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THE EFFECT OF ARTIFICIAL INTELLIGENCE IMPLEMENTATION ON PROCESS OPTIMIZATION IN SMART MANUFACTURING SYSTEMS

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Abstract

The transformation toward smart manufacturing requires adaptive and data-driven process optimization to enhance industrial competitiveness. This study aims to examine the effect of Artificial Intelligence (AI) on operational efficiency, machine downtime reduction, and production quality in smart manufacturing systems. A quantitative explanatory approach with a cross-sectional survey was employed. Data were collected from 210 production managers, operational supervisors, and engineers in manufacturing companies implementing digital technologies. Respondents were selected using purposive sampling, and the data were analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS). The findings reveal that AI has a positive and significant effect on operational efficiency ($\beta = 0.812$; $t = 18.764$; $p < 0.001$), machine downtime reduction ($\beta = 0.746$; $t = 15.283$; $p < 0.001$), and production quality ($\beta = 0.781$; $t = 17.951$; $p < 0.001$). The novelty of this study lies in simultaneously examining these three dimensions of process optimization, providing a more comprehensive perspective on AI-driven smart manufacturing.

Keywords: *Artificial Intelligence; Smart Manufacturing; Process Optimization; Operational Efficiency; Production Quality.*

INTRODUCTION

The development of the Industrial Revolution 4.0 has driven a major transformation in global manufacturing systems through the integration of digital technologies, including the Internet of Things (IoT), big data analytics, cloud computing, and Artificial Intelligence (AI). Smart manufacturing has emerged as a new paradigm that enables production processes to operate in a more adaptive, interconnected, and real-time data-driven manner. In the modern manufacturing environment, companies are required to simultaneously improve productivity, quality, flexibility, and operational efficiency to maintain competitiveness in the global market (Mahfudnurnajamuddin et al., 2026). Consequently, AI has become increasingly important because of its ability to process large amounts of production data and support faster and more accurate decision-making (Sulistyawati, 2024). These developments indicate that AI is not merely a supporting technology but a strategic enabler for achieving sustainable manufacturing performance.

Globally, the adoption of AI in the manufacturing sector has shown a growing trend. Various studies report that AI improves production efficiency through predictive maintenance, automated quality control, production scheduling optimization, and responsive supply chain management (Wahyudi et al., 2025). Machine learning technologies enable manufacturing systems to identify failure patterns before machine breakdowns occur, thereby reducing downtime and operational costs significantly (Hasugian, 2025). Furthermore, the integration of AI in smart manufacturing supports the creation of flexible and customer-oriented production systems in real time (Tjandra et al., 2026). These capabilities suggest that AI has the potential to influence multiple dimensions of manufacturing performance simultaneously.

In Indonesia, the transformation toward smart manufacturing is an important part of the Making Indonesia 4.0 agenda. Various manufacturing companies have started adopting AI technologies to enhance process efficiency and product quality. The implementation of digital technologies in the national manufacturing sector has been reported to increase productivity, reduce waste, and accelerate responses to changing market demands (Djatmika, 2025). In addition, the application of AI in Indonesia's industrial environment is expanding in production control, resource optimization, and data-driven decision-making (Siska et al., 2023). Such developments indicate that AI implementation has become increasingly relevant for supporting industrial competitiveness in the era of digital transformation.

However, the implementation of AI in smart manufacturing still faces several challenges. The availability of high-quality data, integration among production systems, human resource readiness, and the complexity of real-time decision-making remain major obstacles to the effective application of this technology (Bangun et al., 2025). Many companies still implement AI partially in specific activities, such as monitoring or predicting machine failures, without integrating it into a comprehensive process optimization framework. As a result, the benefits of AI are often not fully maximized to support continuous improvements in manufacturing performance.

Previous studies have investigated various aspects of AI implementation in manufacturing. Wang et al. (2020) emphasized the role of AI in improving the flexibility and efficiency of intelligent manufacturing systems. Hartanto (2026) developed the concept of smart manufacturing based on big data and machine learning to support production process management. Similarly, Waqar et al. (2024) demonstrated that AI contributes to improving operational efficiency in the manufacturing industry. Furthermore, Ejjami and Boussalham (2024) identified various AI applications in manufacturing activities, including predictive maintenance, quality monitoring, and supply chain management.

