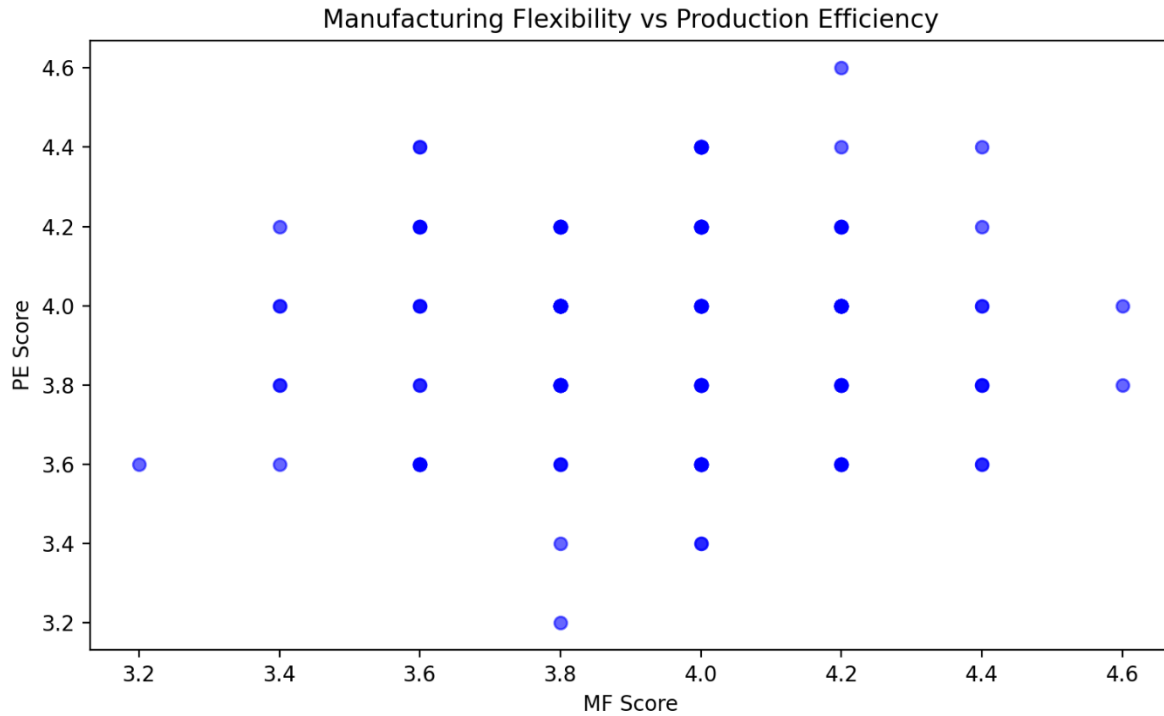


Figure 2: Manufacturing Flexibility vs Production Efficiency (Survey Data).

Figure 2 illustrates the relationship between Manufacturing Flexibility (MF) and Production Efficiency (PE) using a scatter plot of survey responses. The data points are widely dispersed, indicating variability in participants' perceptions across factories. A slight positive trend is visible, consistent with the weak correlation observed in Table 4. This spread suggests that, although higher flexibility may modestly relate to increased efficiency, the association is not strong, highlighting that additional contextual or organizational factors may influence production performance.

Similarly, Figure 3 illustrates Smart Manufacturing versus Production Efficiency, highlighting minimal observable association, consistent with the negligible negative correlation.

