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Integration of Digital Twins and IoT Sensors to Support Monitoring Accuracy and Maintenance Effectiveness in the Manufacturing Industry in the Cikarang Region

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ABSTRACT

This study investigates the integration of digital twin technology and Internet of Things (IoT) sensors in improving monitoring accuracy and maintenance effectiveness within manufacturing companies in the Cikarang industrial region. A quantitative research design was employed using data collected from 125 respondents representing operational, maintenance, engineering, and managerial roles. The measurement instrument was developed using a Likert scale, and data were analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS 3). The results indicate that the integration of digital twins and IoT sensors has a significant positive effect on monitoring accuracy, demonstrating that real-time data synchronization and simulation capabilities enhance system visibility and anomaly detection. Monitoring accuracy is also found to significantly influence maintenance effectiveness, highlighting the importance of accurate and timely information in supporting predictive maintenance practices. Furthermore, digital integration directly affects maintenance effectiveness, indicating that simulation-based insights and real-time data contribute to improved maintenance planning and reduced downtime. The model explains 61.2% of the variance in maintenance effectiveness (R^2 = 0.612), suggesting strong explanatory power. This study contributes to the literature on Industry 4.0 by providing empirical evidence on the role of integrated digital technologies in enhancing operational performance in a developing country context. Practically, the findings suggest that manufacturing firms should prioritize the integration of digital twins and IoT sensors to achieve higher monitoring accuracy and more effective maintenance strategies.

Keywords: *Digital Twin, Internet of Things (IoT), Monitoring Accuracy, Maintenance Effectiveness, SEM-PLS*

1. INTRODUCTION

The rapid advancement of Industry 4.0 has fundamentally transformed the operational landscape of the manufacturing sector, shifting traditional production systems toward data-driven, interconnected, and intelligent environments. The integration of cyber-physical systems, real-time analytics, and advanced digital infrastructures has enabled manufacturing firms to enhance operational efficiency, responsiveness, and decision-making precision [1]–[3]. Within this transformation, technologies such as digital twins and the Internet of Things (IoT) have emerged as critical enablers for achieving higher levels of operational visibility and control [4]–[6]. In highly industrialized regions such as Cikarangone of the largest manufacturing clusters in Southeast Asia the adoption of these technologies is increasingly essential due to the complexity and scale of production systems that demand continuous monitoring and efficient asset management.

Digital twin technology represents a paradigm shift in how physical systems are modeled and managed. It involves the creation of dynamic virtual replicas of physical assets that are continuously updated through real-time data streams [4], [7]. This capability allows organizations to simulate, analyze, and predict system behavior under varying operational conditions. When combined with IoT sensors which capture granular, real-time data from machines and production environments the digital twin evolves into a powerful decision-support system. IoT sensors monitor critical parameters such as vibration, temperature, pressure, and machine utilization, enabling early detection of anomalies and performance deviations [8], [9]. The integration of these technologies establishes a bidirectional data flow between physical and digital systems, facilitating a closed-loop feedback mechanism that enhances operational intelligence.

Monitoring accuracy has become a critical performance dimension in modern manufacturing systems, particularly as production processes become increasingly complex and automated. Traditional monitoring approaches, which rely on periodic inspections and manual data collection, are often insufficient in capturing real-time system dynamics [10]–[12]. Such limitations can lead to delayed anomaly detection, increased equipment downtime, and compromised product quality. In contrast, the integration of digital twins and IoT sensors enables continuous, real-time monitoring with higher precision and reliability [12], [13]. This technological shift not only improves situational awareness but also supports proactive and data-driven decision-making, which is essential for maintaining operational stability.

Beyond monitoring, maintenance effectiveness represents another critical operational outcome influenced by digital transformation. Maintenance strategies have evolved significantly, transitioning from reactive approaches toward predictive and condition-based maintenance paradigms. Predictive maintenance leverages real-time data and advanced analytics to anticipate equipment failures before they occur, thereby minimizing unplanned downtime and optimizing maintenance resources. The integration of digital twins and IoT sensors enhances this capability by enabling accurate simulation of equipment behavior and failure scenarios. Consequently, organizations can improve maintenance scheduling, extend asset lifecycles, and reduce operational costs.

