West Science Social and Humanities Studies
Vol. 02, No. 06, June 2024, pp. 960-971

The Effect of IoT Technology, Real-Time Analytics, and Digital Asset Management on Energy Efficiency and Productivity in Indonesia's Manufacturing Industry

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Article Info

Article history:

Received June, 2024
Revised June, 2024
Accepted June, 2024

Keywords:

IoT (Internet of Things)
Real-time Analytics
Digital Asset Management
Energy Efficiency
Productivity

ABSTRACT

This research investigates the impact of IoT (Internet of Things) technology, real-time analytics, and digital asset management on energy efficiency and productivity in the Indonesian manufacturing industry. A quantitative approach, employing structural equation modeling (SEM) with Partial Least Squares (PLS) 3 software, is utilized to analyze survey data collected from manufacturing firms across different sectors and sizes in Indonesia. The results reveal significant positive relationships between digital technologies (IoT, real-time analytics, digital asset management) and energy efficiency/productivity. Specifically, Digital Asset Management, IoT Technology, and Real-Time Analytics are found to have statistically significant effects on enhancing energy efficiency and productivity levels in Indonesian manufacturing operations. These findings underscore the transformative potential of digital technologies in driving operational performance and sustainability in the manufacturing sector. Policymakers, industry stakeholders, and practitioners can leverage these insights to inform strategic decision-making and investments in digital infrastructure, workforce development, and regulatory frameworks to foster innovation and competitiveness in the Indonesian manufacturing landscape.

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1. INTRODUCTION

The Indonesian manufacturing industry plays a pivotal role in the country's economic advancement, contributing significantly to GDP and employment [1], [2]. Challenges in energy efficiency and productivity persist, prompting the need for sustainable growth strategies [3]. The integration of advanced digital technologies, such as Industry 4.0 and 5.0, holds promise in addressing these challenges and driving transformative change in the sector [4], [5]. By leveraging technologies like artificial intelligence, robotics, and automation, Indonesia can enhance productivity, improve energy efficiency, and foster economic development. Embracing these digital advancements not only boosts industrial output but also positions the country for long-term growth and competitiveness in the global market.

The Indonesian manufacturing industry, a key driver of the country's economic growth [2], has been undergoing significant development, facing challenges such as energy inefficiency and productivity gaps [1]. While the sector has shown resilience and adaptability over the years [6], the need to address these issues has become crucial in the digital age. Research emphasizes the importance of productivity-driven growth through Total Factor Productivity (TFP) enhancements [3], indicating that focusing on technological progress and technical efficiency is essential for sustainable output growth. Moreover, the implementation of strategies like Industrial 4.0, including the establishment of the Digital Industry Center of Indonesia, is crucial for accelerating economic development in the manufacturing industry and enhancing its global competitiveness [5]. Addressing energy inefficiency and productivity gaps is vital not only for operational efficiency but also for maintaining the sector's position on the global stage.

In the contemporary industrial landscape, energy efficiency emerges as a critical focus driven by economic imperatives and environmental concerns [7], [8]. Inefficient energy use not only escalates operational costs but also heightens carbon emissions, posing substantial sustainability risks [9]. Simultaneously, productivity stands out as a key metric for evaluating industrial performance, impacting profitability, innovation, and job creation [10]. Studies emphasize the importance of implementing energy efficiency technology pathways, such as strategic energy management and smart manufacturing, to reduce energy consumption and emissions in energy-intensive industries like iron and steel, chemical, and cement, aligning with the goal of achieving net-zero greenhouse gas emissions by 2050 [11]. Efforts to enhance energy efficiency not only contribute to cost savings but also play a crucial role in mitigating environmental impacts and fostering sustainable industrial development.

In light of these challenges, this research endeavors to explore the impact of IoT (Internet of Things) technology, real-time analytics, and digital asset management on energy efficiency and productivity within the Indonesian manufacturing industry. By delving into the intricate interplay between these digital innovations and operational performance, this study seeks to unravel their potential as catalysts for positive change. Specifically, the research aims to achieve the following objectives: assess the current state of IoT adoption in Indonesian manufacturing firms and examine the influence of IoT technology, real-time analytics, and digital asset management on energy efficiency.