Despite these findings, several research gaps remain. Most previous studies have focused on specific operational functions, such as predictive maintenance, quality control, or production data analysis separately (Baskoro et al., 2025). Consequently, empirical evidence regarding the comprehensive role of AI in manufacturing process optimization is still limited, particularly in smart manufacturing environments undergoing digital transformation. Moreover, only a few studies have simultaneously examined the effect of AI on operational efficiency, machine downtime reduction, and production quality within a single integrated framework. This limitation results in an incomplete understanding of the relative contribution of AI to different dimensions of process optimization. Since operational efficiency, machine downtime reduction, and production quality represent key indicators of manufacturing performance, investigating these dimensions simultaneously is essential for providing a more holistic understanding of the strategic role of AI in smart manufacturing systems.

Based on these gaps, this study aims to analyze the effect of Artificial Intelligence implementation on operational efficiency, machine downtime reduction, and production quality in smart manufacturing systems. Specifically, this study examines how AI capabilities in real-time data processing, predictive analytics, and decision automation contribute to improving manufacturing operational performance. Therefore, this research is expected to provide a more comprehensive understanding of the strategic role of AI in supporting production process optimization in the era of digital transformation.

The contribution of this study is expected to provide both theoretical and practical benefits. Theoretically, this study enriches the Industrial Engineering literature regarding the integration of Artificial Intelligence within the framework of smart manufacturing and process optimization. Practically, the findings can serve as a basis for manufacturing companies in designing more effective AI implementation strategies to improve productivity, reduce operational costs, and strengthen industrial competitiveness in the digital transformation era. In addition, the findings may serve as a reference for policymakers in accelerating the adoption of smart manufacturing technologies in Indonesia.

The novelty of this study lies in the development of an empirical model that simultaneously examines the effect of Artificial Intelligence on the three principal dimensions of manufacturing process optimization, namely operational efficiency, machine downtime reduction, and production quality. Unlike previous studies that generally focused on a single operational function, this research provides new empirical evidence regarding the integrated contribution of AI to manufacturing performance within the smart manufacturing framework and offers a more comprehensive perspective on AI-driven process optimization.

Based on theoretical considerations and previous studies, Artificial Intelligence is expected to improve production process optimization through predictive analytics, intelligent decision support, automated process control, and data-driven manufacturing. The implementation of AI enables companies to reduce operational inefficiencies, minimize machine downtime, and enhance product quality through faster and more accurate decision-making. Therefore, this study proposes the following hypotheses:

H1: Artificial Intelligence has a positive effect on operational efficiency in smart manufacturing systems.

H2: Artificial Intelligence has a positive effect on reducing machine downtime in smart manufacturing systems.

H3: Artificial Intelligence has a positive effect on improving production quality in smart manufacturing systems.

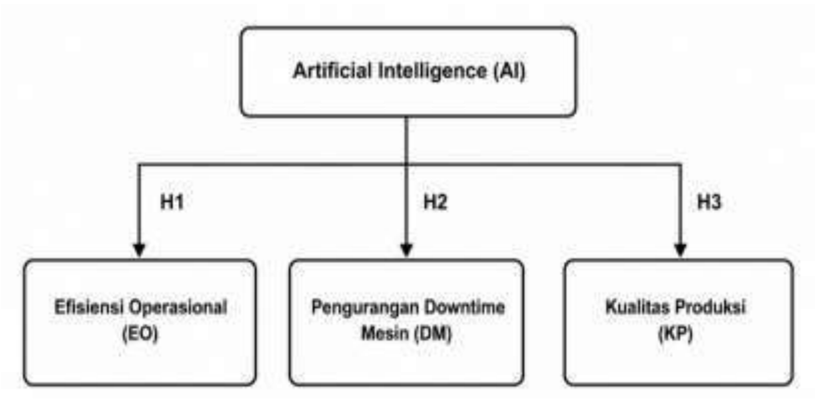

Figure 1. Research Conceptual Framework.

METHODE

This study employed a quantitative approach with an explanatory research design to investigate the effect of Artificial Intelligence (AI) implementation on process optimization in smart manufacturing systems. A cross-sectional survey design was adopted, in which data were collected within a specific period to examine the causal relationships among variables using statistical analysis (Timotius, 2017). The explanatory approach was considered appropriate because it enables the testing of direct relationships between AI implementation and three key dimensions of manufacturing process optimization, namely operational efficiency, machine downtime reduction, and production quality.