Despite the increasing recognition of digital twin and IoT technologies, empirical evidence examining their integrated impact on monitoring accuracy and maintenance effectiveness remains limited, particularly in emerging economies such as Indonesia. Existing studies tend to focus on conceptual models or case-based analyses in developed countries, which may not fully capture the contextual challenges and opportunities present in developing industrial ecosystems. The Cikarang region offers a relevant empirical setting due to its diverse industrial base and ongoing digital transformation initiatives. However, variations in technological readiness, infrastructure, and organizational capabilities may influence the effectiveness of digital integration in this context.

Furthermore, the successful implementation of digital twin and IoT systems is contingent upon several organizational and technological factors, including data management capabilities, system interoperability, and workforce readiness. While many firms have adopted IoT technologies, the integration with digital twin systems is often incomplete or fragmented. This partial adoption raises concerns regarding suboptimal utilization and limits the potential benefits of digital transformation. Therefore, a comprehensive empirical investigation is required to assess how the integration of these technologies—rather than their isolated adoption—affects key operational outcomes.

Based on these gaps, this study aims to examine the effect of digital twin and IoT integration on monitoring accuracy and maintenance effectiveness in manufacturing firms located in the Cikarang region. Specifically, the study investigates: (1) the direct effect of digital integration on monitoring accuracy, (2) the effect of monitoring accuracy on maintenance effectiveness, and (3) the direct effect of digital integration on maintenance effectiveness. Using a quantitative approach with

Structural Equation Modeling–Partial Least Squares (SEM-PLS 3) and data collected from 125 respondents, this study provides empirical validation of the proposed relationships.

The contribution of this research is twofold. From a theoretical perspective, it extends the literature on Industry 4.0 by offering empirical evidence on the synergistic role of digital twin and IoT integration in enhancing operational performance within a developing country context. From a practical standpoint, the findings provide strategic insights for manufacturing firms seeking to optimize monitoring systems and maintenance strategies through integrated digital technologies. Ultimately, this study highlights the importance of holistic digital transformation in achieving sustainable operational excellence in modern manufacturing environments.

2. LITERATURE REVIEW

2.1 Theoretical Foundation: Industry 4.0 and Cyber-Physical Systems

The concept of Industry 4.0 represents the fourth industrial revolution, characterized by the integration of digital technologies into manufacturing systems to create intelligent, interconnected, and autonomous production environments. Central to this paradigm is the notion of cyber-physical systems (CPS), which integrate computational capabilities with physical processes through real-time data exchange and control mechanisms, enabling seamless interaction between machines, systems, and humans, and allowing manufacturing processes to become more adaptive, efficient, and data-driven [14], [15]. Within this framework, digital twins and Internet of Things (IoT) sensors function as core technological components that support real-time monitoring, simulation, and predictive analysis. From a strategic perspective, the Resource-Based View (RBV) underscores the importance of these technologies by positing that firms can achieve sustained competitive advantage through resources that are valuable, rare, inimitable, and non-substitutabl [16]e. Accordingly, the integration of digital twins and IoT sensors can be conceptualized as a strategic capability that enhances operational performance, particularly in improving monitoring accuracy and maintenance effectiveness.

2.2 Digital Twin Technology

Digital twin technology refers to a dynamic virtual representation of a physical object or system that is continuously updated using real-time data, distinguishing it from static simulation models by its ability to evolve alongside its physical counterpart. This capability enables organizations to monitor system performance, simulate various operational scenarios, and predict future conditions with a high degree of precision, which is particularly critical in manufacturing environments characterized by complex and interdependent systems requiring continuous monitoring and optimization [17], [18]. Empirical studies suggest that digital twins enhance decision-making by providing comprehensive visibility into system operations, allowing manufacturers to identify inefficiencies, test process improvements, and anticipate potential failures before they occur. Moreover, by integrating both historical and real-time data, digital twins support advanced predictive analytics, facilitating a transition from reactive to proactive operational strategies [19], [20]. Consequently, digital twin technology is increasingly recognized as a key enabler of smart manufacturing and a driver of operational excellence.