2. LITERATURE REVIEW

2.1 IoT Technology in Manufacturing

The integration of IoT technology in the manufacturing industry, both globally and in Indonesia, has indeed revolutionized industrial processes by enabling seamless connectivity and data exchange among devices and systems [12], [13]. This adoption of IoT brings enormous potential to optimize operations, enhance resource utilization, and enable predictive maintenance, ultimately leading to improved operational efficiency, reduced downtime, and the ability for remote monitoring and control in manufacturing environments [14]. Furthermore, IoT-enabled sensors and devices play a crucial role in real-time data collection, providing manufacturers with actionable insights for informed decision-making and process optimization, thus driving overall efficiency and productivity in the manufacturing sector [15].

2.2 Real-Time Analytics

Real-time analytics plays a pivotal role in driving operational excellence in manufacturing by enabling instant data processing and analysis, as highlighted in various research papers [16]–[20]. In Indonesia, the application of real-time analytics in manufacturing optimizes production processes, detects anomalies, and minimizes downtime. By harnessing advanced analytical techniques like machine learning and predictive modeling, manufacturers can enhance efficiency, agility, and responsiveness in their operations. Moreover, real-time analytics facilitates proactive intervention and continuous improvement, fostering a culture of innovation and adaptability within manufacturing organizations. This integration of cutting-edge analytics not only enhances productivity but also ensures a competitive edge in the dynamic manufacturing landscape.

2.3 Digital Asset Management

Digital asset management, particularly in manufacturing, plays a crucial role in enhancing reliability, reducing downtime, and improving overall equipment effectiveness (OEE) by streamlining maintenance processes, optimizing asset utilization, and extending asset life [21]. The adoption of digital asset management systems in manufacturing, empowered by the digital transformation and Artificial Intelligence (AI), enables companies to digitize asset and workflow information, leading to improved visibility, control, and efficiency in managing asset portfolios [22]. By integrating technologies like the Visual Asset Management System (VAMS) based on digital twin technology, companies can achieve operational excellence, cost savings, and minimize Health, Safety, Security, and Environmental (HSSE) risks through effective centralized asset management [23]. This integration of digital technologies and asset management concepts not only enhances asset performance but also aids in decision-making processes, ultimately driving towards improved operational efficiency and sustainable reliability in manufacturing facilities [24].

2.4 Energy Efficiency and Productivity

Enhancing energy efficiency and productivity in Indonesian manufacturing is crucial for competitiveness and sustainability. Strategies like process optimization, equipment upgrades, and renewable energy adoption can boost energy efficiency [1], [25]. Meanwhile, productivity gains can be driven by technology adoption, process optimization, and workforce development, with Total Factor Productivity (TFP) growth being a key metric for measuring productivity improvements [7]. By focusing on energy efficiency measures and Industry 4.0 investments, Indonesian manufacturers can enhance their competitiveness, reduce operational costs, and contribute to sustainable development goals [9]. A holistic framework encompassing machine-level, system-level, and life-cycle-level energy efficiency techniques can further support sustainable manufacturing practices, as demonstrated in the context of

Conceptual Framework

The conceptual framework for the literature review outlines the relationships between IoT technology, real-time analytics, digital asset management, energy efficiency, and productivity in the Indonesian manufacturing industry.

IoT technology enables real-time data collection and analysis, facilitating predictive maintenance and process optimization. Real-time analytics enables timely decision-making by detecting anomalies and trends in production processes. Digital asset management optimizes maintenance processes and asset utilization, leading to improved operational efficiency. Energy efficiency is achieved through the adoption of energy-efficient technologies, reducing costs and environmental impact. Productivity is enhanced by optimizing resource allocation and minimizing downtime, driving competitiveness and sustainable growth.