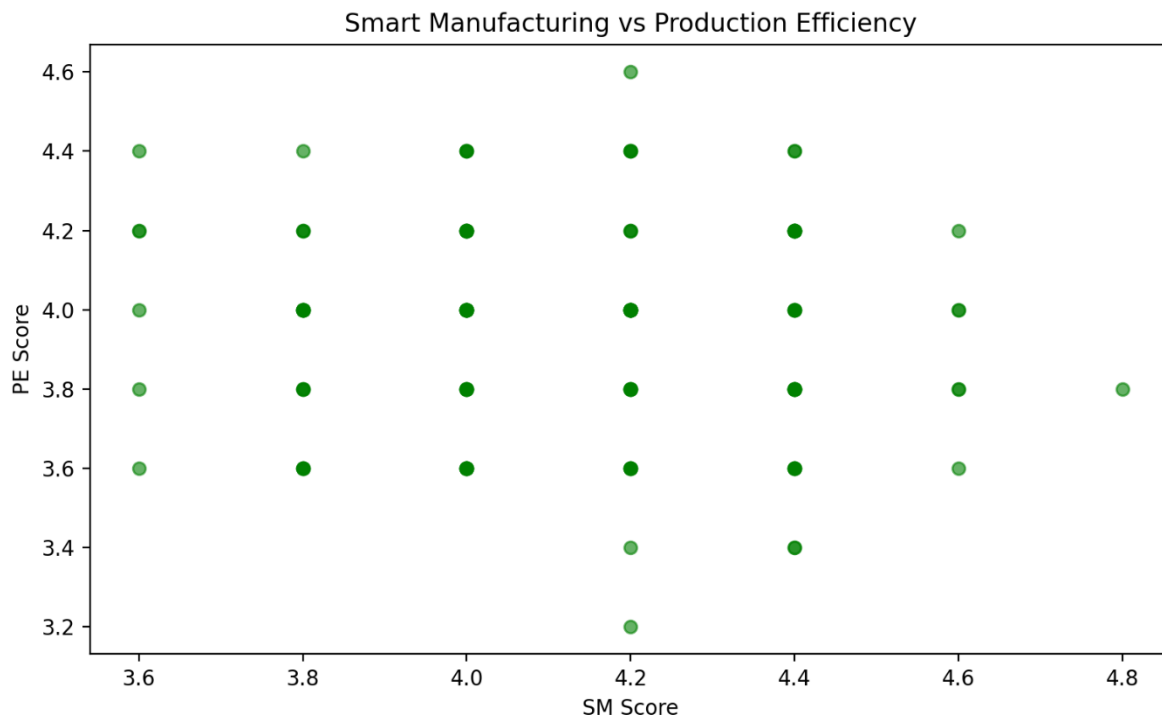


Figure 3: Smart Manufacturing vs Production Efficiency (Survey Data).

Figure 3 depicts the relationship between Smart Manufacturing (SM) and Production Efficiency (PE) using a scatter plot of survey responses. The data points are broadly scattered, showing considerable variability in participants’ perceptions. A slight negative trend is noticeable, reflecting the very weak negative correlation reported in Table 4. This pattern suggests that, within this sample, higher perceived adoption of smart manufacturing technologies does not strongly correspond to increased production efficiency. The dispersion emphasizes the potential impact of contextual factors, such as organizational implementation quality or workforce capabilities, on operational outcomes.

5.4 Multiple Regression Analysis

A multiple regression analysis was conducted to evaluate the combined predictive effect of MF and SM on PE. Table 5 summarizes the results.

Table 5: Multiple Regression Results for the Predictive Effects of Manufacturing Flexibility (MF) and Smart Manufacturing (SM) on Production Efficiency (PE).

Predictor	Coefficient (B)	Std. Error	t-value	p-value
Constant	3.980	0.489	8.132	< .001
Manufacturing Flexibility (MF)	0.058	0.083	0.695	.488
Smart Manufacturing (SM)	-0.066	0.086	-0.761	.448

Table 5 summarizes the results of a multiple regression analysis examining the combined influence of Manufacturing Flexibility and Smart Manufacturing on Production Efficiency. The coefficients indicate that neither MF nor SM significantly predicts PE in this sample. The constant term is significant, but the predictors’ low t-values and high p-values suggest minimal explanatory power. The overall model was not statistically significant ($R^2 = 0.007$, $F(2,147) = 0.539$, $p = .584$), confirming that perceived flexibility and smart manufacturing adoption have weak standalone and joint effects on production efficiency. These findings highlight the potential role of mediating factors, such as

organizational practices or workforce competency, in translating perceived capabilities into measurable efficiency outcomes.