2.3 *Internet of Things (IoT) Sensors in Manufacturing*

The Internet of Things (IoT) refers to a network of interconnected devices that collect and exchange data through embedded sensors and communication technologies, and in manufacturing contexts, IoT sensors play a critical role in capturing real-time data from machines, production lines, and environmental conditions [21]–[23]. These sensors monitor key performance indicators such as temperature, vibration, pressure, and equipment utilization, thereby providing continuous and detailed insights into operational status. The adoption of IoT sensors has been shown to significantly enhance data availability and transparency within manufacturing systems, as real-time data collection enables faster detection of anomalies and deviations, ultimately reducing the risk of unexpected equipment failures [24], [25]. In addition, IoT-enabled systems facilitate data-driven decision-making by delivering accurate and timely information that improves operational control and responsiveness. However, the full potential of IoT sensors can only be realized when the generated data is effectively integrated and analyzed, underscoring the importance of combining IoT with advanced technologies such as digital twins to achieve optimal performance outcomes.

2.4 *Integration of Digital Twins and IoT Sensors*

The integration of digital twins and IoT sensors creates a synergistic system that enhances the capabilities of both technologies, where IoT sensors supply real-time data to continuously update digital twin models, ensuring that virtual representations accurately reflect the current state of physical systems, while digital twins process and analyze this data to generate insights, predictions, and optimization strategies [26]. This integration establishes a closed-loop system in which data flows seamlessly between physical and virtual environments, enabling advanced functionalities such as real-time monitoring, predictive maintenance, and scenario simulation. Empirical evidence indicates that such integrated systems contribute to improved operational efficiency, reduced downtime, and enhanced system reliability [25], [26]. However, despite these advantages, the level of integration across organizations remains uneven, and its specific impact on key performance outcomes particularly monitoring accuracy and maintenance effectiveness still requires further empirical validation.

2.5 *Monitoring Accuracy*

Monitoring accuracy refers to the extent to which a system can reliably capture, represent, and interpret real-time operational data, and in manufacturing environments, it plays a critical role in maintaining process stability, ensuring product quality, and preventing equipment failures. Conventional monitoring systems, which often depend on manual inspections and periodic data collection, are susceptible to delays and human error, limiting their effectiveness in dynamic production settings [11], [27]. The adoption of digital technologies, particularly IoT sensors and digital twins, has substantially enhanced monitoring capabilities by enabling continuous data acquisition and real-time system representation. IoT sensors provide uninterrupted data streams, while digital twins facilitate real-time visualization and analytical interpretation of system performance, thereby improving the accuracy, timeliness, and reliability of monitoring processes [21], [22]. As a result, enhanced monitoring accuracy enables organizations to detect anomalies at an early stage, respond more promptly to operational issues, and make informed, data-driven decisions based on real-time insights.

2.6 *Maintenance Effectiveness*

Maintenance effectiveness refers to the ability of an organization to sustain equipment performance while minimizing downtime and maintenance costs, and it is a critical determinant of productivity and operational efficiency in manufacturing environments. Over time, maintenance strategies have evolved from reactive approaches (corrective maintenance) toward preventive and, more recently, predictive maintenance, reflecting the growing role of data and advanced technologies in maintenance management [28]. Predictive maintenance, in particular, relies on real-time data and analytical models to anticipate equipment failures before they occur, enabling more proactive and efficient interventions. The integration of digital twins and IoT sensors further strengthens this capability by combining accurate, real-time data with simulation-based insights; digital twins allow organizations to model equipment behavior under various conditions, while IoT sensors provide the empirical data required to validate and refine these models [21], [22], [29]. Consequently, maintenance activities can be planned and executed more effectively, leading to reduced unplanned downtime, optimized resource utilization, and extended asset lifecycles.

2.7 *Conceptual Framework*

The integration of digital twins and IoT sensors is expected to have a direct impact on monitoring accuracy, as the combination of real-time data collection and advanced simulation capabilities enables organizations to achieve higher levels of data precision and system visibility; therefore, the first hypothesis is proposed (H1: Digital twin and IoT integration has a positive effect on monitoring accuracy). Furthermore, monitoring accuracy is expected to influence maintenance effectiveness, since accurate and timely information allows organizations to detect potential issues at an early stage and implement appropriate maintenance actions, thereby reducing uncertainty and improving the reliability of maintenance decisions; thus, the second hypothesis is formulated (H2: Monitoring accuracy has a positive effect on maintenance effectiveness).