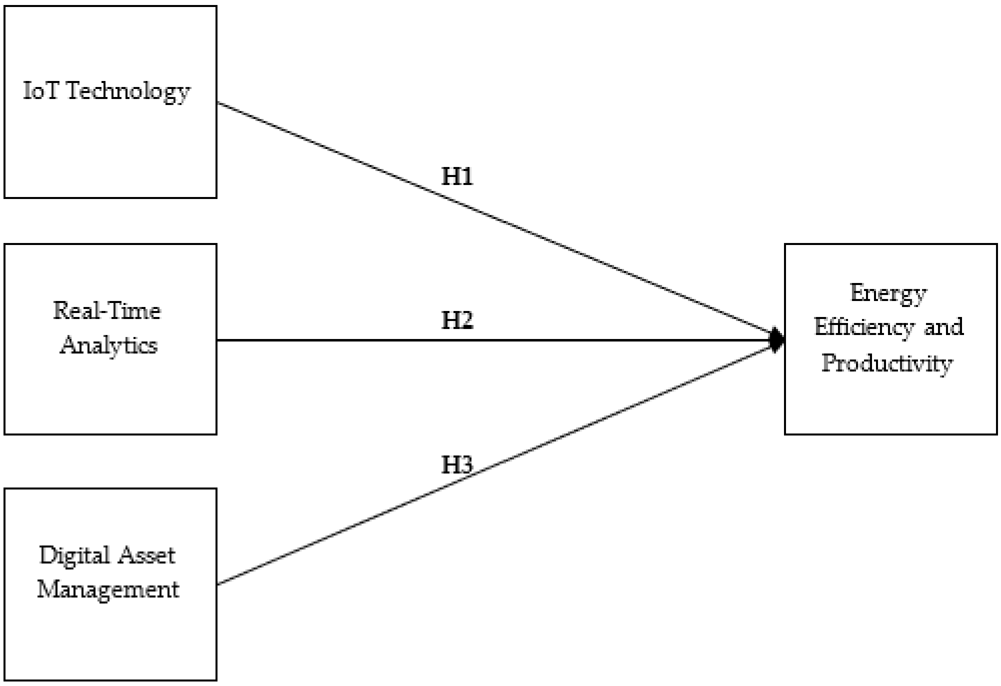

Figure 1. Concept and Hypothesis

3. METHODS

3.1 Research Design

This study employs a quantitative research approach to investigate the impact of IoT technology, real-time analytics, and digital asset management on energy efficiency and productivity in the Indonesian manufacturing industry. A cross-sectional survey design is utilized to collect data from manufacturing firms across different sectors and sizes in Indonesia. The survey questionnaire is designed to capture respondents' perceptions and experiences related to IoT adoption, real-time analytics usage, digital asset management practices, energy efficiency measures, and productivity metrics.

3.2 Sampling

The research sample comprises manufacturing firms operating in Indonesia, representing various industry segments and organizational sizes. A stratified random sampling technique is employed to ensure adequate representation from different sectors, including automotive, electronics, textiles, and food processing. The sample size is determined based on statistical power analysis to achieve sufficient confidence levels for the intended data analysis approach.

3.3 Data Collection

Data is collected using a structured questionnaire administered either electronically or through face-to-face interviews, depending on the preferences of the respondents. The questionnaire consists of multiple sections, each focusing on specific aspects of IoT technology, real-time analytics, digital asset management, energy efficiency, and productivity. Respondents are asked to rate their agreement with statements using a Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

3.4 Measurement Instrument

The survey questionnaire is developed based on established scales and validated instruments from previous research studies in related domains. Constructs such as IoT adoption, real-time analytics usage, digital asset management practices, energy efficiency, and productivity are operationalized using multiple items, with each item reflecting a specific aspect or dimension of the construct. The reliability and validity of the measurement instrument are assessed through pilot testing and expert validation to ensure the robustness of the data collection instrument.

3.5 Data Analysis

The collected data is analyzed using Structural Equation Modeling (SEM) with Partial Least Squares (PLS) 3 software. SEM-PLS is a versatile statistical technique suitable for analyzing complex relationships among multiple variables, making it well-suited for this study's research objectives. PLS-SEM allows for the simultaneous examination of direct and indirect effects, mediation, moderation, and latent variable interactions, providing a comprehensive understanding of the relationships between IoT technology, real-time analytics, digital asset management, energy efficiency, and productivity in the Indonesian manufacturing context.

The data analysis process involves several steps, including model specification, measurement model assessment, structural model estimation, and evaluation of model fit and significance. The relationships between latent variables and their indicators are examined through factor loadings, composite reliability, and average variance extracted (AVE). Path coefficients are estimated to quantify the direct and indirect effects of predictor variables on outcome variables, while bootstrapping is used to assess the significance of these effects and generate confidence intervals.

