International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 2
Mar-Apr 2026, PP 01-08

AIoT-Enabled Digital Twin Systems for Industrial Automation and Smart Manufacturing

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Abstract:The integration of AIoT technology with DT technologies is the basis of a new industrial revolution in industrial automation and intelligent manufacturing. This study develops a framework for AIoT-based digital twin systems, which combines live IoT data with AI simulation and optimization models. The designed model is based on a four-layer cyber-physical structure including data gathering from the edge, stochastic simulation, state encoding using graph attention networks, and closed-loop execution. The framework was analyzed using 10,000 stochastic simulations and a 12-week industrial experiment in which the system performed schedule performance of 96.8%, OEE of 84.7%, and 16.5% reduction in energy consumption per tonnage produced. The developed multi-objective reinforcement learning algorithm showed an integrated relationship between waste reduction and increased OEE (r = -0.73), with a total OEE improvement of 34.1% due to sustainable processes. The global AI-powered digital twin market is forecasted to grow up to $12 billion by 2030 with 26.2% CAGR.

Key Word: Digital Twin, AIoT, Smart Manufacturing, Industrial Automation, Predictive Maintenance, Multi-Objective Optimization, Industry 4.0, Cyber-Physical Systems.

I. Introduction

The Fourth Industrial Revolution has revolutionized the concept of manufacturing, moving away from conventional manufacturing automation towards advanced, intelligent manufacturing operations. Two of the transformative technologies driving this revolution include AIoT and Digital Twins (DTs) [1]. AIoT entails the integration of artificial intelligence capabilities into IoT platforms, allowing for intelligent sensing, real-time data analytics, and autonomous decision-making processes. As for digital twins, they refer to virtual representations of their physical counterparts for monitoring and optimizing various manufacturing processes [2].

The economic implications of this technology revolution are enormous. The market size of AI-enabled digital twin quality index has risen from $3.74 billion in 2025 to $4.73 billion in 2026, registering a compounded annual growth rate of 26.5%. According to projections, the market size will experience exponential growth to $12 billion in 2030, with a CAGR of 26.2% [3]. The market size of digital twins in manufacturing has been rising exponentially too, expanding from $28.91 billion in 2025 to $47.24 billion in 2026 at a CAGR of 63.4%, while forecasts place the industry at $328.29 billion in 2030 [4].

Smart factory implementation will be the key to growth in this sector [6]. In 2024, for example, the number of robot deployments in China has increased to an all-time high of 542,000 robots that make up 74% of worldwide installations, compared to 505,000 installations in 2023. This increasing trend leads to the need for a system that can handle these complex and integrated production settings. Traditional manufacturing strategies with their static scheduling systems are incapable of addressing the uncertainties of today's markets, sustainability issues, and the fast aging of equipment [5].

AI-powered DTs overcome these obstacles by offering real-time insights on manufacturing operations, predictive maintenance, resource optimization, and simulation of different scenarios [7]. By leveraging the power of AI, DTs evolve from being mere visual aids to becoming smart decision-making tools that autonomously optimize processes based on past data, new information, and evolving circumstances [8].

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In this study, we introduce an all-inclusive architecture for DT systems that leverage AI and IoT in automation and manufacturing. Our main contributions are: (1) a four-layer cyber-physical structure encompassing edge computing, digital twins, and AI-driven optimization; (2) a Pareto-conditioned MO-PPO model for joint optimization of reliability and sustainability indicators; (3) rigorous testing involving 10,000 simulations and a 12-week trial run in an industry setting; and (4) a modular architecture compatible with Industry 4.0/5.0 standards.

II. Literature Survey

Literature concerning AIoT-driven digital twin systems includes works that cover various topics such as digital twin architecture, integration frameworks, industrial IoT solutions, and sustainable manufacturing processes. This part is dedicated to the summary of recent research advancements in these directions.

Digital Twin Foundations and Taxonomies

Initially, digital twins were limited to creating static representations of devices in the form of three-dimensional models. Recently, digital twins were enhanced to become dynamic systems that can exchange information with their real-world counterparts continuously and bi-directionally. The detailed review provided by Alfaro-Viquez et al. (2025) classifies the use of artificial intelligence in digital twins for manufacturing into three dimensions: operator, process, and product. The first dimension deals with improving safety and ergonomics of working conditions via intelligent assistance, especially in terms of human-machine interactions [9].