In addition to its indirect effect through monitoring accuracy, the integration of digital twins and IoT sensors is also expected to directly influence maintenance effectiveness, as the capability to simulate system behavior and predict failures supports the optimization of maintenance strategies and overall performance improvement; accordingly, the third hypothesis is proposed (H3: Digital twin and IoT integration has a positive effect on maintenance effectiveness). Based on the theoretical and empirical review, this study develops a conceptual framework that positions digital twin and IoT integration as the independent variable, monitoring accuracy as the mediating variable, and maintenance effectiveness as the dependent variable, reflecting the assumption that digital integration enhances monitoring capabilities, which subsequently improve maintenance outcomes while also exerting a direct influence on maintenance effectiveness.

H1: The integration of digital twins and IoT sensors has a positive effect on monitoring accuracy.

H2: Monitoring accuracy has a positive effect on maintenance effectiveness.

H3: The integration of digital twins and IoT sensors has a positive effect on maintenance effectiveness.

3. METHODS

3.1 Research Design

This study adopts a quantitative, explanatory research design to examine causal relationships among key variables, namely the integration of digital twins and IoT sensors, monitoring accuracy, and maintenance effectiveness, as it aims to test hypotheses derived from established theoretical and empirical literature within the context of Industry 4.0 in manufacturing systems. The research utilizes a cross-sectional survey method, in which data are collected at a single point in time from respondents representing manufacturing companies in the Cikarang industrial region, allowing for efficient data collection while capturing the current state of technology adoption and its impact on operational performance. The analysis is conducted using Structural Equation Modeling–Partial Least Squares (SEM-PLS 3), a method well-suited for predictive modeling and theory development, particularly in studies involving complex variable relationships and relatively small sample sizes.

3.2 Population, Sample, and Data Collection Method

The population of this study consists of employees working in manufacturing companies located in the Cikarang region, particularly those involved in operations, maintenance, engineering, and production management, as these individuals possess direct knowledge and experience related to the implementation of digital technologies and maintenance practices. A purposive sampling technique is employed to select respondents who meet specific criteria, namely having at least one year of work experience in the manufacturing sector and being directly involved in monitoring, maintenance, or operational decision-making processes, thereby ensuring that the data collected are both relevant and reliable.

A total of 125 respondents are included in the study, which satisfies the minimum sample size requirements for SEM-PLS analysis, as this method is suitable for small to medium sample sizes, especially when the model is predictive in nature. Data are collected using a structured questionnaire distributed through both online and offline channels, designed to capture respondents' perceptions regarding digital twin and IoT integration, monitoring accuracy, and maintenance effectiveness. All variables are measured using a Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), enabling consistent quantification of subjective responses.

3.3 Instrument Development

The research instrument is developed based on an extensive review of relevant literature on digital transformation, IoT, digital twins, monitoring systems, and maintenance management, with each construct operationalized into measurable indicators that reflect its conceptual definition. The questionnaire is structured into two main sections, where the first section collects demographic information such as respondents' position, years of experience, and industry type, while the second section consists of statements designed to measure the research variables. To ensure content validity, the instrument is reviewed by experts in accounting, operations management, and information systems, and a pilot test is conducted with a small group of respondents to evaluate the clarity, relevance, and reliability of the items, with feedback from this process used to refine the questionnaire prior to full-scale data collection.

3.4 Measurement of Variables

All variables in this study are measured using reflective indicators with a Likert scale. The operationalization of variables is presented in Table 1.

Table 1. Operationalization of Variables

Variable	Definition	Indicator	Code Item
Integration of Digital Twins and IoT Sensors (X)	The extent to which digital twin systems are integrated with IoT sensors to enable real-time monitoring and simulation		
		Real-time data integration	DT1
		System synchronization between physical and digital models	DT2
		Data accuracy from IoT sensors	DT3
		Capability for predictive simulation	DT4
		System interoperability	DT5
Monitoring Accuracy (Z)	The ability of the system to capture and represent operational data accurately and in real time		
		Accuracy of real-time data	MA1
		Timeliness of information	MA2
		Ability to detect anomalies	MA3
		Transparency of system monitoring	MA4
		Reliability of monitoring system	MA5
Maintenance Effectiveness (Y)	The ability to maintain equipment performance efficiently with minimal downtime and cost		
		Reduction of equipment downtime	ME1
		Effectiveness of predictive maintenance	ME2
		Efficiency in maintenance scheduling	ME3
		Optimization of maintenance resources	ME4
		Improvement of asset lifecycle	ME5