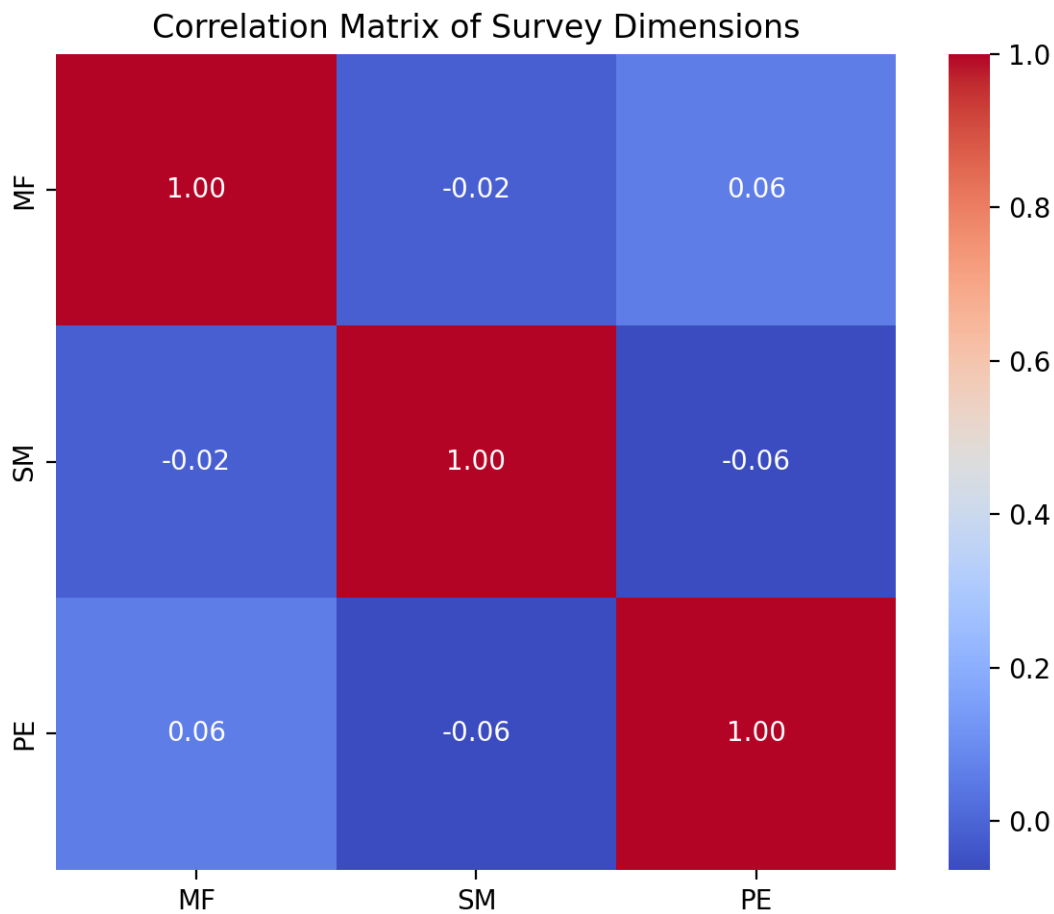


Figure 4: Correlation Matrix of MF, SM, and PE.

Figure 4 depicts the correlation matrix among MF, SM, and PE, highlighting the weak linear relationships between the constructs. The heatmap shows that MF has a slight positive association with PE, while SM displays a small negative correlation with PE. Overall, the visualization reinforces the minimal predictive strength of these variables, suggesting that additional contextual or organizational factors may influence production performance outcomes. The use of color gradients provides an intuitive view of the strength and direction of the relationships.

5.5 Principal Component Analysis (PCA)

PCA was conducted to identify the key components underlying the three constructs. The first two components explained 36.47% and 32.82% of the variance, respectively, with a cumulative 69.29%. Figure 5 displays the results of Principal Component Analysis conducted on the three study constructs: Manufacturing Flexibility (MF), Smart Manufacturing (SM), and Production Efficiency (PE). The biplot shows that the first two principal components capture a cumulative 69.29% of the total variance, indicating that these dimensions retain substantial and distinct informational contributions. The spread of data points suggests that MF, SM, and PE are related yet conceptually separate constructs. This visualization supports the multidimensional nature of operational performance, emphasizing that efficiency outcomes are influenced by multiple interdependent factors rather than a single dominant variable.