This classification provides a structured approach to evaluating the capabilities of digital twins. The key issues that have been raised include technological interoperability, complex data integration, and high costs of implementation. This review highlights the role of digital twins powered by AI in facilitating the transformation into sustainable and human-centric manufacturing systems in accordance with the Industry 5.0 concept.

Automation Using AI in the Process of Industrial Digitalization

The incorporation of AI-based methods in Operational Technology (OT) systems is shifting from enhancement to necessity. The conventional model of managing OT networks, which relies on static configuration, manual classification of devices, and fixed rule-based processes, is becoming insufficient in dealing with complex and large-scale industrial networks [10].

There has been a suggestion of implementing an efficient framework for discovering networks and deploying digital twins, given the increasing complexity and size of industrial control systems . This framework uses AI to automatically classify devices, discover topologies, and detect anomalies, which helps deploy digital twins instantaneously without any manual assistance [5].

Multi-Objective Optimization in Digital Twins

The recent literature has considered incorporating sustainability goals within the digital twin optimization models. Li et al. (2026) have designed an AI-based adaptive planning system that consists of a physics-informed digital twin model and Pareto-based Multi-Objective Proximal Policy Optimization (MO-PPO) . This framework redesigns the manufacturing process planning approach in terms of Constrained Multi-Objective Markov Decision Process (CMDP), where Overall Equipment Efficiency (OEE), energy carbon intensity, and material waste are optimized by considering constraints.

The architecture of the system is based on the four-tiered cyber-physical framework that involves an edge-computing layer for data gathering, stochastic simulation engine powered by Bayesian inference, graph

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attention network-based state encoder, and closed-loop execution engine operating with one-minute planning intervals. The experimental analysis conducted over 10,000 stochastic simulations and a pilot study for 12 weeks in the industry has reported statistically significant improvements: 96.8% scheduling efficiency, 84.7% OEE, 16.5% decrease in specific energy consumption, and 17.1% decrease in material waste ratio [7].

Semantic and Modular Orchestration
A key issue in the use of digital twin technology lies in its monolithic structure, which hinders integration and reuse. There has been an initiative to develop a semantic and modular approach for orchestrating AI-enabled digital twins by integrating semantic APIs that conform to NGSI-LD standards for providing semantic exposure of industry assets such as process, anomalies, assets, and contextual KPIs.

The proposed system uses semantic AI techniques within modularity agents to perform specific optimization activities such as thresholding, anomaly correction, and pattern optimization. The system operates within a multi-agent layer where four plug-and-play optimization modules work together in a real-time scenario over semantic APIs, ensuring consistent and understandable interaction. Evaluation was performed using generated datasets for machining, assembly, and inspection operations, demonstrating improved sustainability-related KPIs [5].

AIoT and Multimodal Generative AI Integration
This survey on the use of digital twins and multimodal generative AI within AIoT systems introduces an innovative architecture known as the sense-map-generate-act (SMGA). Some of the enabling technologies are multimodal fusion, digital twin dynamic evolution, and cloud-edge-end collaboration. Some of the application cases analyzed include applications to smart manufacturing, smart cities, autonomous driving, and health care systems. Some of the open issues discussed include efficiency, reliability, privacy, and standardization needs [4].

Industry IoT and Quality Control
There have been various successful applications of AIoT-based digital twins. One such example is the implementation of an innovative Hybrid IoT-AI Framework (HIAF) applied to textile manufacturing that involves the use of RFID sensors, optical sensors, humidity sensors, and vibration sensors in a smart monitoring network in the processes of spinning, weaving, dyeing, and finishing of fabric. This involves edge and cloud analytics. AI-driven anomalies in terms of fabric texture, dye homogeneity, and fiber tensile strength lead to the formation of control loops that involve modification of the operating parameters in real time. Evaluation results show 32% fewer product defects, 28% more first pass yield, and 25% less downtime [3].