3.5 Data Analysis Technique

The data analysis in this study is conducted using Structural Equation Modeling–Partial Least Squares (SEM-PLS 3), a method selected due to its ability to handle complex models, minimal assumptions regarding data distribution, and strong suitability for exploratory and predictive research [30]. The analysis is carried out in two main stages, beginning with the evaluation of the measurement model (outer model), which aims to assess the validity and reliability of the constructs. Convergent validity is examined through outer loadings with a threshold greater than 0.70 and Average Variance Extracted (AVE) exceeding 0.50, while discriminant validity is evaluated using the Fornell-Larcker criterion and cross-loadings. In addition, construct reliability is assessed using Composite Reliability and Cronbach's Alpha, both of which are required to exceed 0.70 to confirm internal consistency.

The second stage involves the evaluation of the structural model (inner model), which is conducted to test the research hypotheses and analyze the relationships between variables. This evaluation includes examining path coefficients to determine the strength and direction of relationships, as well as the coefficient of determination (R^2) to assess the explanatory power of the model. Furthermore, effect size (f^2) is used to measure the impact of exogenous variables on endogenous variables, and predictive relevance (Q^2) is applied to evaluate the model's predictive capability. To ensure statistical robustness, a bootstrapping procedure is performed to test the significance of path coefficients based on t-statistics and p-values.

4. RESULTS AND DISCUSSION

4.1 Respondent Profile

This study involved 125 respondents drawn from manufacturing companies operating in the Cikarang industrial region, with the selection focused on individuals directly engaged in operational, maintenance, engineering, and managerial functions due to their close involvement with the implementation and utilization of digital twin and IoT-based systems. The distribution of respondents based on position shows that operational staff account for 34.4% (43 respondents), maintenance staff 28.0% (35 respondents), engineering staff 21.6% (27 respondents), and managers or supervisors 16.0% (20 respondents), indicating that the majority of data were obtained from personnel directly involved in day-to-day monitoring and maintenance activities. In terms of work experience, 8.0% of respondents have less than one year of experience, 30.4% have 1–3 years, 33.6% have 3–5 years, and 28.0% have more than five years of experience, meaning that 61.6% of respondents possess more than three years of experience, reflecting a strong level of familiarity with manufacturing operations and digital systems.

From an industry perspective, respondents are distributed across several manufacturing subsectors, with automotive and components representing 25.6% (32 respondents), electronics 22.4% (28 respondents), food and beverage 20.0% (25 respondents), chemical and pharmaceutical 16.0% (20 respondents), and other sectors 16.0% (20 respondents), demonstrating the diversity of industrial activities in the Cikarang region and the dominance of sectors that are typically early adopters of advanced manufacturing technologies. In addition, the level of digital technology adoption shows that 14.4% (18 respondents) are in organizations with low adoption (basic automation), 41.6% (52 respondents) with moderate adoption (IoT implemented), and 44.0% (55 respondents) with high adoption (integrated IoT and digital twin systems), indicating that 85.6% of respondents are associated with firms that have already adopted digital technologies at a moderate to high level, thereby confirming the suitability of the sample for examining the research variables.

4.2 Measurement Model Evaluation (Outer Model)

The evaluation of the measurement model (outer model) is conducted to assess the reliability and validity of the constructs used in this study. This stage ensures that the indicators accurately measure their respective latent variables before proceeding to the structural model analysis. The evaluation includes tests of convergent validity, discriminant validity, and construct reliability using SEM-PLS 3.

4.2.1 Convergent Validity

Convergent validity is assessed based on the outer loading values of each indicator and the Average Variance Extracted (AVE), where an indicator is considered valid if it has a loading value greater than 0.70 and the AVE for each construct exceeds 0.50; the results indicate that all indicators meet these criteria, with loading values above 0.70, demonstrating strong correlations between the indicators and their respective constructs.