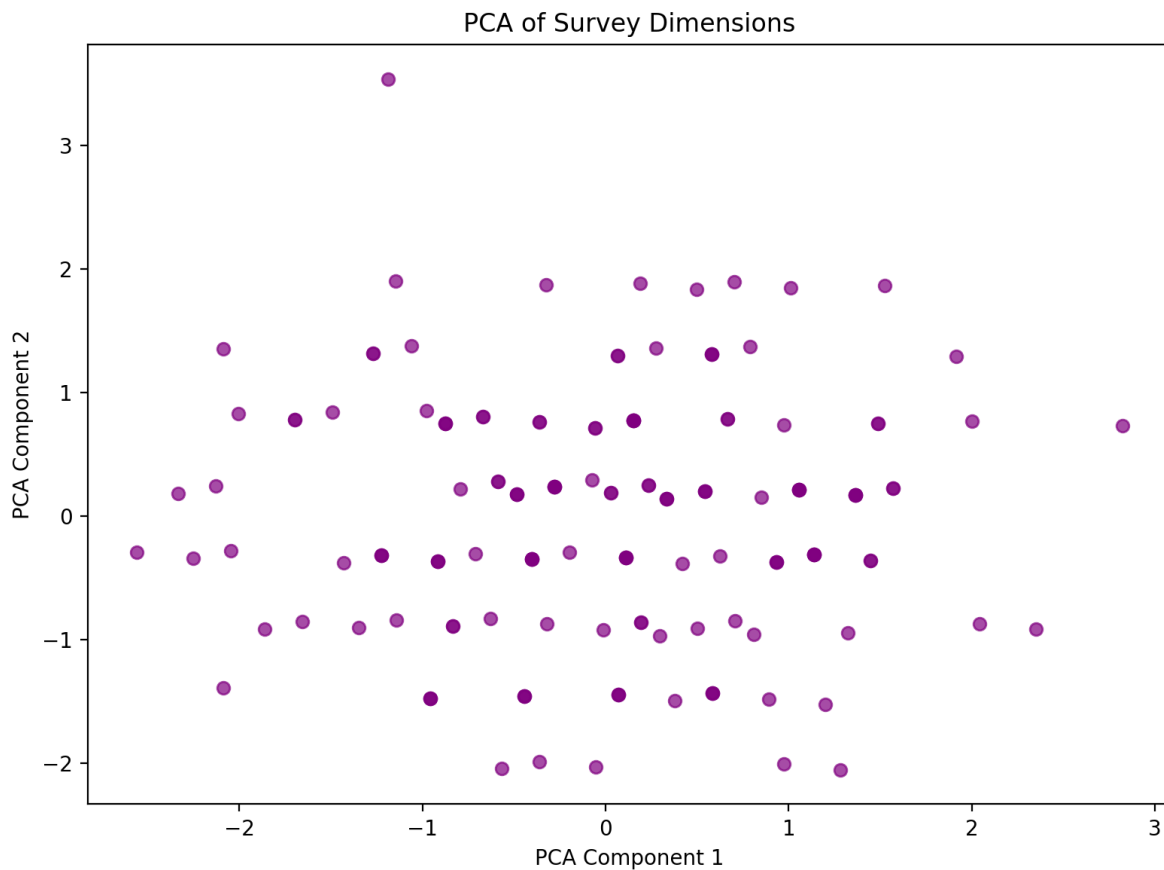


Figure 5: PCA Biplot of Survey Constructs.

5.6 Production Efficiency by Job Title

Figure 6 illustrates the distribution of Production Efficiency (PE) scores across different job roles, including technicians, supervisors, engineers, and managers. The boxplot shows that perceptions of efficiency are relatively consistent across all roles, with only minor variations in median values and interquartile ranges. This suggests that occupational role had limited influence on reported PE, reflecting a broadly shared perception of operational performance among participants regardless of their position within the organization. The visual representation underscores the uniformity in perceptions of efficiency across hierarchical levels in the surveyed industrial settings.

