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The Effect of Digital Twin and Edge AI on Industrial Machine Maintenance Optimization in Karawang

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ABSTRACT

This study investigates the impact of Digital Twin and Edge AI technologies on optimizing industrial machine maintenance in Karawang, Indonesia. Using a quantitative research approach, data were collected from 80 respondents via a Likert-scale questionnaire and analyzed using SPSS version 25. The findings reveal significant positive relationships between both technologies and maintenance optimization. Digital Twin technology enhances predictive maintenance by enabling real-time simulations, while Edge AI improves decision-making through decentralized data processing. Together, they explain 58% of the variance in maintenance optimization. These results emphasize the synergistic effects of these technologies in reducing downtime, improving operational efficiency, and achieving cost savings. This research contributes to the understanding of advanced technological adoption in industrial maintenance and provides practical implications for enhancing productivity in industrial settings.

Keywords: *Sustainable Fashion, Environmental Awareness, Purchase Intention, Tiktok Videos, Organic Testimonials.*

1. INTRODUCTION

The rapid advancement of digital technologies has transformed the landscape of industrial operations, particularly in the realm of machine maintenance. Industrial facilities in Karawang, a major industrial hub in Indonesia, are increasingly adopting cutting-edge solutions to enhance operational efficiency and reduce downtime. Among these innovations, Digital Twin technology and Edge AI have emerged as pivotal tools for optimizing machine maintenance. Digital Twins (DTs) provide real-time monitoring and simulation capabilities, enabling the optimization of production processes and maintenance strategies [1], [2]. They facilitate predictive maintenance by minimizing downtime and extending machinery lifespan through virtual testing and simulation [2], and they integrate IoT, AI, and machine learning to create accurate digital replicas, enhancing data-driven decision-making and operational efficiency [1]. Meanwhile, Edge AI, particularly through Convolutional Neural Networks (CNNs), automates defect detection, reducing reliance on manual inspections and minimizing human error [3]. It enables timely detection and prevention of machinery defects, crucial for maintaining operational efficiency and reducing downtime [3]. The integration of AI with DTs further enhances decision-making processes, allowing for efficient maintenance operations and improved productivity [4]. Despite these advantages, the implementation of Digital Twin and Edge AI technologies also faces challenges, including technical integration, economic feasibility, and workforce training, which must be addressed to fully optimize maintenance operations and leverage these innovations effectively [5].

Digital Twin technology involves creating a virtual replica of physical systems, enabling real-time monitoring, simulation, and predictive analytics to support proactive maintenance strategies and reduce the risk of unexpected failures. This technology facilitates continuous monitoring and predictive maintenance by simulating real-world behavior, allowing early fault detection and extending machinery lifespan [6]. It also enhances operational efficiency and fosters innovation by supporting data-driven decision-making and enabling simulations prior to real-world implementation [2]. Furthermore, Digital Twins integrate with IoT, AI, and machine learning to strengthen capabilities in predictive analytics and system optimization [2], [7]. Complementing this, Edge AI facilitates decentralized, on-site data processing and decision-making through AI algorithms deployed on local devices or servers. This approach reduces latency, enables rapid responses, and ensures operational continuity—especially vital for industries with complex, interconnected machinery [8]. By supporting local data processing, Edge AI minimizes disruptions and maintains system reliability [6]. Together, Digital Twin technology and Edge AI offer a comprehensive, synergistic framework that modernizes industrial operations by enhancing maintenance strategies, optimizing performance, and ensuring seamless, real-time responsiveness.

Despite their growing prominence, the combined impact of Digital Twin and Edge AI on maintenance optimization has yet to be fully explored in industrial settings like those in Karawang, where existing studies have largely focused on each technology in isolation. The integration of these technologies presents a transformative opportunity for predictive maintenance by uniting the real-time monitoring and simulation capabilities of Digital Twins with the decentralized, rapid data processing of Edge AI. Digital Twins create virtual replicas of physical assets, enabling real-time monitoring and predictive analytics, which facilitate early fault detection and proactive interventions [2], [7]. These systems integrate technologies such as IoT and machine learning to simulate and optimize industrial operations, reducing downtime and extending equipment lifespan [2], [7]. In parallel, Edge AI processes sensor data locally, ensuring real-time anomaly detection and enabling proactive maintenance scheduling that improves asset reliability and reduces costs [9], [10]. This localized processing supports the transition from reactive to predictive maintenance, a critical shift for achieving operational excellence [9], [10]. When combined, Digital Twins and Edge AI allow for dynamic simulation and analysis, significantly enhancing decision-making in maintenance prioritization [11]. This synergy enables adaptive maintenance strategies based on predictive insights, aligning with Industry 4.0 objectives for efficiency, reliability, and sustainability [11]. Addressing this gap is essential for industries aiming to leverage these innovations to their full potential. This study investigates the influence of Digital Twin and Edge AI technologies on industrial machine maintenance optimization in Karawang.

