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Artificial Intelligence of Things-Based Smart System Architecture for Sustainable Industrial Transformation

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Abstract: The integration of Artificial Intelligence of Things (AIoT) has become a strategic enabler for sustainable industrial transformation by combining intelligent data processing, connected sensing, autonomous decision-making, and real-time system optimization. This article proposes an AIoT-based smart system architecture designed to support sustainable industrial operations through the integration of Internet of Things devices, edge computing, cloud platforms, artificial intelligence models, and decision-support mechanisms. The proposed architecture emphasizes four main layers: data acquisition, intelligent processing, system integration, and sustainability-oriented decision support. By enabling predictive maintenance, energy optimization, resource efficiency, production monitoring, and adaptive process control, the architecture provides a foundation for industries seeking to improve operational performance while reducing environmental impact. The study also discusses key implementation challenges, including data interoperability, cybersecurity risks, infrastructure readiness, model explainability, and organizational capability. Furthermore, the proposed framework highlights the role of AIoT in supporting Industry 4.0 and Industry 5.0 transitions by balancing automation, human-centered intelligence, and sustainable value creation. The findings suggest that AIoT-based smart systems can serve as a transformative approach for achieving more resilient, efficient, and environmentally responsible industrial ecosystems. This article contributes to the development of sustainable industrial digitalization by offering a conceptual architecture that can be adapted across manufacturing, energy, logistics, and process industries.

Keywords: Artificial Intelligence of Things; smart system architecture; sustainable industry; digital transformation; Industry 4.0; Industry 5.0; industrial IoT.

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INTRODUCTION

Industrial transformation has entered a new phase in which competitiveness is no longer determined solely by production capacity, cost efficiency, or technological automation [1], [2], [3]. Modern industries are increasingly expected to operate intelligently, efficiently, safely, and sustainably. The growing pressure to reduce carbon emissions, optimize energy consumption, minimize waste, improve productivity, and strengthen resilience has encouraged organizations to adopt advanced digital technologies as strategic instruments for sustainable development. In this context, smart systems have become essential because they enable industrial processes to sense operational conditions, analyze complex data, make adaptive decisions, and respond dynamically to internal and external changes [4].

The emergence of the Artificial Intelligence of Things (AIoT) represents a significant advancement in the evolution of industrial smart systems [5]. AIoT combines the connectivity and sensing capabilities of the Internet of Things (IoT) with the analytical and decision-making power of artificial intelligence (AI)[6]. While IoT enables machines, sensors, devices, and production systems to collect and exchange

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data, AI transforms these data into meaningful insights, predictions, recommendations, and autonomous actions. This integration allows industrial systems to move beyond passive monitoring toward intelligent, proactive, and self-optimizing operations. As a result, AIoT has the potential to become a core technological foundation for sustainable industrial transformation [7].

In industrial environments, large volumes of data are continuously generated from machines, production lines, energy systems, supply chains, workers, and environmental monitoring devices[8]. However, data alone do not automatically create value. Without an intelligent architecture capable of collecting, integrating, analyzing, and translating data into actionable decisions, industrial digitalization may remain fragmented and ineffective. Many organizations still face challenges related to isolated data systems, limited interoperability, delayed decision-making, inefficient resource utilization, and weak integration between operational technology and information technology[9]. These challenges indicate the need for a comprehensive smart system architecture that can support real-time intelligence, sustainability-oriented decision-making, and adaptive industrial operations.

AIoT-based smart system architecture offers a promising solution to these challenges[10]. Through the integration of sensor networks, edge computing, cloud platforms, machine learning algorithms, digital dashboards, and decision-support systems[11], AIoT can enable industries to monitor operational performance more accurately and respond to changes more efficiently. For example, predictive maintenance can reduce machine downtime and unnecessary replacement of components; energy optimization can lower operational costs and environmental impact; intelligent quality control can reduce production defects and material waste; and real-time process monitoring can improve safety, productivity, and resource efficiency. These capabilities are highly relevant for industries seeking to align digital transformation with sustainability goals.