The population of this study consisted of production managers, operational supervisors, and engineers working in manufacturing companies that had implemented digital technologies. The sample was selected using purposive sampling based on two criteria: respondents had at least three years of work experience and were directly involved in the implementation of AI or industrial analytics systems. Based on these criteria, 210 eligible respondents were obtained. This sample size was considered sufficient for SEM analysis because it satisfied the recommended sample requirements for multivariate structural models (Amaliana & Fernandes, 2019). The selected respondents were expected to possess adequate knowledge and experience regarding the application of AI in manufacturing operations, thereby providing reliable information for evaluating the relationships among the research variables.

Data were collected using a structured questionnaire with a five-point Likert scale. This study employed four constructs consisting of Artificial Intelligence as the independent variable and Operational Efficiency, Machine Downtime Reduction, and Production Quality as dependent variables. Artificial Intelligence was measured through predictive analytics, intelligent decision support, automated process control, and data-driven manufacturing indicators adapted from (Apdillah & Sari, 2025) and (Lazaroiu et al., 2022). Operational Efficiency was measured through production productivity and resource utilization efficiency indicators. Machine Downtime Reduction was assessed through indicators related to early detection of machine failures and the reduction of production downtime. Production Quality was measured using indicators of product quality consistency and defect reduction adapted from (Shivani et al., 2025). Instrument validity was evaluated using outer loading and Average Variance Extracted (AVE), whereas reliability was assessed through Cronbach's Alpha and Composite Reliability (Tentama & Situmorang, 2019). These measurements were intended to ensure that the constructs accurately represented the dimensions of AI-driven process optimization in smart manufacturing environments.

The research process began with a literature review and the development of research instruments based on previous studies. Subsequently, a pilot test involving 30 respondents was conducted to ensure the clarity and comprehensibility of the questionnaire. After the pilot testing stage, the questionnaire was distributed online to respondents who met the predetermined criteria during January–March 2025. The collected data then underwent screening, coding, and cleaning procedures before further statistical analysis was performed (Fathoni et al., 2025). These procedures were carried out to ensure the quality and completeness of the data used in hypothesis testing.

Data analysis was conducted using Structural Equation Modeling–Partial Least Squares (SEM-PLS) with the assistance of SmartPLS 4. The measurement model evaluation included convergent validity, discriminant validity, and construct reliability assessments, while the structural model evaluation comprised the examination of R^2, f^2, Q^2, and SRMR values (Al Faisal et al., 2025). Hypothesis testing was performed using the bootstrapping procedure with a significance level of 5% to determine the magnitude and significance of the effects of Artificial Intelligence on operational efficiency (H1), machine downtime reduction (H2), and production quality improvement (H3) in smart manufacturing systems. The relationships among variables were evaluated based on path coefficients (β), t-statistics, and p-values to provide a more comprehensive interpretation of the strength and significance of each relationship.

RESULTS AND DISCUSSION

Respondent Characteristics

This study involved 210 respondents consisting of production managers, operational supervisors, and engineers in manufacturing companies that have implemented digital technology and Artificial Intelligence (AI). Based on position, respondents were dominated by production managers at 38.1%, followed by engineers at 34.3%, and operational supervisors at 27.6%. Based on work experience, the majority of respondents have more than five years of experience (61.4%), while the rest have between three to five years of experience (38.6%). In terms of technology implementation, as many as 72.9% of companies have implemented AI for more than two years.

Table 1. Respondent Characteristics

Features	Category	Frequency	Percentage (%)
Departments	Production Manager	80	38,1
	Operational Supervisor	58	27,6
	Engineer	72	34,3
Work Experience	3–5 Years	81	38,6
	>5 Years	129	61,4
AI Implementation	1–2 Years	57	27,1
	>2 Years	153	72,9

Based on Table 1, the majority of respondents possess sufficient experience in managing manufacturing operations and implementing AI technology. This indicates that the respondents have adequate knowledge regarding smart manufacturing practices, thereby allowing the collected data to reflect the actual conditions of AI implementation in manufacturing companies.

Evaluation Results of Measurement Model (Outer Model)

Evaluation of the measurement model was conducted to assess the validity and reliability of the research constructs. The results showed that all indicators had outer loading values above 0.70. In addition, the Average Variance Extracted (AVE), Composite Reliability, and Cronbach's Alpha values of all variables met the recommended thresholds.