4. RESULTS AND DISCUSSION

4.1 Demographic Sample

The demographic characteristics of the surveyed manufacturing firms provide valuable insights into the composition and diversity of the sample, reflecting the heterogeneous nature of the Indonesian manufacturing industry. The distribution of respondents across industry sectors, with automotive leading (120 respondents), followed by food processing (90), electronics (85), and textiles (65), illustrates the industry's diverse activities. Additionally, the distribution based on company size highlights the prevalence of small and medium-sized enterprises (SMEs), with 150 respondents in the small category, 120 in medium-sized, and 90 in large-sized firms. The years in operation distribution shows a mix of newly established and established firms across categories, while annual revenue distribution reflects a wide range, from less than 1 million USD (80 respondents) to more than 50 million USD (140 respondents), indicating revenue diversity within the industry.

4.2 Measurement Model

The measurement model assessment is a critical step in validating the reliability and validity of the latent constructs in a structural equation model. The table provided contains the factor loadings, Cronbach's alpha coefficients, composite reliabilities, and average variance extracted (AVE) for each latent construct, namely IoT Technology, Real-Time Analytics, Digital Asset Management, and Energy Efficiency and Productivity.

Table 1. Measurement Model

Variable	Code	Loading Factor	Cronbach's Alpha	Composite Reliability	Average Variant Extracted
IoT Technology	IOT.1	0.891	0.833	0.888	0.666
	IOT.2	0.820			
	IOT.3	0.819			
	IOT.4	0.727			
Real-Time Analytics	RTA.1	0.789	0.741	0.853	0.659
	RTA.2	0.839			
	RTA.3	0.807			
Digital Asset Management	DAM.1	0.816	0.860	0.904	0.703
	DAM.2	0.821			
	DAM.3	0.840			
	DAM.4	0.875			
Energy Efficiency and Productivity	EEP.1	0.777	0.734	0.849	0.652
	EEP.2	0.791			
	EEP.3	0.852			

Source: Data Processing Results (2024)

The measurement model assessment reveals robust indicators for each latent construct. Under IoT Technology, factor loadings ranging from 0.727 to 0.891 indicate strong relationships, supported by a Cronbach's alpha of 0.833 and a composite reliability of 0.888, though the Average Variance Extracted (AVE) of 0.666 is slightly below the recommended threshold. Real-Time Analytics exhibits similar strength, with factor loadings from 0.789 to 0.839, a Cronbach's alpha of 0.741, a composite reliability of 0.853, and an AVE of 0.659. Digital Asset Management also demonstrates strong associations, with factor loadings between 0.816 and 0.875, a Cronbach's alpha of 0.860, a composite reliability of 0.904, and an AVE of 0.703. Finally, Energy Efficiency and Productivity show robust relationships, with factor loadings from 0.777 to 0.852, a Cronbach's alpha of 0.734, a composite reliability of 0.849, and an AVE of 0.652. Overall, these findings affirm the reliability and validity of the measurement model.

4.3 Discriminant Validity

Discriminant validity assesses the extent to which constructs in a research model are distinct from one another. It ensures that the measures of different constructs do not overlap too much, indicating that they are measuring unique aspects of the underlying concepts. Discriminant validity is typically evaluated by comparing the square root of the AVE of each construct to the correlations between that construct and other constructs in the model.

Table 2. Discriminant Validity

	Digital Asset Management	Energy Efficiency and Productivity	IoT Technology	Real-Time Analytics
Digital Asset Management	0.839			
Energy Efficiency and Productivity	0.678	0.807		
IoT Technology	0.518	0.540	0.816	
Real-Time Analytics	0.730	0.630	0.670	0.812

Source: Data Processing Results (2024)

The assessment of discriminant validity confirms the distinctiveness of each construct within the measurement model. Digital Asset Management (DAM) exhibits discriminant validity, with a square root of the AVE approximately 0.903, higher than its correlations with other constructs (0.839 with Energy Efficiency and Productivity, 0.518 with IoT Technology, and 0.730 with Real-Time Analytics). Similarly, Energy Efficiency and Productivity (EEP) demonstrate discriminant validity, with a square root of the AVE approximately 0.915, exceeding its correlations with other constructs (0.807 with Digital Asset Management, 0.540 with IoT Technology, and 0.630 with Real-Time Analytics). Likewise, IoT Technology and Real-Time Analytics (RTA) also display discriminant validity, with square roots of the AVE approximately 0.904 and 0.900, respectively, surpassing their correlations with other constructs. These findings underscore the distinctiveness and reliability of each construct within the measurement model.