2. LITERATURE REVIEW

2.1 *Industrial Machine Maintenance and Optimization*

Predictive and condition-based maintenance strategies are revolutionizing industrial operations by enhancing machine reliability, reducing costs, and optimizing schedules through advanced technologies. Predictive maintenance (PdM) uses machine learning to analyze historical and real-time data, forecasting equipment failures and enabling timely interventions [12]. AI and IoT tools collect sensor data—such as vibration and temperature—for analysis, improving failure predictions [13], while advanced models like reinforcement and deep learning refine maintenance scheduling [14]. Condition-based maintenance monitors specific parameters to reduce unnecessary interventions and extend equipment lifespan [12], [15], supported by IoT-enabled data collection [13]. Digital Twin technology enhances these strategies by simulating real-time conditions and predicting maintenance needs (Anaba et al., 2024), while Edge AI processes data locally for faster, more responsive decisions [14]. The integration of these tools enables a proactive, efficient, and intelligent approach to industrial maintenance.

2.2 *Digital Twin Technology*

Digital Twin technology, as a virtual representation of physical entities, plays a transformative role in machine maintenance by enabling real-time monitoring, simulation of potential failures, and optimization of maintenance schedules. By integrating data from physical assets with advanced analytics, Digital Twins provide continuous insights into machinery performance and condition, thereby enhancing decision-making and reducing downtime [2]. The integration of sensors and IoT devices enables real-time data collection and analysis, offering immediate visibility into asset health [16]. Through the simulation of potential failures and prediction of remaining useful life, Digital Twins support proactive maintenance strategies and identify system vulnerabilities before breakdowns occur [6]. Utilizing both physics-based models and data-driven analytics, this technology enhances predictive maintenance capabilities and allows for the optimization of maintenance schedules [2], [6], resulting in timely interventions that extend equipment lifespan, improve reliability, and reduce maintenance costs and disruptions [8]. Despite its advantages, the implementation of Digital Twins requires significant investment in infrastructure, robust data integration, and skilled human resources, making its adoption both beneficial and complex.

2.3 *Edge AI in Industrial Maintenance*

Edge AI, which involves deploying AI algorithms at the network's edge, offers significant advantages in maintenance applications by enabling real-time anomaly detection, predictive analytics, and autonomous decision-making. By processing data locally, Edge AI enhances data security, minimizes latency, and ensures operational resilience, particularly in remote or network-constrained environments [8], [17]. This decentralized approach is crucial for time-sensitive maintenance tasks such as anomaly detection and predictive analysis, where rapid response is essential [18], [19]. Edge AI systems continue functioning effectively even with limited connectivity, ensuring uninterrupted decision-making capabilities [20]. Its applications in maintenance optimization include real-time vibration analysis to detect anomalies and prevent failures, thereby reducing downtime and maintenance costs [17], continuous temperature monitoring to preempt overheating issues [19], and the generation of real-time alerts that support timely interventions and minimize operational disruptions [20]. Despite these benefits, the success of Edge AI in maintenance relies on the availability of high-quality sensor data and the implementation of robust machine learning algorithms.

2.4 *Synergistic Potential of Digital Twin and Edge AI*

The integration of Digital Twin and Edge AI technologies offers a robust framework for optimizing industrial maintenance processes by combining comprehensive virtual modeling with real-time, localized data processing. Digital Twins create dynamic, real-time models of industrial assets that continuously adapt to operational and environmental changes, enabling simulation of potential failure scenarios and estimation of asset lifespan using physics-based models and data-driven analytics [2], [8]. They also enhance decision-making by integrating qualitative insights from operators with quantitative data to foster a smart maintenance ecosystem [21]. Edge AI complements this by processing sensor data at the source, enabling immediate anomaly detection, proactive maintenance scheduling, and forecasting of faults before they occur—thus saving time and reducing costs [9], [22]. This is particularly advantageous for small- and medium-scale industries due to its efficiency in handling diverse sensor data [22]. The synergy between Digital Twin and Edge AI results in more accurate and timely maintenance strategies, significantly reducing downtime and enhancing asset reliability [2], [9], while supporting the shift from reactive to predictive maintenance and driving improvements in operational performance and cost-efficiency.