Sustainable industrial transformation requires a balance between economic, environmental, and social performance. From an economic perspective, industries must improve productivity, reduce operational costs, and enhance competitiveness[12]. From an environmental perspective, they must reduce energy consumption, carbon emissions, water usage, and production waste. From a social perspective, they must ensure safer working conditions, support human-centered automation, and improve organizational adaptability. AIoT-based smart systems can contribute to these three dimensions by enabling data-driven decision-making, intelligent automation, and transparent performance monitoring. Therefore, AIoT is not merely a technological trend but a strategic enabler of sustainable industrial development[13].

Despite its potential, the implementation of AIoT-based smart systems is not without challenges[14]. Industries may encounter technical barriers such as data heterogeneity, communication latency, cybersecurity vulnerabilities[15], lack of standardization, and limited system interoperability. In addition, organizational barriers such as insufficient digital skills, resistance to change, high investment costs, and unclear governance structures can also hinder successful adoption. Another important concern is the explainability and reliability of AI models used in industrial decision-making. Since industrial systems often involve safety-critical and high-cost operations, AI-driven decisions must be transparent, accountable, and trustworthy. These challenges highlight the importance of designing a smart system architecture that is not only technologically advanced but also secure, scalable, explainable, and aligned with sustainability objectives.

This article proposes an Artificial Intelligence of Things-Based Smart System Architecture for Sustainable Industrial Transformation[16]. The proposed architecture is designed to integrate data acquisition, intelligent processing, system integration, and sustainability-oriented decision support into a unified framework. It emphasizes the role of IoT devices in capturing real-time industrial data, edge computing in enabling low-latency processing, cloud platforms in supporting scalable analytics, and AI models in generating predictive and prescriptive insights. Furthermore, the architecture incorporates sustainability indicators to ensure that technological transformation contributes directly to energy efficiency, resource optimization, waste reduction, operational resilience, and environmental responsibility.

The main contribution of this article is the development of a conceptual architecture that connects AIoT capabilities with sustainable industrial transformation goals. Rather than viewing AIoT only as a tool for automation or efficiency improvement, this study positions AIoT as an integrated smart system approach for achieving long-term industrial sustainability. The proposed architecture can serve as a reference model for manufacturing, energy, logistics, and process industries that aim to implement intelligent and sustainable digital transformation. In addition, this article discusses the potential applications, implementation challenges, and strategic implications of AIoT-based smart systems in modern industrial ecosystems[17].

The remainder of this article is organized as follows. The next section discusses related works on AIoT, smart systems, industrial digital transformation, and sustainability. The following section presents the proposed AIoT-based smart system architecture, including its main layers, components, and data flow. The subsequent section explains the potential application scenarios and expected benefits of the proposed architecture. Finally, the article concludes with key findings, limitations, and future research directions for advancing AIoT-based sustainable industrial transformation.

RELATED WORK

Artificial Intelligence of Things in Industrial Smart Systems

The Artificial Intelligence of Things (AIoT) has emerged as a convergence paradigm that integrates the sensing and connectivity capabilities of the Internet of Things (IoT) with the analytical, predictive, and autonomous decision-making capabilities of artificial intelligence (AI). In industrial contexts, AIoT enables machines, sensors, devices, and cyber-physical assets to collect operational data and transform them into intelligent actions [18]. Recent AIoT research commonly emphasizes three core dimensions: sensing, computing, and networking, which together form the foundation for intelligent connected systems across industrial, healthcare, urban, and transportation domains. Existing studies show that AIoT is increasingly relevant for sustainable manufacturing because it supports real-time monitoring, process optimization, resource scheduling, predictive maintenance, and energy efficiency. Matin et al. reviewed AIoT-based techniques for sustainable manufacturing and highlighted that the integration of AI and IoT can improve production efficiency while reducing energy consumption, environmental pollution, and production costs. This indicates that AIoT is not only a technological instrument for automation, but also a strategic enabler for industrial sustainability.