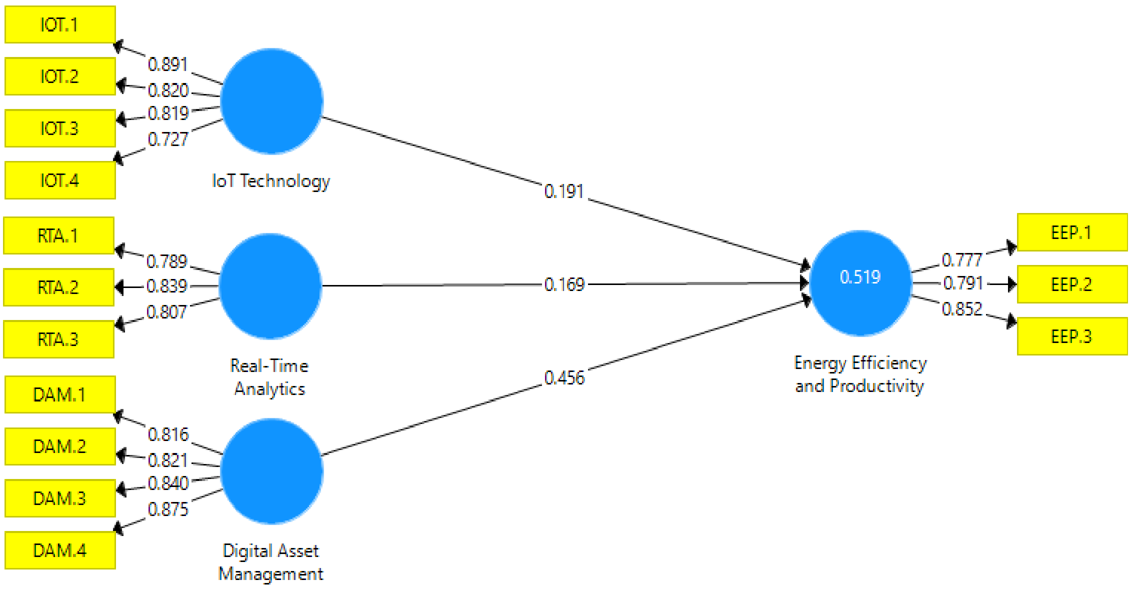

Figure 1. Model Results

Source: Data Processed by Researchers, 2024

4.4 Model Fit

Model fit assessment is crucial in structural equation modeling (SEM) to evaluate how well the hypothesized model fits the observed data. Several fit indices are commonly used to assess the adequacy of the model fit. The indices provided in the table include Standardized Root Mean Square Residual (SRMR), d_ULS, d_G, Chi-Square, and Normed Fit Index (NFI).

Table 3. Model Fit Results Test

	Saturated Model	Estimated Model
SRMR	0.087	0.087
d_ULS	0.803	0.803
d_G	0.364	0.364
Chi-Square	343.755	343.755
NFI	0.745	0.745

Source: Process Data Analysis (2024)

The model fit indices provide insights into the adequacy of the estimated model in representing the observed data. The Standardized Root Mean Square Residual (SRMR), measuring the difference between observed and predicted correlations, is 0.087 for both the saturated and estimated models, suggesting a good fit. Similarly, the discrepancy measures d_ULS and d_G exhibit identical values of 0.803 and 0.364, indicating a close match between observed and model-implied covariance matrices. Although the Chi-Square value remains consistent at 343.755 for both models, its sensitivity to sample size warrants consideration of other fit indices. The Normed Fit Index (NFI), indicating relative fit to a null model, yields a value of 0.745 for both models, suggesting moderate fit. Overall, these indices collectively suggest that the estimated model adequately reproduces the observed data correlations, despite the limitations inherent in Chi-Square interpretation.