Table 2. Construct Validity and Reliability

Variabel	AVE	Composite Reliability	Cronbach's Alpha
Artificial Intelligence	0,721	0,912	0,885
Operational Efficiency	0,744	0,921	0,896
Reduced Machine Downtime	0,732	0,914	0,887
Production Quality	0,758	0,926	0,902

Table 2 demonstrates that all constructs satisfy the requirements of convergent validity and reliability. The AVE values exceed 0.50, indicating that each construct adequately explains the variance of its indicators. Moreover, Composite Reliability and Cronbach's Alpha values are above 0.70, confirming that the measurement instruments are internally consistent and reliable. Therefore, all constructs are considered appropriate for further structural model evaluation.

Results of Structural Model Evaluation (Inner Model)

Structural model evaluation was performed to determine the ability of Artificial Intelligence to explain variations in each endogenous variable. The results indicate that the model possesses satisfactory predictive capability.

Table 3. Structural Model Evaluation Results

Variable endogenous	R^2	Q^2
Operational Efficiency	0,659	0,478
Reduced Machine Downtime	0,557	0,401
Production Quality	0,610	0,445

As presented in Table 3, Artificial Intelligence explains 65.9% of the variance in operational efficiency (R^2 = 0.659), 55.7% of the variance in machine downtime reduction (R^2 = 0.557), and 61.0% of the variance in production quality (R^2 = 0.610). These values indicate moderate to substantial explanatory power. Furthermore, the Q^2 values ranging from 0.401 to 0.478 are all greater than zero, demonstrating that the model has good predictive relevance and is capable of predicting the endogenous constructs effectively.

Hypothesis testing was conducted using the bootstrapping procedure in SmartPLS 4 with a significance level of 5%. The results indicate that all hypotheses are supported, as evidenced by t-statistics greater than 1.96 and p-values below 0.05.

Table 4. Hypothesis Testing Results

Hipotesis	Relationships Between Variables	b	t-value	p-value	Verdict
H1	Artificial Intelligence → Operational Efficiency	0,812	18,764	0,000	Accepted
H2	Artificial Intelligence → Reduction of Machine Downtime	0,746	15,283	0,000	Accepted
H3	Artificial Intelligence → Production Quality	0,781	17,951	0,000	Accepted

Table 4 reveals that all relationships are positive and statistically significant. The strongest effect is observed in the relationship between Artificial Intelligence and operational efficiency (β = 0.812; t = 18.764; $p < 0.001$), indicating a very strong influence of AI on improving manufacturing operational performance. The effect of Artificial Intelligence on production quality is also substantial (β = 0.781; t = 17.951; $p < 0.001$), followed by its effect on machine downtime reduction (β = 0.746; t = 15.283; $p < 0.001$). These findings suggest that a higher level of AI implementation is associated with greater improvements in productivity, operational reliability, and product quality. The relatively high path coefficients further indicate that AI represents a key enabling factor in smart manufacturing environments.

Descriptive Analysis of Research Variables

Descriptive analysis was performed to identify the indicators with the highest average scores for each research variable.

Table 5. Average Value of Research Variable Indicators

Variabel	Indicator	Mean
Artificial Intelligence	Predictive Analytics	4,32
	Automated Process Control	4,26
	Data-Driven Manufacturing	4,21
	Intelligent Decision Support	4,18
Operational Efficiency	Production Productivity	4,41

	Resource Usage Efficiency	4,37
Reduced Machine Downtime	Early Detection of Machine Damage	4,28
	Reduction of Production Downtime	4,24
Production Quality	Product Quality Consistency	4,35
	Defective Product Reduction	4,31

Based on Table 5, predictive analytics obtained the highest mean score among AI indicators (4.32), indicating that data-driven prediction capabilities constitute the most widely utilized AI application in manufacturing companies. Among the outcome variables, production productivity achieved the highest mean score (4.41), followed by product quality consistency (4.35). These findings imply that the benefits of AI implementation are primarily reflected in improved operational efficiency and production quality. The relatively high mean values across all indicators also indicate that respondents perceive AI implementation positively and consider it beneficial for supporting process optimization.