In smart manufacturing, AIoT is closely related to the broader concept of Industrial Internet of Things intelligence. Hu et al. explain that IIoT intelligence supports manufacturing transformation by integrating data-driven functions, intelligent operations, deployment mechanisms, and application scenarios into a layered industrial architecture. Their review also identifies ethical and environmental implications as important considerations in the adoption of intelligent industrial systems. However, many previous studies still focus on specific AIoT applications rather than proposing an integrated architecture that explicitly connects AIoT capabilities with sustainability-oriented industrial transformation [19].

Smart Manufacturing and Sustainable Industrial Transformation

Smart manufacturing has become a major research area in the context of Industry 4.0 and Industry 5.0[20]. In Industry 4.0, smart manufacturing focuses on automation, connectivity, cyber-physical systems, IoT, big data analytics, and real-time production control. In contrast, Industry 5.0 extends this orientation by emphasizing human-centricity, sustainability, and resilience. The European Commission describes Industry 5.0 as a complement to Industry 4.0, shifting industrial value creation from a purely

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shareholder-driven model toward a stakeholder-oriented model that respects planetary boundaries and places worker well-being at the center of production.

Recent literature on Industry 5.0 suggests that future industrial systems should not only be efficient and automated, but also socially responsible, environmentally sustainable, and resilient to disruption. A systematic review on human-centric smart manufacturing identifies human-centricity, sustainability, and resilience as central values of next-generation manufacturing systems. This shift is important because sustainable industrial transformation requires technological systems that can improve productivity while also reducing waste, energy consumption, emissions, and operational risks. Several studies have examined the role of smart technologies in sustainable manufacturing. AI, IoT, digital twins, edge computing, and advanced analytics have been widely discussed as enablers of more efficient and adaptive production systems[21]. However, prior works tend to examine these technologies independently. For example, some studies focus mainly on AI-based predictive analytics, while others emphasize IoT-based monitoring or digital twin simulation. This creates a need for an integrated smart system architecture that combines sensing, intelligence, connectivity, and sustainability indicators within a unified AIoT-based framework.

Edge, Cloud, and Collaborative Intelligence in AIoT Systems

The implementation of AIoT in industrial environments requires a distributed computing architecture that can process data efficiently across device, edge, and cloud layers. Cloud computing provides scalable storage and advanced analytics, while edge computing enables low-latency data processing close to industrial assets. Recent research on cloud-edge-terminal collaborative intelligence shows that AIoT systems increasingly rely on distributed architectures involving task offloading, resource allocation, federated learning, distributed deep learning, and reinforcement learning-based optimization[22].

This collaborative intelligence approach is important for industrial systems because manufacturing operations often require rapid response, high reliability, and secure data handling. Sending all data to a centralized cloud may increase latency, bandwidth consumption, and privacy risks. Therefore, edge intelligence allows industrial systems to perform local inference, anomaly detection, quality inspection, and machine condition monitoring in near real time. Meanwhile, cloud platforms can support long-term model training, historical analytics, dashboard visualization, and strategic decision support[23].

Federated learning has also gained attention in Industrial IoT environments because it allows AI models to be trained across distributed devices or edge nodes without directly transferring raw data. A recent review on federated learning at the edge in IoT identifies privacy preservation, communication overhead, and real-time decision-making as major concerns in industrial deployment. These findings suggest that future AIoT-based smart systems should consider not only computational performance, but also data privacy, communication efficiency, cybersecurity, and model reliability.