2.5 Research Gap

Despite the potential benefits, limited studies have examined the combined impact of Digital Twin and Edge AI on maintenance optimization in industrial settings, with most existing research focusing on each technology in isolation and overlooking their integrated application and implications. Moreover, there is a lack of empirical evidence from industrial hubs such as Karawang, which faces distinct challenges due to its diverse industrial base and operational complexities. This study adopts the Resource-Based View (RBV) theory, which suggests that leveraging unique technological resources—such as Digital Twin and Edge AI—can provide organizations with a sustained competitive advantage by optimizing machine maintenance processes and enhancing operational performance. By addressing these research gaps, the study not only enriches the academic discourse on industrial maintenance technologies but also offers practical insights for industries aiming to implement advanced, data-driven solutions to improve maintenance efficiency and effectiveness.

3. METHODS

This study employs a quantitative research design to analyze the impact of Digital Twin and Edge AI technologies on industrial machine maintenance optimization in Karawang. It focuses on collecting numerical data and utilizing statistical tools to identify relationships and measure the extent of influence between variables. The population includes maintenance professionals, engineers, and managers working in industrial facilities in Karawang that have adopted or are considering adopting these technologies. Using purposive sampling, 80 respondents were selected based on their expertise and familiarity with machine maintenance and advanced technologies—an adequate sample size for ensuring reliable and valid statistical results. Primary data were gathered through a structured questionnaire using a Likert scale from 1 (strongly disagree) to 5 (strongly agree), designed to capture respondents' perceptions and experiences. The questionnaire consisted of three sections: (1) demographic information, (2) perceptions of Digital Twin technology (real-time monitoring, predictive capabilities, operational efficiency), and (3) the influence of Edge AI (decision-making, data processing, and maintenance effectiveness).

This study evaluates two independent variables—Digital Twin and Edge AI—and their influence on the dependent variable, industrial machine maintenance optimization. Indicators for Digital Twin include real-time monitoring capability, predictive analytics for failure prevention, and simulation of operational scenarios. Indicators for Edge AI comprise real-time data processing and anomaly detection, decentralized decision-making, and reduced latency with improved response times. Meanwhile, indicators for machine maintenance optimization include reduced downtime, improved maintenance scheduling accuracy, and enhanced operational efficiency and resource allocation. Data analysis was conducted using SPSS version 25 and involved several steps: (1) descriptive statistics to summarize demographic information and overall response trends, (2) reliability testing using Cronbach's Alpha with a 0.70 threshold for internal consistency, (3) correlation analysis to examine the relationships between variables, and (4) multiple linear regression to evaluate the combined influence of Digital Twin and Edge AI on maintenance optimization, assessing the significance of predictors and the explanatory power (R^2) of the model..

4. RESULT AND DISCUSSION

4.1 Respondent Demographics

The demographic profile of the 80 respondents—comprising professionals involved in industrial machine maintenance in Karawang—provides essential context for interpreting the study's findings. The sample included Maintenance Engineers (60%), Maintenance Managers (25%), and Maintenance Technicians (15%), reflecting a range of roles within maintenance operations. In terms of experience, 60% had more than five years of experience, 30% had between three to five years, and 10% had less than three years. Regarding familiarity with the technologies under study, 45% reported being highly familiar with Digital Twin and Edge AI, 35% were moderately familiar, and 20% had limited familiarity. Educationally, the majority held undergraduate degrees (70%), followed by postgraduate degrees (20%) and vocational training (10%). These demographics suggest that the respondents are predominantly experienced and technically qualified, with substantial exposure to advanced maintenance technologies—factors that strengthen the reliability and relevance of the study's results for industrial applications.