Summary of Research Findings

The results demonstrate that Artificial Intelligence has positive and significant effects on operational efficiency, machine downtime reduction, and production quality in smart manufacturing systems. Among these relationships, the effect on operational efficiency is the strongest ($\beta = 0.812$), followed by production quality ($\beta = 0.781$) and machine downtime reduction ($\beta = 0.746$). These findings highlight the strategic role of AI in improving manufacturing performance through enhanced data processing, intelligent decision-making, and automated process control.

The strong relationship between AI and operational efficiency indicates that AI contributes to higher productivity and more efficient resource utilization by enabling faster and more accurate decision-making. In addition, the significant effect of AI on machine downtime reduction suggests that predictive analytics capabilities facilitate early detection of potential machine failures, thereby supporting predictive maintenance and minimizing production interruptions. Furthermore, AI contributes to improved production quality through real-time monitoring and defect detection mechanisms, which enhance product consistency and reduce the occurrence of defective products.

From a practical perspective, these findings imply that manufacturing managers and engineers should prioritize AI integration in production planning, maintenance management, and quality control systems. The results also suggest that the successful implementation of AI can support higher operational reliability, lower production costs, and improved competitiveness in smart manufacturing environments.

DISCUSSION

The results of this study demonstrate that the implementation of Artificial Intelligence (AI) has positive and significant effects on operational efficiency, machine downtime reduction, and production quality in smart manufacturing systems. These findings reinforce the understanding that AI is not merely a supporting technology but also a strategic capability that transforms manufacturing processes into more adaptive, predictive, and data-driven systems. The positive path coefficients and high t-values obtained for all relationships indicate that greater utilization of AI through predictive analytics, automated process control, intelligent decision support, and data-driven manufacturing leads to better manufacturing process performance. These findings are consistent with Sutrisno et al. (2025), who emphasized that the maturity of Industry 4.0 technologies strengthens organizational agility and operational resilience. Similarly, the results support Sariwardani and Si (2024), who argued that AI-based smart production management plays a crucial role in predictive maintenance, real-time scheduling, quality control, and supply chain optimization.

The strongest effect of AI was observed on operational efficiency, with a path coefficient of $\beta = 0.812$, $t = 18.764$, and $p < 0.001$. This result indicates that AI contributes substantially to accelerating work processes, reducing waste, increasing productivity, and improving resource utilization. From the perspective of Industrial Engineering, these findings reflect the principle of process optimization, which aims to maximize output while minimizing inputs, waiting time, and non-value-added activities. AI enables companies to process production data in real time, allowing operational decisions to be based on objective and accurate information rather than relying solely on human intuition. These findings are in accordance with Kurniawan (2025), who suggested that the new direction of lean manufacturing is increasingly associated with smart manufacturing, machine learning, and lean production as instruments for process performance improvement. Therefore, AI can be viewed as an advanced extension of lean principles because it not only identifies inefficiencies but also predicts and prevents them before they adversely affect production performance.

The results of hypothesis H2 indicate that AI has a positive and significant effect on machine downtime reduction, with a path coefficient of $\beta = 0.746$, $t = 15.283$, and $p < 0.001$. Although this relationship is slightly weaker than the effects on operational efficiency and production quality, the magnitude of the coefficient still indicates a strong relationship. These findings suggest that AI capabilities in predictive analytics and machine learning support the early detection of machine abnormalities before actual failures occur. In smart manufacturing environments, machine downtime represents not only technical disruptions but also losses in productivity, increased maintenance costs, delays in production schedules, and reduced operational reliability. Therefore, predictive maintenance becomes one of the most important mechanisms through which AI improves manufacturing performance. These results are in line with Kurniawan (2025), who explained that machine learning can be employed to classify machine failures within predictive maintenance systems. The findings are further supported by Imaduddin et al. (2024), who highlighted that AI- and IoT-based predictive maintenance constitutes an important instrument for improving manufacturing efficiency and sustainability.

The influence of AI on production quality was also found to be positive and significant, with a path coefficient of $\beta = 0.781$, $t = 17.951$, and $p < 0.001$. This result indicates that AI integration contributes considerably to improving product consistency and reducing production defects. Compared with machine downtime reduction, the effect on production quality is relatively stronger, suggesting that AI-based quality management systems are increasingly effective in modern manufacturing environments. Technically, AI enables real-time monitoring, anomaly detection, and rapid identification of deviations in production parameters, thereby allowing corrective actions to be implemented promptly. In addition, AI-based defect detection systems enhance product consistency and reduce the occurrence of defective products. These findings are consistent with Simangunsong et al. (2025), who emphasized the importance of technology-based defect detection, particularly computer vision, in maintaining quality in high-speed manufacturing processes. Likewise, Larisang et al. (2026) reported that AI implementation in predictive maintenance contributes not only to machine reliability but also to the stability of production output quality.