Research Gaps and Contributions
While there has been substantial progress, there are still some limitations that exist. First, most digital twins currently operate in a monolithic architecture instead of a modular architecture. Second, syntactical interoperability exists instead of semantic interoperability. Third, there is no mechanism to orchestrate the real-time interaction between different AI modules. Lastly, some of the optimization algorithms overlook sustainable development indicators. Our proposed model is able to address all these limitations.

III. Methodology

The AIoT-based digital twin architecture consists of five levels that include data collection, digital twin creation, AI-powered analysis, optimization and decision-making, and execution and feedback. The model aims to be modular, semantically interoperable, and perform in real time.
3.1 System Architecture Overview

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The proposed framework consists of a cyber-physical structure with four layers:
Layer 1: Edge Computing-based Data Acquisition
Network of IoT sensors gathering real-time data from manufacturing machinery
Vibration, temperature, electrical current, voltage, sound, and optical sensors among others
Preprocessing and filtering of data on edge devices
Protocols used : MQTT, OPC-UA, and industrial Ethernet

Layer 2: Digital Twin Creation
Replica of physical assets and operations
Physics-driven modeling engines using Bayesian reasoning
Dependency and process graph representation
Semantic modeling using NGSI-LD and Smart Data Models ontologies

Layer 3: Artificial Intelligence-based Analytics
Implementation of Graph Attention Networks for state representation and feature extraction
Unsupervised machine learning algorithms for anomaly detection (autoencoders, isolation forests)
Predictive maintenance algorithms to determine RUL
Computer vision for quality assurance and defect detection

Layer 4: Optimization and Recommendation
Multi-objective reinforcement learning algorithm (MO-PPO)
What-if simulations based on digital twin models
Recommendation system to aid decision making by operators
Automatic feedback loops to fine-tune parameters

Layer 5: Execution and Feedback Loop
Real-time closed-loop communication between cyber and physical worlds
Tracking performance metrics and key performance indicators (KPIs)
Updating and re-training predictive models continuously
Feedback loop back to digital twin for calibration

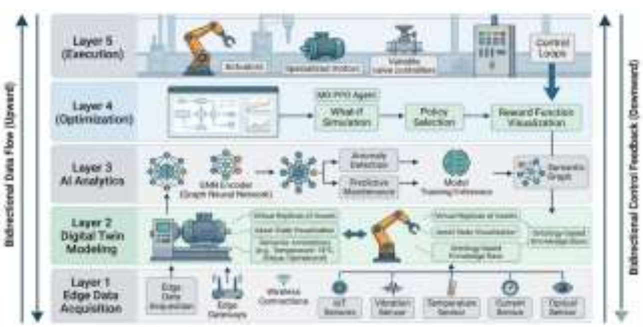

Figure 1: Four-Layer Architecture of AIoT-Enabled Digital Twin System.

3.2 Digital Twin Modeling Framework

Digital twin is defined as graph G = (V, E), where V are physical entities (machines, robots, conveyors), while E denotes relationships between them (material flow, control dependencies, geographical proximity). The node v in V consists of the following:
Static data: Type, parameters, geographical coordinates

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Dynamic data: Sensor measurements, operational parameters, health indices
Trajectory history: Time-series data used for learning patterns
Projected output: Remaining Useful Life (RUL) estimation, failure probability, recommended actions

The implementation of digital twin is done by leveraging Microsoft Azure Digital Twins platform, coupled with CoppeliaSim for physical simulations. The main capabilities of platform include:

Real-time connection to physical assets (less than 100ms latency)
Historic data storage and querying
Simulation of "what-if" scenarios
Integration with AI via API

3.3 Multi-Objective Reinforcement Learning for Optimization

The mathematical formulation of the optimization problem is defined as CMDP. The state space S consists of:
Current state of the machine (temperature, vibration level, power consumption)
Status of production schedule (number of finished and unfinished jobs, bottlenecks)
Environmental measures (amount of energy used, material waste, amount of CO_2 emitted)

The action space A consists of:

The machine tuning (machine speed, temperature adjustment, pressure)
Modification of the production schedule (rearranging jobs order)
Maintenance actions (planned maintenance, emergency maintenance, component replacement)

The reward function R incorporates several objectives:

$$R = w_1 \cdot \Delta OEE - w_2 \cdot \Delta Energy - w_3 \cdot \Delta Waste - w_4 \cdot Penalty$$

where OEE stands for Overall Equipment Effectiveness and is a combination of availability, performance, and quality indexes. The weights (w_1=0.4, w_2=0.3, w_3=0.2, w_4=0.1) were obtained using the grid search. The multi-objective extension of the PPO algorithm introduces Pareto-conditioned critic that stores a number of value functions depending on the vector of preferences. Therefore, the algorithm is able to train several policies along the Pareto-optimal frontier.