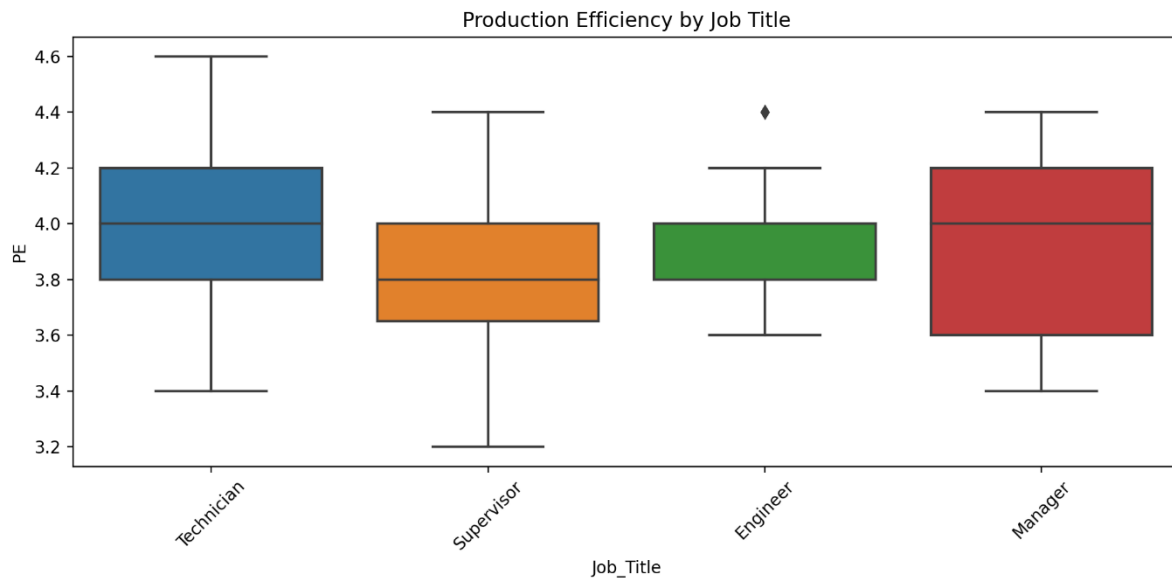


Figure 6: Production Efficiency by Job Title.

5.7 Operational Dataset Insights

The supporting operational dataset from Smart Manufacturing Process Data included process variables such as temperature, machine speed, vibration level, energy consumption, and optimal operating conditions. Descriptive statistics are summarized in Table 6.

Table 6: Descriptive Statistics of Operational Process Variables.

Variable	Mean	SD	Min	Max
Temperature (°C)	74.99	1.99	67.58	82.47
Machine Speed (RPM)	1499.56	29.06	1450	1549
Production Quality Score	8.50	0.29	8.0	9.0
Vibration Level (mm/s)	0.065	0.021	0.03	0.10
Energy Consumption (kWh)	1.499	0.288	1.0	2.0
Optimal Conditions	0.097	0.295	0	1

Table 6 summarizes key operational process variables collected from the Smart Manufacturing Process Data, including temperature, machine speed, vibration level, energy consumption, production quality scores, and adherence to optimal operating conditions. The descriptive statistics provide an overview of the range, central tendency, and variability of each variable within the dataset. Regression analysis indicated that none of these individual process variables significantly predicted Production Quality Score ($R^2 < 0.001$, $F(5,9994) = 0.834$, $p = .525$), suggesting that single-factor effects were minimal. This implies that quality outcomes in these manufacturing settings are likely influenced by complex, multifactorial interactions rather than isolated process parameters. The table thus offers an essential context for interpreting the operational environment and supports the combined analysis with survey-based perceptions of manufacturing flexibility, smart manufacturing, and production efficiency.

5.8 Summary

The results reveal that while participants reported high perceptions of Manufacturing Flexibility, Smart Manufacturing, and Production Efficiency, the statistical relationships among these constructs were weak. Regression

analyses confirmed that neither MF nor SM individually, nor jointly, significantly predicted PE. PCA analysis demonstrated that the constructs remain distinct yet related dimensions of operational performance.

The combination of survey data and operational dataset insights suggests that perceptions of advanced manufacturing practices may not translate directly into measurable improvements in production efficiency, highlighting the potential influence of mediating factors such as workforce capability, implementation quality, or organizational strategy.

6. Discussion

The present study investigated the impact of Manufacturing Flexibility (MF) and Smart Manufacturing (SM) on Production Efficiency (PE) in Iraqi industrial settings, integrating both survey-based perceptions and operational dataset analyses. Although participants reported relatively high levels of MF, SM, and PE, the statistical analyses revealed weak and non-significant relationships among these constructs.

6.1 Interpretation of Survey Results

The Pearson correlations and multiple regression results indicated that neither MF nor SM significantly predicted PE within this sample. The negligible correlation coefficients (MF–PE: $r = 0.058$; SM–PE: $r = -0.063$) and the non-significant regression coefficients suggest that perceived flexibility and digital technology adoption do not translate directly into perceived production efficiency. This finding may reflect context-specific factors, such as organizational structure, degree of technology utilization, workforce skills, or managerial practices, which may moderate the relationship between operational capabilities and efficiency outcomes.

Figure 1 illustrated the distribution of Production Efficiency scores, confirming that most participants perceived their operational outcomes positively, with relatively little variability. Figure 2 highlighted the dispersed pattern between MF and PE, consistent with the weak correlation, while Figure 3 confirmed the minimal association between SM and PE. These visual representations support the quantitative findings, emphasizing that perceptions of flexibility and technology adoption are not automatically linked to efficiency gains.