Compared with previous studies, the novelty of this research lies in the separation of process optimization outcomes into three empirical dimensions, namely operational efficiency, machine downtime reduction, and production quality. Previous studies generally treated process optimization as a broad concept or investigated AI applications in isolated functions, such as maintenance, quality control, or production planning. In contrast, this study provides new empirical evidence by demonstrating that AI exerts different levels of influence across the three dimensions, with operational efficiency representing the strongest effect, followed by production quality and machine downtime reduction. Therefore, this study extends the smart manufacturing literature by offering a more measurable and practically applicable model for manufacturing companies undergoing digital transformation. These findings also complement the results of Qudus (2025), who emphasized the importance of production planning based on process time and work capacity, since AI has been empirically shown to simultaneously strengthen efficiency, reliability, and quality dimensions.

The differences in the magnitude of the relationships indicate that the benefits of AI are not distributed uniformly across all aspects of manufacturing processes. The strongest effect on operational efficiency may occur because companies are generally able to implement AI more easily in production monitoring, workflow management, and operational data analysis than in maintenance or quality systems that require sophisticated sensors, machine connectivity, and historical databases. Meanwhile, the comparatively lower coefficient associated with machine downtime reduction suggests that predictive maintenance requires higher levels of technological readiness, sensor accuracy, machine integration, and technical competence among operators. These observations are consistent with Murugesan et al. (2023), who argued that the successful implementation of automation and AI depends not only on technological infrastructure but also on the readiness of production systems and human resources. Consequently, the effectiveness of AI implementation depends on the organization's capability to integrate technology, data, processes, and human competencies.

From a theoretical perspective, this study contributes to the development of Industrial Engineering literature by strengthening the integration among smart manufacturing, process optimization, and data-driven decision-making concepts. The findings demonstrate that AI can be conceptualized as an operational capability that links production data with improved process performance. From a practical perspective, the results imply that manufacturing managers and engineers should prioritize AI implementation in areas that provide the greatest impact on operational efficiency before extending its application to predictive maintenance and quality assurance systems. Such initiatives may include strengthening sensor infrastructures, integrating machine data, enhancing operator competencies, and developing real-time analytical dashboards. Through these strategies, AI implementation can evolve from being merely a technological investment into a mechanism that generates measurable improvements in manufacturing performance, operational reliability, and product quality.

Although the results provide strong support for all hypotheses, several limitations should be acknowledged. First, the study relied on survey data and respondents' perceptions rather than objective operational indicators such as OEE, defect rate, cycle time, or mean time between failures. Second, the cross-sectional design does not allow the long-term effects of AI implementation to be captured. Third, the study did not distinguish among industrial sectors, company size, and levels of digital maturity, which may influence the effectiveness of AI adoption. Therefore, future studies are recommended to employ longitudinal designs, combine survey data with actual operational data, and incorporate mediating or moderating variables such as digital readiness, absorptive capacity, human–AI collaboration, and data quality. Such approaches would provide a deeper understanding not only of whether AI affects process optimization, but also of the mechanisms and organizational conditions under which its effects become most substantial.

CONCLUSION

This study demonstrates that Artificial Intelligence (AI) has positive and significant effects on operational efficiency, machine downtime reduction, and production quality in smart manufacturing systems. Among these relationships, the strongest effect was found on operational efficiency, indicating that AI capabilities in predictive analytics, intelligent decision support, automated process control, and data-driven manufacturing contribute substantially to increasing productivity and improving resource utilization. In addition, AI supports machine downtime reduction through predictive maintenance capabilities and enhances production quality through real-time monitoring and more accurate defect detection. These findings confirm that AI serves not only as a technological tool but also as a strategic capability for process optimization in smart manufacturing environments.

The main contribution of this study lies in providing empirical evidence and developing an integrated model that simultaneously examines the influence of AI on the three key dimensions of manufacturing process optimization, namely operational efficiency, machine downtime reduction, and production quality. Compared with previous studies that generally focused on specific operational functions, this study offers a more comprehensive perspective on the role of AI in improving manufacturing performance within the smart manufacturing framework.