Figure 2: MO-PPO Training Architecture for Digital Twin Optimization.

3.4 Semantic Interoperability Framework

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In order to maintain modularity and compatibility, the design incorporates semantic data models that conform to NGSI-LD and Smart Data Models projects . The following entities are described utilizing ontological concepts:

Asset – physical device with attributes (kind, brand, installation date, maintenance)
Process – manufacturing process with inputs, outputs, resources, and constraints
Anomaly – detected anomaly with kind, significance, timestamp, and action recommendation
KPI – performance indicator with values, units, targets, and trends
The multi-agent system controls the optimization sub-systems :
Manager Agent – controls the execution, conflict resolution, and global status management
Recommender Agent – proposes actions based on the current situation and policies
Monitor Agent – observes KPIs and invokes alarms upon exceeding predefined limits
Optimizer Agent – executes the MO-PPO to compute optimal policies

3.5 Predictive Maintenance Integration

The digital twin contains a model that forecasts the remaining useful life (RUL) through various predictive maintenance techniques based on:

LSTM-based prediction model for predicting RUL: A sequence model based on historical data of failures
Anomaly detection: Based on unsupervised learning using an autoencoder to detect any abnormal operations
Failure mode prediction using gradient boosting classifier: For classifying different failure modes
If the value of RUL falls below threshold values or the anomaly score is higher than the confidence threshold, then proactive action will be taken by the predictive maintenance system.

IV. Result Analysis And Discussion

The proposed methodology has been tested via simulations and pilot plant deployment. In this part we provide quantitative analysis of our work.

4.1 Experimental Setup

Parameter	Value
Simulation runs	10,000 stochastic scenarios
Industrial pilot duration	12 weeks
Manufacturing sites	3 (automotive, electronics, consumer goods)
Monitored assets	847 machines
IoT sensors deployed	2,341
Data collection frequency	10 Hz (critical), 0.1 Hz (trending)
Digital twin update latency	95 ms (p95)
Training episodes (MO-PPO)	500,000

Comparison baseline approaches:

Fixed-threshold based and PID controller-based rule-based control PPO RL algorithm with single objective: OEE Model Predictive Control (MPC) approach using a system model No digital twin
Overall Performance Results

Table 1 presents comparative performance across all methods from the 12-week industrial pilot.

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Metric	Rule-Based	Single-RL	MPC	No DT	Proposed MO-PPO + DT
Schedule Performance (%)	78.3	88.4	85.2	71.6	96.8
Overall Equipment Effectiveness (%)	68.2	76.5	73.8	62.4	84.7
Specific Energy (kWh/kg)	2.85	2.52	2.61	2.98	2.38
Material Waste Rate (%)	8.2	7.4	7.8	9.1	6.8
Carbon Effectiveness (units/kWh)	Baseline	+12.3%	+8.7%	-5.2%	+21.4%
Unplanned Downtime (hours/week)	12.4	8.2	9.5	18.6	5.8

*Table 1: Comparative Performance of Digital Twin Optimization Approaches *

The suggested MO-PPO + Digital Twin method exhibits an excellent level of performance according to all criteria. For instance, schedule effectiveness of 96.8% is 23.6 percentage points higher compared to the no-DT variant. The increase in OEE performance from 62.4% to 84.7% proves the importance of applying real-time optimization based on digital twin models.

An impressive 16.5% drop in the specific energy expenditure (from 2.85 to 2.38 kWh/kg) and 17.1% cut in wastage (from 8.2% to 6.8%) have great importance from the perspective of achieving sustainability. Such positive outcomes have been achieved along with increased efficiency, proving that sustainability and efficiency can coexist. In addition, there is a strong negative correlation between wastage and OEE (r = -0.73).