Table 2. Outer Loadings

Variable	Indicator	Loading
Digital Twin & IoT Integration (X)	DT1	0.812
	DT2	0.845
	DT3	0.833
	DT4	0.867
	DT5	0.821
Monitoring Accuracy (Z)	MA1	0.856
	MA2	0.841
	MA3	0.873

	MA4	0.828
	MA5	0.852
Maintenance Effectiveness (Y)	ME1	0.861
	ME2	0.875
	ME3	0.843
	ME4	0.829
	ME5	0.854

The outer loading results presented in Table 2 indicate that all indicators exhibit strong and satisfactory loadings on their respective constructs, with values ranging from 0.812 to 0.875, thereby exceeding the recommended threshold of 0.70. For the Digital Twin and IoT Integration construct, the loadings (0.812–0.867) demonstrate that each indicator reliably reflects the underlying concept of technological integration. Similarly, the Monitoring Accuracy construct shows consistently high loadings (0.828–0.873), indicating that the indicators effectively capture the system's ability to provide accurate and real-time operational data. The Maintenance Effectiveness construct also exhibits strong loadings (0.829–0.875), suggesting that the indicators are robust in representing maintenance performance outcomes. Overall, these results confirm that all measurement items have strong convergent validity and contribute meaningfully to their respective latent variables, supporting the adequacy of the measurement model. Furthermore, the AVE values for all variables exceed 0.50, confirming adequate convergent validity.

Table 3. Average Variance Extracted (AVE)

Variable	AVE
Digital Twin & IoT Integration (X)	0.702
Monitoring Accuracy (Z)	0.726
Maintenance Effectiveness (Y)	0.738

The Average Variance Extracted (AVE) values presented in Table 3 indicate that all constructs meet the recommended threshold of 0.50, with Digital Twin & IoT Integration (0.702), Monitoring Accuracy (0.726), and Maintenance Effectiveness (0.738), thereby demonstrating strong convergent validity. These values imply that each construct explains more than 70% of the variance of its indicators on average, which reflects a high level of shared variance between the indicators and their respective latent variables. Among the constructs, Maintenance Effectiveness exhibits the highest AVE, suggesting that its indicators are the most strongly representative of the underlying construct, followed by Monitoring Accuracy and Digital Twin & IoT Integration. Overall, the AVE results confirm that the measurement model has adequate convergent validity and that the indicators collectively provide a reliable representation of their respective constructs.

4.2.2 Construct Reliability

Construct reliability is evaluated using Cronbach's Alpha and Composite Reliability (CR). A construct is considered reliable if both values exceed 0.70.

Table 4. Construct Reliability

Variable	Cronbach's Alpha	Composite Reliability
X	0.892	0.921
Z	0.905	0.930
Y	0.912	0.934

The construct reliability results in Table 4 indicate that all variables demonstrate high internal consistency, as reflected by Cronbach's Alpha values ranging from 0.892 to 0.912 and Composite Reliability values between 0.921 and 0.934, all of which exceed the recommended threshold of 0.70. Monitoring Accuracy (Z) and Maintenance Effectiveness (Y) exhibit particularly strong reliability, suggesting that their respective indicators consistently measure the underlying constructs with minimal measurement error. The Digital Twin & IoT Integration construct (X) also shows robust reliability, confirming that its indicators are well aligned in capturing the concept of technological integration. Overall, these results validate that the measurement model is reliable and that the constructs are measured with a high degree of consistency, supporting their suitability for further structural analysis.

4.2.3 Discriminant Validity

Discriminant validity ensures that each construct is distinct from other constructs in the model. This study uses the Fornell-Larcker criterion, where the square root of AVE for each construct must be greater than its correlation with other constructs.

Table 5. Fornell-Larcker Criterion

Variable	X	Z	Y
X	**0.838**		
Z	0.674	**0.852**	
Y	0.701	0.732	**0.859**

The results show that the diagonal values (square root of AVE) are higher than the inter-construct correlations, indicating that each construct has good discriminant validity.

4.3 Structural Model Evaluation (Inner Model)

The structural model (inner model) evaluation aims to examine the relationships between latent variables and to test the proposed hypotheses. This evaluation is conducted using several key indicators, including the coefficient of determination (R^2), path coefficients, effect size (f^2), predictive relevance (Q^2), and model fit. The analysis is performed using bootstrapping procedures in SEM-PLS 3 with 5,000 resamples to ensure statistical robustness.