From a managerial perspective, the findings imply that manufacturing managers and engineers should prioritize investments in AI infrastructure, predictive analytics systems, machine data integration, and real-time monitoring technologies. Furthermore, strengthening employees' digital competencies and enhancing collaboration between humans and AI are essential to ensure that AI implementation generates measurable improvements in productivity, operational reliability, and product quality. Therefore, successful AI adoption requires not only technological readiness but also organizational capabilities in integrating data, processes, and human resources.

Despite providing strong support for the proposed hypotheses, this study has several limitations. First, the analysis relies on survey data based on respondents' perceptions rather than objective operational indicators. Second, the respondents were limited to production managers, operational supervisors, and engineers. Third, this study did not distinguish differences among manufacturing sectors, company size, and levels of digital maturity, which may influence the effectiveness of AI implementation. In addition, the cross-sectional design limits the ability to observe the long-term impact of AI adoption.

Therefore, future research is recommended to combine survey data with actual operational indicators and to employ longitudinal research designs. Further studies are also encouraged to investigate the roles of organizational readiness, digital maturity, human–AI collaboration, absorptive capacity, and data quality in explaining the effectiveness of AI implementation across different manufacturing contexts.

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REFERENCES

Al Faisal, M. W., Alparij, P., & Ihsan, M. (2025). Pengaruh otomatisasi mesin produksi dan efisiensi terhadap produktivitas kerja karyawan di PT Clama Indonesia. *Journal Industrial Engineering and Management (JUST-ME), 6*(2), 163–170.

Amaliana, L., & Fernandes, A. A. R. (2019). *Metode statistika multivariat generalized structured component analysis (GSCA) pemodelan persamaan struktural (SEM).* Universitas Brawijaya Press.

Apdillah, D., & Sari, K. (2025). *Kecerdasan buatan dalam pendidikan: Meningkatkan kualitas pembelajaran dengan teknologi.* Dira Media Kreasindo.

Bangun, R. B., Manullang, R. M. V., & Simamora, S. A. (2025). Akuntansi manajemen strategis di tengah digitalisasi: Analisis literatur tentang perubahan, manfaat, dan hambatan. *Jurnal Akademik Ekonomi dan Manajemen, 2*(4), 148–159.

Baskoro, S. E., Mardiah, M., Rustiyana, H. R., Nurdiyah, D., Juansa, A., Hendratni, T. W., Kusjani, A., Budiasto, J., Saputra, O., & Damanik, F. H. S. (2025). *Kecerdasan buatan dalam kehidupan nyata: Konsep, algoritma dan penerapan.* Star Digital Publishing.

Djatmika, G. H. (2025). Peran transformasi digital dalam meningkatkan efisiensi operasional pada industri manufaktur di Indonesia. *Tartib: Journal of Educational Management, 4*(1), 56–81.

Ejjami, R., & Boussalham, K. (2024). Resilient supply chains in Industry 5.0: Leveraging AI for predictive maintenance and risk mitigation. *International Journal for Multidisciplinary Research, 6*(4), 25116.

Fathoni, F., Ansori, A. F., Ramadhani, I. N., Anissa, C. R., & Putri, S. A. (2025). Analisis sentimen masyarakat Indonesia di Twitter terhadap sistem perpajakan 'Coretax' menggunakan metode Naïve Bayes. *JATI (Jurnal Mahasiswa Teknik Informatika), 9*(4), 6749–6753.

Hartanto, S. (2026). *Sistem manufaktur cerdas: Inovasi, teknologi, dan strategi industri modern.* PT Ghani Press Group.

Hasugian, P. S. (2025). Sistem pakar identifikasi kerusakan mesin Tanshi Tsuke dengan menggunakan metode certainty factor pada PT Sagami Indonesia. *Journal Data Science Penusa (JDSP), 2*(1), 101–107.

Imaduddin, I., Sari, S. A. A., Hermansyah, T. A., & Tenridolong, A. C. T. R. (2024). Pengaruh teknologi industri 5.0 terhadap efisiensi manajemen produksi di perusahaan manufaktur. *EKOMA: Jurnal Ekonomi, Manajemen, Akuntansi, 4*(1), 2376–2384.

Kurniawan, D. (2025). *PT Musashi Auto Parts Indonesia: Strategi manufaktur komponen presisi dan peran kunci dalam rantai pasok otomotif nasional.* Afdan Rojabi Publisher.