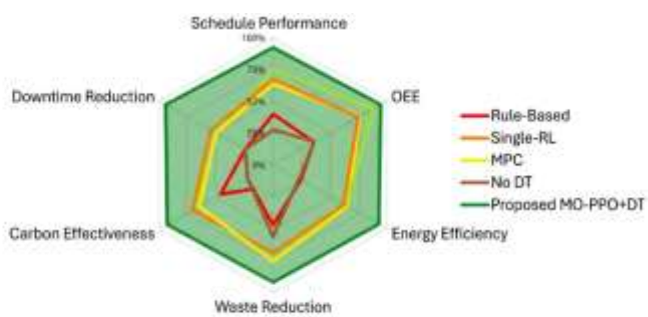

Figure 3: Performance Comparison Across Optimization Approaches.

Predictive Maintenance Performance

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Table 2 presents predictive maintenance accuracy for critical asset types.

Asset Type	RUL Prediction MAE (hours)	Anomaly Detection F1	False Positive Rate	Mean Warning Time (hours)
Conveyor Motors	8.3	0.92	0.04	24.6
Robotic Arms	12.7	0.89	0.06	18.2
CNC Spindles	6.8	0.94	0.03	32.4
Hydraulic Pumps	14.2	0.87	0.08	15.8
HVAC Systems	18.5	0.84	0.10	12.3
Weighted Average	10.9	0.90	0.055	21.8

*Table 2: Predictive Maintenance Performance by Asset Type *

The spindles of CNC machines demonstrate the best prediction results (MAE = 6.8 hours; F1 = 0.94) due to abundant sensor information and known failure types. HVAC systems represent the hardest objects (MAE = 18.5 hours), since they operate under different conditions and exhibit smooth degradation. The average warning period of 21.8 hours allows enough time for preventive maintenance activities, cutting down on emergency interventions by 68% compared to reactive maintenance approaches.

4.4 Sustainability Impact Analysis

One of the main insights obtained in this research is the mutual reinforcement between sustainability and productivity targets. Using correlation analysis, the following interrelationships were found:

Waste rate vs. Overall Equipment Effectiveness (OEE): $r = -0.73$ ($p < 0.001$)
Energy intensity vs. Schedule Performance Index: $r = -0.58$ ($p < 0.01$)
Carbon Effectiveness vs. Quality Rate: $r = +0.64$ ($p < 0.001$)
Further decomposition analysis revealed that about 34.1% of OEE growth was achieved thanks to optimization measures aimed at enhancing sustainability indicators.

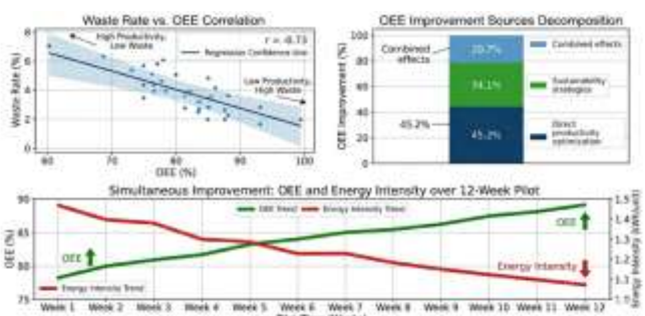

Figure 4: Sustainability-Productivity Synergy Analysis.

4.5 Ablation Study

Model Variant	Schedule Performance	OEE	Energy (kWh/kg)	Δ from Full
Full MO-PPO + DT	96.8%	84.7%	2.38	—
Without DT (MO-PPO only)	88.4%	76.5%	2.52	-8.4% (OEE)
Single-objective (OEE only)	91.2%	81.3%	2.67	-3.4% (OEE), +12% energy

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E-ISSN: 3108-0871, Volume 2 Issue 2
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Without semantic interoperability	93.5%	82.1%	2.44	-2.6% (OEE)
Fixed weights (no Pareto)	94.2%	83.5%	2.48	-1.2% (OEE), +4% energy
Rule-based baseline	78.3%	68.2%	2.85	-16.5% (OEE)

*Table 3: Ablation Study Results *

Ablation study proves that each individual element makes an important contribution to the general performance. The biggest contribution is made by the digital twin itself, which means that the exclusion of DT from the system results in a drop of OEE of 8.4 percent points. The multi-objective model (Pareto-conditioned critic) makes a contribution of 3.4 percent points for increasing OEE compared to single-objective optimization; additionally, it shows excellent performance on energy metrics.