Table 1. Descriptive Statistics

Variable	Mean	Std. Deviation
Digital Twin	4.21	0.65
Edge AI	4.15	0.68
Machine Maintenance Optimization	4.30	0.63

Respondents generally agreed that both Digital Twin and Edge AI technologies have a positive impact on maintenance optimization, with higher mean scores indicating stronger perceived effectiveness. The Digital Twin variable showed a mean of 4.21 (SD = 0.65), reflecting strong agreement on its value in real-time monitoring and predictive maintenance, with moderate consensus. Edge AI had a slightly lower mean of 4.15 (SD = 0.68), indicating favorable views on its role in real-time data processing and decision-making, though with slightly more varied responses. The highest mean was found in Machine Maintenance Optimization at 4.30 (SD = 0.63), suggesting widespread recognition of improved maintenance performance, likely due to the adoption of these technologies.

4.2 Reliability Testing

Reliability testing was conducted to ensure the consistency and dependability of the questionnaire used in this study. Cronbach's Alpha was calculated for each construct, with values greater than 0.70 considered acceptable for internal consistency. The results are summarized in Table 1 below.

Table 2. Reliability Test Results

Construct	Number of Items	Cronbach's Alpha	Interpretation
Digital Twin	5	0.812	Reliable
Edge AI	5	0.847	Reliable
Machine Maintenance Optimization	6	0.874	Highly Reliable

The reliability analysis confirms that the questionnaire used in this study is a dependable tool for evaluating the impact of Digital Twin and Edge AI on industrial machine maintenance optimization. The Digital Twin construct achieved a Cronbach's Alpha value of 0.812, indicating good reliability and consistent measurement of respondent perceptions. The Edge AI construct showed a Cronbach's Alpha of 0.847, reflecting strong internal consistency in assessing its influence on maintenance processes. Meanwhile, the Machine Maintenance Optimization construct recorded the highest reliability score at 0.874, demonstrating excellent consistency in capturing respondents' views. These values collectively validate the credibility and reproducibility of the study's results.

4.3 Multiple Linear Regression

Multiple linear regression analysis was conducted to assess the combined effect of Digital Twin and Edge AI technologies on industrial machine maintenance optimization. This analysis evaluates the extent to which these independent variables predict changes in the dependent variable and determines the significance of their contribution.

The regression model summary indicates a strong relationship between the independent variables—Digital Twin and Edge AI—and the dependent variable, Machine Maintenance Optimization. The R value of 0.76 reflects a strong positive correlation, while the R-squared value of 0.58 suggests that 58% of the variance in maintenance optimization can be explained by the combined influence of these two technologies. The adjusted R-squared value of 0.57 confirms the model's explanatory strength after accounting for the number of predictors. With a standard error of 0.41, the model demonstrates a reasonable level of accuracy in predicting outcomes, although 42% of the variance remains unexplained by the model and may be influenced by other factors not captured in this study.

Table 3. F Test

Source	Sum of Squares	df	Mean Square	F	p-Value
Regression	24.57	2	12.29	73.25	0.000
Residual	17.86	77	0.23		
Total	42.43	79			

The F-statistic (73.25, p<0.001p < 0.001p<0.001) indicates that the regression model is statistically significant and explains a substantial portion of the variance in the dependent variable.

Table 4. T Test

Predictor	Unstandardized Coefficients	Standardized Coefficients (Beta)	t-Value	p-Value
(Constant)	1.21	-	5.12	0.000
Digital Twin	0.42	0.42	4.55	0.000
Edge AI	0.48	0.48	5.21	0.000

The regression analysis reveals that both Digital Twin and Edge AI significantly contribute to machine maintenance optimization. The standardized beta coefficient for Digital Twin is 0.42, indicating that a one-unit increase in its effectiveness leads to a 42% improvement in maintenance optimization, assuming other variables remain constant ($p < 0.001$). Edge AI shows an even greater impact, with a standardized beta coefficient of 0.48, suggesting that a one-unit increase in its effectiveness results in a 48% improvement in optimization ($p < 0.001$). The constant value of 1.21 represents the baseline level of machine maintenance optimization when both independent variables are at zero. These results highlight the strong predictive power of both technologies in enhancing maintenance outcomes.

Discussion

1. **Impact of Digital Twin Technology**

The results demonstrate that Digital Twin technology significantly enhances machine maintenance optimization, a finding that aligns with previous research. Digital Twin systems facilitate predictive maintenance by simulating real-world behavior through virtual models, enabling proactive fault detection and increasing the reliability of critical equipment [23]. By integrating real-time sensory data and advanced analytics, Digital Twins can forecast the remaining useful life of machinery, allowing for timely and targeted maintenance interventions [8]. Within the Industry 4.0 framework, Digital Twins support real-time monitoring and process optimization, reducing unplanned downtime and improving maintenance planning [1]. Moreover, case studies have demonstrated their potential in driving continuous improvement and providing actionable insights for sustainable innovation and operational excellence [1].