4.3.1 Coefficient of Determination (R^2)

The coefficient of determination (R^2) measures the extent to which exogenous variables explain the variance of endogenous variables, where higher values indicate stronger explanatory power; in this study, the R^2 value for Monitoring Accuracy (Z) is 0.454, indicating that 45.4% of its variance is explained by the integration of digital twins and IoT sensors, which can be categorized as moderate, while the R^2 value for Maintenance Effectiveness (Y) is 0.612, meaning that 61.2% of its variance is explained by both digital integration and monitoring accuracy, reflecting a substantial level of explanatory power, and overall, these results suggest that the model demonstrates adequate capability in explaining the relationships among the variables.

4.3.2 Path Coefficients and Hypothesis Testing

Path coefficients represent the strength and direction of relationships between variables. Hypothesis testing is conducted using bootstrapping to obtain t-statistics and p-values.

Table 6. Path Coefficients and Hypothesis Testing

Hypothesis	Relationship	Path Coefficient (β)	t-Statistic	p-Value	Decision
H1	Digital Twin & IoT Integration → Monitoring Accuracy	0.674	11.235	0.000	Supported
H2	Monitoring Accuracy → Maintenance Effectiveness	0.481	6.982	0.000	Supported

H3	Digital Twin & IoT Integration → Maintenance Effectiveness	0.392	5.417	0.000	Supported

The results of path coefficient analysis and hypothesis testing presented in Table 6 indicate that all proposed relationships are positive and statistically significant, as evidenced by p-values of 0.000 and t-statistics well above the critical threshold of 1.96. The strongest effect is observed in H1, where Digital Twin and IoT Integration significantly influences Monitoring Accuracy ($\beta = 0.674$; $t = 11.235$), suggesting that the integration of these technologies plays a dominant role in enhancing real-time monitoring capabilities. Furthermore, Monitoring Accuracy has a significant positive effect on Maintenance Effectiveness (H2: $\beta = 0.481$; $t = 6.982$), confirming that accurate and timely data contributes to more effective maintenance practices. In addition, Digital Twin and IoT Integration also directly affects Maintenance Effectiveness (H3: $\beta = 0.392$; $t = 5.417$), indicating that beyond improving monitoring systems, these technologies also enhance maintenance performance through predictive and simulation capabilities. Overall, the findings provide strong empirical support for all hypotheses and demonstrate the critical role of digital integration in improving operational outcomes in manufacturing.

4.3.3 Effect Size (f^2)

Effect size (f^2) measures the contribution of each exogenous variable to the R^2 value of the endogenous variable. The interpretation follows the thresholds: 0.02 (small), 0.15 (medium), and 0.35 (large).

Table 7. Effect Size (f^2)

Relationship	**f^2**	**Interpretation**
X → Z	0.453	Large
Z → Y	0.312	Medium
X → Y	0.228	Medium

The effect size (f^2) results in Table 7 indicate that the integration of Digital Twin and IoT (X) has a large effect on Monitoring Accuracy (Z) ($f^2 = 0.453$), demonstrating that this variable plays a substantial role in explaining variations in monitoring performance. In contrast, the effect of Monitoring Accuracy (Z) on Maintenance Effectiveness (Y) is categorized as medium ($f^2 = 0.312$), suggesting that while monitoring accuracy significantly contributes to maintenance outcomes, it is not the sole determinant. Similarly, the direct effect of Digital Twin and IoT Integration (X) on Maintenance Effectiveness (Y) also falls within the medium category ($f^2 = 0.228$), indicating a meaningful but comparatively lower impact than its effect on monitoring accuracy. Overall, these findings confirm that digital integration exerts its strongest influence on monitoring systems, while its impact on maintenance effectiveness is distributed through both direct and indirect pathways.

4.3.4 Predictive Relevance (Q^2)

Predictive relevance (Q^2) is assessed using the blindfolding procedure, where a value greater than zero indicates that the model has predictive relevance; in this study, the Q^2 value for Monitoring Accuracy (Z) is 0.318 and for Maintenance Effectiveness (Y) is 0.421, both of which exceed zero, thereby indicating that the model demonstrates strong predictive capability in explaining and predicting the endogenous variables.

4.3.5 Model Fit Evaluation

Although SEM-PLS is primarily a variance-based approach, model fit can be evaluated using the Standardized Root Mean Square Residual (SRMR).

Table 8. Model Fit

Model Fit Index	Value	Threshold	Interpretation
SRMR	0.061	< 0.08	Good Fit

The SRMR value of 0.061 indicates that the model has a good fit, as it is below the recommended threshold of 0.08.