Larisang, L., Tarigan, P. P., Wiranto, I., Muhida, R., Irsyam, M., Merjani, A., Saputro, H., Maghfiroh, A. M., Irwan, H., & Purbasari, A. (2026). *Rekayasa teknologi industri dan manufaktur cerdas.* CV Edu Akademi.

Lazaroiu, G., Androniceanu, A., Grecu, I., Grecu, G., & Neguriță, O. (2022). Artificial intelligence-based decision-making algorithms, Internet of Things sensing networks, and sustainable cyber-physical management systems in big data-driven cognitive manufacturing. *Oeconomia Copernicana, 13*(4), 1047–1080.

Mahfudnurnajamuddin, M., Serang, S., Amiruddin, M., & Rahmah, M. N. (2026). Literature review manajemen operasional: Manajemen operasional. *Jurnal Ekonomi, Akuntansi dan Manajemen Nusantara, 4*(3), 476–485.

Murugesan, U., Subramanian, P., Srivastava, S., & Dwivedi, A. (2023). A study of artificial intelligence impacts on human resource digitalization in Industry 4.0. *Decision Analytics Journal, 7*, 100249.

Qudus, L. (2025). Leveraging artificial intelligence to enhance process control and improve efficiency in manufacturing industries. *International Journal of Computer Applications Technology and Research, 14*(2), 18–38.

Sariwardani, A., & Si, S. E. M. (2024). Manajemen produksi dan operasi. *Manaj. Produksi dan Operasi Era Revolusi Industri, 4*, 35.

Shivani, K., Sharma, M. A., & Jain, S. (2025). Results of manufacturing efficiency improvement through defect reduction, quality enhancement, and process optimization. *International Journal of Research & Technology, 13*(4), 675–682.

Simangunsong, H., Simanullang, J., & Wayahdi, M. R. (2025). Analisis peran AI dalam meningkatkan efisiensi dan inovasi di industri manufaktur. *JUTEK: Jurnal Teknologi, 1*(2), 68–73.

Siska, M., Siregar, I., Saputra, A., Juliana, M., & Afifudin, M. T. (2023). Kecerdasan buatan dan big data dalam industri manufaktur: Sebuah tinjauan sistematis. *Nusantara Technology and Engineering Review, 1*(1), 41–53.

Sulistyawati, U. S. (2024). Decoding big data: Mengubah data menjadi keunggulan kompetitif dalam pengambilan keputusan bisnis. *Jurnal Manajemen dan Teknologi, 1*(2), 58–71.

Sutrisno, S., Ausat, A. M. A., & Junaidi, A. (2025). Analisis peran strategis human capital agility dan digital readiness dalam mengoptimalkan kinerja tim virtual pada dinamika lingkungan kerja hibrida berbasis teknologi adaptif. *Jurnal Minfo Polgan, 14*(2), 2850–2861.

Tentama, F., & Situmorang, N. Z. (2019). Pengujian validitas dan reliabilitas konstruk hope. *Jurnal Psikologi Terapan dan Pendidikan, 1*(2), 128–135.

Timotius, K. H. (2017). *Pengantar metodologi penelitian: Pendekatan manajemen pengetahuan untuk perkembangan pengetahuan.* Penerbit Andi.

Tjandra, S., Deviyanti, I. G. A. S., Prihartanti, W., Rahmanto, A., Widari, N. S., & Fais, M. A. (2026). *Transformasi manufaktur cerdas dalam pengembangan startup di era Industri 4.0.* PT Ghani Press Group.

Wahyudi, B., Danu, M., Mawasandi, F., Aziz, Z. N., & Rosyadi, M. F. G. (2025). Transformasi manajemen rantai pasokan berbasis internet of things (IoT): Tinjauan literatur. *Jurnal Teknologi dan Manajemen Industri Terapan, 4*(1), 32–44.

Wang, Y., Zheng, P., Peng, T., Yang, H., & Zou, J. (2020). Smart additive manufacturing: Current artificial intelligence-enabled methods and future perspectives. *Science China Technological Sciences, 63*(9), 1600–1611.

Waqar, M., Bhatti, I., & Khan, A. H. (2024). AI-powered automation: Revolutionizing industrial processes and enhancing operational efficiency. *Revista de Inteligencia Artificial en Medicina, 15*(1), 1151–1175.