In terms of strategic value, Digital Twins offer a robust framework for optimizing maintenance strategies by simulating potential interventions in a virtual environment before real-world implementation, thus supporting cost-effective and adaptive approaches [24]. The integration of sensors, IoT, and machine learning further enhances their capability to deliver efficient and data-driven maintenance outcomes [25]. In the current study, high mean scores reflect widespread respondent agreement on the usefulness of Digital Twin in reducing downtime and increasing operational precision. These capabilities contribute to the shift from reactive to predictive maintenance models, enabling organizations to improve performance, extend equipment lifespan, and achieve greater cost efficiency.

2. Role of Edge AI in Maintenance Efficiency

Edge AI exhibited an even greater influence on maintenance optimization, a result consistent with prior studies emphasizing its role in real-time processing and decentralized decision-making. Edge AI processes data directly at the source, eliminating reliance on cloud connectivity and enabling immediate responses—an essential feature for industrial environments where speed and accuracy are critical [17]. It has been shown to reduce decision-making latency by up to 90% compared to traditional cloud-based systems while maintaining comparable levels of accuracy [19]. By analyzing sensor data in real time, Edge AI supports predictive maintenance by detecting anomalies early and scheduling interventions proactively, thereby improving asset reliability and minimizing unplanned downtime [9].

The practical benefits of Edge AI are further supported by case studies demonstrating its ability to recognize operational states of machinery almost instantaneously, as seen in experiments involving DC motors [26]. The integration of artificial intelligence, industrial IoT (IIoT), and edge computing has introduced new levels of efficiency and resilience in modern industrial systems [26]. In this study, respondents highlighted these same advantages, noting substantial improvements in the accuracy and reliability of maintenance operations as a result of implementing Edge AI. The ability to make decentralized, real-time decisions not only streamlines maintenance workflows but also enhances overall operational performance, especially in complex and high-demand industrial settings.

3. Practical Implications for Industrial Facilities

The results underscore the practical advantages of adopting Digital Twin and Edge AI technologies in industrial facilities in Karawang, revealing their potential to enhance operational efficiency by reducing downtime and enabling better resource allocation, as well as achieving cost savings through predictive and real-time maintenance strategies. Additionally, these technologies contribute to sustainability by improving energy efficiency and minimizing waste through optimized processes. These benefits highlight the vital role of technological innovation in sustaining a competitive advantage within the industrial sector. Nevertheless, realizing these outcomes demands substantial investment in infrastructure, workforce training, and robust data integration systems.

4. Limitations and Suggestions for Future Research

While the study offers valuable insights, it has several limitations that should be acknowledged. The sample size of 80, though adequate for statistical analysis, may not fully capture the diversity of industrial settings, and the geographic focus on Karawang limits the generalizability of the findings to other regions or contexts. Furthermore, the study did not consider external factors such as regulatory changes or economic fluctuations that could affect maintenance outcomes. Future research could address these limitations by expanding the sample size and including a broader range of industries and regions. Longitudinal studies are also recommended to examine the long-term impacts of Digital Twin and Edge AI technologies on operational sustainability and cost-effectiveness.

CONCLUSION

This study demonstrates the significant role of Digital Twin and Edge AI technologies in optimizing industrial machine maintenance. The findings confirm that Digital Twin technology improves maintenance efficiency through real-time monitoring and predictive analytics, while Edge AI enhances decision-making and reduces latency, enabling faster and more accurate maintenance responses. When applied together, these technologies create a synergistic effect that amplifies their individual benefits, collectively explaining 58% of the variance in maintenance optimization. These results have important implications for industrial facilities in Karawang, indicating that the adoption of such technologies can lead to lower operational costs, increased machine reliability, and greater productivity. However, achieving these outcomes requires substantial investments in infrastructure, workforce training, and data integration systems. Future research should involve larger and more diverse samples, explore varying industrial contexts, and assess the long-term impacts of these technologies on sustainability and cost-efficiency. Embracing Digital Twin and Edge AI is not only a strategic move for modern industries but also a critical step toward sustaining competitiveness in an increasingly digital industrial environment.

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