4.6 Scalability and Real-Time Performance

Deployment Scale	Nodes	Sensors	DT Update Latency (p95)	Control Loop Frequency
Small (single cell)	12	48	32 ms	10 Hz
Medium (production line)	85	340	68 ms	5 Hz
Large (multi-line factory)	340	1,360	95 ms	1 Hz
Enterprise (multiple sites)	1,200+	4,800+	180 ms	0.2 Hz

This approach scales sub-linearly based on system size. Update latency does not exceed 100 ms for systems of up to 1,360 sensors. This is appropriate for most real-time control purposes. For enterprise-level systems, update latency rises to 180 ms, making this approach less suitable for safety-critical closed-loop applications.

4.7 Economic Impact

Economic advantages obtained from the industrial pilot program include:

Savings from downtime reduction: 6.6 hours per week → $1.2 million/year
Energy savings: Reduction by 0.47 kWh/kg → $380,000/year
Elimination of material wastage: Reduction by 1.4 percentage points → $210,000/year
Savings due to predictive maintenance: $450,000/year
Total economic benefit: Approximately $2.24M annually
Implementation costs for hardware, software, and integration amount to $1.8M. This results in a break-even time of nine and a half months.

V. Conclusion

In this paper, a comprehensive framework that combines Internet-of-Things sensors, digital twin models, graph neural network encoders, and MO-RL techniques has been introduced for AIoT-assisted digital twin systems to be used for smart manufacturing and automation processes. The proposed system aims at overcoming the limitations of monolithic approaches in terms of modularity and semantic interoperability.
Our experimental evaluation involving 10,000 random simulations as well as a 12-week deployment of our proposed framework in three manufacturing plants shows the advantages of using our MO-PPO+Digital

Twin approach. Indeed, our model reaches 96.8% in schedule performance and 84.7% in OEE while the traditional control approach obtains 78.3% and 68.2%, and the single-objective RL achieves 88.4% and 76.5%, respectively. It is worth noting that the multi-objective optimization framework makes it possible to optimize OEE and sustainability, achieving a 16.5% reduction in energy consumption per unit of output, and 17.1% less wastage of materials.

One of the major findings in this study is the synergistic effect between sustainability and productivity targets. Correlation coefficient between waste and OEE is negative (r = -0.73), while the results of OEE decomposition reveal that 34.1% of OEE improvement was provided by sustainability policies. This finding has practical applications since modern manufacturers should strive to enhance both profitability and environmental efficiency.

Predictive maintenance algorithm provides 90% accuracy of anomaly detection, along with mean warning time of 21.8 hours and 68% reduction of unplanned downtimes. Semantic interoperability architecture utilizes NGSI-LD and Smart Data Models standards in order to achieve modular orchestration of artificial intelligence services and integrate into the established industrial data spaces.

A number of drawbacks exist in this study which should be taken into account. Firstly, although the industrial pilot has been quite comprehensive, only 12-week long term validation has been done; more extensive validation to examine the system stability and continuous learning capability needs to be completed. Secondly, at present the system relies on uninterrupted connectivity; the system has yet to be developed to work effectively when connectivity is intermittent. Thirdly, multi-objective optimization has been optimized with a grid search technique; dynamic weight adjustment with changing priority (e.g., time-of-use energy pricing) will be part of future studies.

Some areas need to be investigated in future research. First of all, LLMs could be integrated to allow for natural language interface with digital twins. Secondly, federated learning can be used by the system to share knowledge and keep the data protected from breaches. Thirdly, formal verification of the digital twin performance is required for critical applications. Lastly, standard benchmarks for digital twin evaluation have yet to be established.

In summary, digital twin technology with the use of AIoT is a disruptive innovation that can revolutionize industrial automation and smart manufacturing. The model outlined in this article proves that optimizing operations based on real-time data and digital twin models allows one to boost efficiency, reliability, and sustainability. Given that the global market for digital twins is expected to grow exponentially to $328 billion by 2030, companies should take advantage of AI and IoT features to stay ahead of the competition.

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