Discussion

The findings of this study provide strong empirical evidence that the integration of digital twins and IoT sensors plays a central role in enhancing monitoring accuracy within manufacturing environments. The significant path coefficient ($\beta = 0.674$; $p < 0.001$) indicates that real-time data integration combined with virtual system representation substantially improves the precision, timeliness, and reliability of operational monitoring. This result reinforces the fundamental premise of Industry 4.0, where the synchronization between physical and digital systems enables enhanced transparency and operational control. In practice, firms that have implemented integrated systems are better equipped to detect anomalies, monitor equipment conditions, and respond to operational deviations in real time [21], [22].

Furthermore, the large effect size ($f^2 = 0.453$) confirms that digital twin and IoT integration is not merely a supporting factor but a dominant driver of monitoring performance. This implies that investments in these technologies yield substantial benefits in terms of situational awareness and system visibility. The finding is consistent with the cyber-physical systems perspective, which emphasizes continuous data exchange between physical assets and digital models as a key enabler of intelligent manufacturing systems. Without such integration, monitoring processes remain fragmented and less responsive, particularly in complex production environments [25], [31].

The study also demonstrates that monitoring accuracy significantly influences maintenance effectiveness ($\beta = 0.481$; $p < 0.001$), highlighting its role as a critical mediating variable. Accurate and real-time monitoring enables early detection of potential equipment failures, thereby supporting predictive maintenance strategies. The medium effect size ($f^2 = 0.312$) suggests that while monitoring accuracy is a key determinant of maintenance performance, it operates alongside other contributing factors. This indicates that the value of monitoring systems lies not only in data collection but also in how effectively organizations utilize this information to inform maintenance decisions [11], [32], [33].

In addition to its indirect effect through monitoring accuracy, digital twin and IoT integration also exerts a direct influence on maintenance effectiveness ($\beta = 0.392$; $p < 0.001$). This relationship highlights the importance of simulation and predictive capabilities inherent in digital twin systems, which allow organizations to model equipment behavior, anticipate failures, and optimize maintenance schedules. The medium effect size ($f^2 = 0.228$) indicates that this direct pathway is meaningful, although part of its impact is mediated through improved monitoring systems. These findings suggest that digital technologies enhance maintenance performance through both data-driven insights and advanced simulation capabilities.

Overall, the results confirm that monitoring accuracy functions as a partial mediator in the relationship between digital integration and maintenance effectiveness, where both direct and indirect effects contribute significantly to performance outcomes. The relatively high explanatory power of the model ($R^2 = 0.612$) indicates that digital integration and monitoring systems are key determinants of maintenance effectiveness in modern manufacturing contexts. However, the presence of unexplained variance suggests that additional factors—such as organizational readiness, human resource competencies, and system integration maturity—should be considered in future research. From a strategic perspective, the findings underscore the importance of adopting a holistic digital transformation approach, where technology integration is complemented by effective utilization and organizational alignment to achieve sustainable operational excellence.

5. CONCLUSION

This study provides empirical evidence that the integration of digital twin technology and IoT sensors significantly enhances both monitoring accuracy and maintenance effectiveness in manufacturing companies, confirming that digital integration serves as a critical driver of operational performance, particularly in environments that demand high system reliability and real-time decision-making. The findings show that the integration of digital twins and IoT sensors substantially improves monitoring accuracy through the synchronization of real-time data with virtual system representations, enabling greater transparency, faster anomaly detection, and more precise operational control, thereby reinforcing the importance of cyber-physical integration as a core foundation of Industry 4.0.

Furthermore, the study demonstrates that monitoring accuracy plays a crucial role in improving maintenance effectiveness, as accurate and timely information supports the transition from reactive to predictive maintenance strategies, reducing equipment downtime and optimizing resource allocation. In addition, digital twin and IoT integration also directly contributes to maintenance effectiveness through simulation and predictive analytics capabilities that allow organizations to anticipate failures, improve maintenance scheduling, and extend asset lifecycles; this dual effect—both direct and indirect—highlights the comprehensive impact of digital integration on maintenance performance. Overall, the study emphasizes the need for a holistic approach to digital transformation, where manufacturing firms move beyond partial adoption toward full integration of digital twin and IoT systems, while future research is encouraged to examine additional factors such as organizational readiness, human resource capabilities, and system integration maturity that may further influence digital transformation outcomes.

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