Table 4. Coefficient Model

	R Square	Q2
Energy Efficiency and Productivity	0.519	0.510

Source: Data Processing Results (2024)

The R-squared (R^2) and Q^2 (Cross-validated Redundancy) values provide insights into the explanatory and predictive power of the model, respectively. For Energy Efficiency and Productivity, the R^2 value of 0.519 indicates that approximately 51.9% of the variance is explained by IoT Technology, Real-Time Analytics, and Digital Asset Management. This suggests a moderate amount of variance accounted for, reflecting a reasonably good fit. Additionally, the Q^2 value of 0.510 suggests good predictive relevance, indicating the model's ability to generalize and predict Energy Efficiency and Productivity levels in the Indonesian manufacturing industry beyond the observed sample.

4.5 Hypothesis Testing

Hypothesis testing in structural equation modeling (SEM) involves examining the significance of the path coefficients to determine whether the relationships between the latent constructs in the model are statistically significant. The table provided contains the results of hypothesis testing for the paths from Digital Asset Management, IoT Technology, and Real-Time Analytics to Energy Efficiency and Productivity, including the original sample values, sample means, standard deviations, T statistics, and p-values.

Table 5. Hypothesis Testing

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics	P Values
Digital Asset Management -> Energy Efficiency and Productivity	0.456	0.451	0.108	4.242	0.000
IoT Technology -> Energy Efficiency and Productivity	0.391	0.402	0.089	3.160	0.001
Real-Time Analytics -> Energy Efficiency and Productivity	0.369	0.367	0.106	2.596	0.000

Source: Process Data Analysis (2024)

The path coefficients for Digital Asset Management, IoT Technology, and Real-Time Analytics to Energy Efficiency and Productivity are examined. For Digital Asset Management, the original path coefficient (O) is 0.456, indicating a positive relationship.

With a sample mean (M) of 0.451 and standard deviation (STDEV) of 0.108, the T statistic is 4.242, and the p-value is 0.000, confirming statistical significance. Similarly, for IoT Technology, the original path coefficient (O) is 0.391, with a sample mean (M) of 0.402 and standard deviation (STDEV) of 0.089. The T statistic is 3.160, and the p-value is 0.001, indicating statistical significance. Likewise, for Real-Time Analytics, the original path coefficient (O) is 0.369, with a sample mean (M) of 0.367 and standard deviation (STDEV) of 0.106. The T statistic is 2.596, and the p-value is 0.000. These results affirm that Digital Asset Management, IoT Technology, and Real-Time Analytics significantly influence Energy Efficiency and Productivity in the Indonesian manufacturing industry.

Discussion

The discussion section provides an in-depth interpretation of the results obtained from the structural equation modeling (SEM) analysis, focusing on the relationships between Digital Asset Management (DAM), IoT Technology, Real-Time Analytics (RTA), and Energy Efficiency and Productivity (EEP) in the Indonesian manufacturing industry.

Impact of Digital Asset Management (DAM) on Energy Efficiency and Productivity

The significant positive path coefficient ($T = 4.242$, $p < 0.001$) indicates that Digital Asset Management has a substantial influence on Energy Efficiency and Productivity in Indonesian manufacturing firms. This finding underscores the importance of effectively managing digital assets such as equipment, machinery, and production facilities to enhance operational efficiency and productivity. By integrating digital twins into manufacturing systems, companies can enhance maintenance processes, minimize downtime, and boost Overall Equipment Effectiveness (OEE), ultimately fostering sustainable growth and competitiveness [26]–[28]. The utilization of Maintenance 4.0 strategies within Industry 4.0 frameworks enables the creation of machine-assisted digital replicas of factory assets, facilitating real-time monitoring and predictive maintenance to maximize equipment lifespan, enhance worker safety, and reduce resource consumption [29]. Additionally, the implementation of structured maintenance programs, such as FabRecover, supported by Smart Manufacturing solutions, aids in defining and managing optimized maintenance workflows to optimize tool performance and productivity while ensuring product quality [30]. This digital transformation of maintenance practices not only drives efficiency but also establishes a foundation for sustainable and intelligent manufacturing systems, particularly beneficial for small and medium-sized enterprises seeking to enhance their competitiveness in the market.