6.2 Comparison with Previous Literature

Previous studies have generally reported positive effects of manufacturing flexibility and Smart Manufacturing adoption on operational efficiency (Khan & Kribs, 2026; Li et al., 2026; Musaigwa & Kalitanyi, 2026). The discrepancy between the present results and prior literature may be explained by several factors:

1. Implementation quality: While survey respondents reported high levels of flexibility and smart technologies, actual utilization levels or effectiveness in production operations may differ from perceptions.
2. Moderating factors: Organizational culture, resource allocation, and workforce competency may influence the degree to which MF and SM affect PE.
3. Contextual variability: Iraqi industrial settings may face infrastructural, economic, or logistical constraints that limit the operational impact of advanced manufacturing practices.

These explanations align with prior empirical reviews that suggest human, managerial, and contextual variables often mediate the effectiveness of Industry 4.0 technologies on production outcomes (Rozhok et al., 2025; Höse et al., 2023).

6.3 Principal Component Analysis Insights

The PCA results indicated that the first two components explained 69.29% of the total variance across MF, SM, and PE. Figure 5 demonstrates that although the constructs are related, each contributes distinct information, confirming the multidimensionality of manufacturing performance measures. This reinforces the notion that efficiency outcomes

are multifaceted, influenced by more than a single operational dimension, and require integrative measurement approaches.

6.4 Operational Dataset Findings

Analysis of the Smart Manufacturing Process Data dataset corroborated the survey findings. Regression analysis with process variables (temperature, machine speed, vibration, energy consumption, and optimal operating conditions) did not significantly predict production quality scores. This suggests that perceived improvements in flexibility or technology adoption may not immediately impact measurable quality outcomes, especially in highly stable production environments. Figure 6 further supports this interpretation, showing similar PE scores across job roles, indicating a broad consensus in perceptions irrespective of occupational function.

6.5 Implications for Practice

Despite the non-significant statistical relationships, the results offer several practical insights:

1. **Perception vs. operational reality:** Managers should recognize that high perceived flexibility or technology presence may not automatically translate into efficiency gains; targeted interventions are necessary.
2. **Training and workforce development:** Effective use of smart manufacturing tools likely depends on employee competency, indicating a need for structured training programs.
3. **Holistic performance management:** Organizations should integrate technological, operational, and human factors to enhance production efficiency, rather than relying solely on flexibility or technology adoption.

6.6 Limitations and Future Research

The study acknowledges several limitations:

- The cross-sectional survey design captures perceptions at a single point in time, which may not reflect dynamic operational changes.
- The weak correlations suggest that unmeasured variables (e.g., organizational maturity, maintenance practices) may play a substantial role.
- The operational dataset analysis was limited to a subset of process variables; inclusion of additional process and workforce metrics may improve explanatory power.

Future research should explore longitudinal designs, larger samples, and integration of qualitative measures, such as managerial interviews, to better capture the complex interplay between flexibility, smart manufacturing, and efficiency.

7. Conclusion

This study explored the relationships among Manufacturing Flexibility (MF), Smart Manufacturing (SM), and Production Efficiency (PE) within Iraqi industrial settings, using both survey-based perceptions from 150 professionals and operational manufacturing data. Respondents reported relatively high levels of MF, SM, and PE, suggesting widespread recognition of adaptive and technology-enabled practices. However, correlation and regression analyses revealed weak and non-significant direct relationships among the constructs, indicating that perceived flexibility and smart manufacturing adoption may not automatically translate into measurable efficiency gains. Principal Component Analysis confirmed that MF, SM, and PE constitute distinct but related dimensions, collectively explaining a substantial proportion of variance. Operational dataset analyses similarly showed that key process variables—such as temperature, machine speed, vibration, and energy consumption—had minimal predictive influence on production quality. These findings emphasize the multifaceted and context-dependent nature of production performance, highlighting the potential role of mediating factors including workforce competence,

managerial practices, and organizational readiness. Despite the weak statistical effects, the study offers practical insights. Industrial managers should recognize that perceived flexibility and technology adoption alone are insufficient to enhance efficiency; targeted interventions, training, and integrated operational frameworks are necessary to convert capabilities into tangible performance outcomes. Theoretically, this research contributes by linking survey-based perceptions with operational data, providing empirical evidence on how smart manufacturing practices and flexibility interact with efficiency in real-world settings. Future studies should consider longitudinal designs, larger samples, and mixed-method approaches to explore moderating and mediating variables, thereby clarifying the mechanisms through which MF and SM influence PE. In conclusion, the study underscores that production efficiency is multidimensional and context-sensitive, and achieving operational improvements requires a combination of technological adoption, flexibility, and human-centered management strategies.

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