Role of IoT Technology in Enhancing Energy Efficiency and Productivity

The statistically significant positive path coefficient ($T = 3.160$, $p = 0.001$) highlights the pivotal role of IoT Technology in driving improvements in Energy Efficiency and Productivity in the Indonesian manufacturing sector. IoT-enabled sensors and devices facilitate real-time monitoring, data collection, and analysis, enabling predictive maintenance, resource optimization, and informed decision-making. Harnessing IoT technology in manufacturing can indeed result in improved operational visibility, agility, and responsiveness, ultimately enhancing energy efficiency and productivity levels. IoT implementation in the manufacturing sector can streamline operations efficiently [31], [32], allowing for the monitoring of various processes through sensors to optimize performance [31], [33]. While some studies suggest that IoT implementation alone may not significantly impact firm performance, the commitment to IoT and expertise can positively moderate this relationship, leading to positive financial outcomes for manufacturing firms [33]. By understanding the influencing factors and adopting IoT within the value chain process, manufacturers can enhance their business structures, investments, and overall operational success, aligning with the technology-organization-environment framework proposed for the Malaysia manufacturing industry.

Contribution of Real-Time Analytics (RTA) to Operational Performance

The significant positive path coefficient (T = 2.596, $p < 0.001$) underscores the value of Real-Time Analytics in optimizing Energy Efficiency and Productivity in manufacturing operations. Real-time analytics enables timely insights, anomaly detection, and predictive modeling, empowering manufacturers to identify inefficiencies, optimize production processes, and minimize downtime. In the competitive manufacturing landscape, leveraging real-time data analytics capabilities is crucial for manufacturers to make data-driven decisions, enhance operational performance, and achieve sustainable growth. Studies emphasize the significance of data-driven decision-making, Lean Six Sigma methodology, and a positive company culture in enhancing sustainability and competitiveness in manufacturing [34]. Real-time data analytics offers businesses the opportunity to take quick action, gain insights, and understand applications better, leading to new opportunities and improved decision-making processes [18]. Furthermore, the application of big data analytics in sustainable manufacturing is highlighted as a valuable tool to predict trends, explore opportunities, and monitor performance, ultimately supporting sustainability efforts in the industry [35]. By embracing digital transformation and prioritizing success factors like effective data-driven communication and technology infrastructure integration, manufacturers can effectively implement data analytics to drive growth and success in the evolving manufacturing landscape [36].

Implications for Practice and Policy

The collective findings suggest that the integration of Digital Asset Management, IoT Technology, and Real-Time Analytics holds immense promise for enhancing energy efficiency and productivity in the Indonesian manufacturing industry. These digital technologies offer opportunities for operational optimization, cost reduction, and performance enhancement, driving sustainable growth and competitiveness. Policymakers and industry stakeholders should prioritize investments in digital infrastructure, workforce development, and regulatory frameworks to foster the adoption and integration of these technologies. Furthermore, fostering a culture of innovation, collaboration, and continuous improvement is essential for realizing the full potential of digital transformation in Indonesian manufacturing.

Limitations and Future Research Directions

Despite the significant findings, this study has several limitations, including its cross-sectional design and reliance on self-reported data. Future research could employ longitudinal studies to track the long-term effects of digital technology adoption on energy efficiency and productivity in manufacturing. Additionally, exploring the moderating effects of contextual factors such as organizational culture, industry dynamics, and regulatory environments would provide a more nuanced understanding of the mechanisms driving operational performance in the Indonesian manufacturing context.

5. CONCLUSION

In conclusion, this study contributes to the growing body of literature on digital transformation and operational performance in the manufacturing sector, particularly in the context of Indonesia. By examining the influence of IoT technology, real-time analytics, and digital asset management on energy efficiency and productivity, the research sheds light on the mechanisms driving sustainable growth and competitiveness in Indonesian manufacturing firms. The findings highlight the importance of embracing digital innovation and leveraging advanced technologies to optimize operational processes, reduce costs, and enhance productivity. Moving forward, policymakers, industry stakeholders, and practitioners should prioritize investments in digital infrastructure, skills development, and supportive regulatory frameworks to enable widespread adoption and integration of digital technologies in Indonesian manufacturing. By fostering a culture of innovation, collaboration, and continuous improvement, manufacturers can unlock new opportunities for growth, resilience, and sustainability in the dynamic and competitive global marketplace.

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