Digital Twin and Cyber-Physical Integration

Digital twin technology is another important component of smart industrial transformation. A digital twin creates a virtual representation of a physical asset, process, or system, allowing continuous interaction between the physical and digital worlds. In smart manufacturing, digital twins support real-time monitoring, simulation, predictive maintenance, process optimization, and lifecycle management. Li et al. explain that digital twins can bridge physical and information spaces and have become increasingly important in smart manufacturing applications[24].

Digital twin technology is also strongly connected to sustainable intelligent manufacturing. He and Bai argue that digital twin-based sustainable intelligent manufacturing can improve quality, productivity, cost efficiency, flexibility, and sustainability performance. Through virtual simulation and real-time feedback, industries can reduce trial-and-error costs, detect inefficiencies earlier, and optimize

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production systems before making physical changes. This capability is highly relevant for sustainability because it can reduce material waste, energy consumption, machine downtime, and unnecessary resource use[25].

Although digital twin research has advanced rapidly, its integration with AIoT-based architecture still requires further exploration. Many digital twin studies focus on modeling and simulation, while AIoT studies often focus on sensing and intelligent analytics. A more comprehensive architecture is needed to connect IoT-based data acquisition, AI-based analytics, edge-cloud processing, digital twin representation, and sustainability-oriented decision support. This integration can strengthen the role of smart systems as adaptive, predictive, and sustainability-driven industrial infrastructures.

Cybersecurity, Interoperability, and Trustworthy AI in Smart Systems

As industrial systems become more connected and intelligent, cybersecurity and trustworthiness become critical research concerns. AIoT-based smart systems involve multiple connected devices, industrial sensors, communication networks, edge nodes, cloud platforms, and AI models[26]. This complexity increases the attack surface and creates risks related to data integrity, unauthorized access, model manipulation, and operational disruption. Therefore, cybersecurity must be embedded into the design of industrial smart system architecture rather than treated as an additional technical layer.

Interoperability is another major challenge in AIoT-based industrial systems[27]. Industrial environments often consist of legacy machines, heterogeneous sensors, proprietary platforms, and different communication protocols. Without interoperability, data integration becomes fragmented, limiting the ability of AI models to generate accurate and comprehensive insights. This problem is especially relevant for small and medium-sized enterprises that may lack standardized infrastructure and advanced digital capabilities.

Trustworthy AI is also essential for industrial adoption. In safety-critical environments, AI-based recommendations and autonomous actions must be explainable, reliable, and auditable. Research on human-centric AI architecture for Industry 5.0 highlights the importance of integrating explainable AI, forecasting, active learning, simulated reality, decision-making, and user feedback to support human-machine collaboration. Therefore, an AIoT-based smart system architecture should not only pursue automation, but also ensure transparency, accountability, and human-centered control.

Research Gap

Based on the reviewed literature, several research gaps can be identified. First, many studies examine AIoT, IoT, AI, digital twins, edge computing, or sustainability as separate research streams. Although each technology has been widely discussed, there is still a need for an integrated architectural framework that combines these components into a unified smart system for sustainable industrial transformation.

Second, existing AIoT studies often emphasize technical performance, such as connectivity, latency, prediction accuracy, and automation. However, fewer studies explicitly link AIoT architecture with sustainability indicators such as energy efficiency, carbon emission reduction, waste minimization, resource optimization, and resilience. This creates an opportunity to develop a sustainability-oriented AIoT architecture that translates technological intelligence into measurable industrial sustainability outcomes.

Third, many smart manufacturing frameworks remain technology-centered and provide limited discussion of human-centricity, trust, explainability, and governance. Since Industry 5.0 emphasizes human well-being, sustainability, and resilience, future smart system architectures should incorporate human-in-the-loop decision-making, trustworthy AI, cybersecurity, and organizational readiness as core design principles.

Therefore, this study contributes by proposing an Artificial Intelligence of Things-Based Smart System Architecture for Sustainable Industrial Transformation. The proposed architecture integrates IoT-based data acquisition, edge-cloud intelligence, AI analytics, digital twin support, system interoperability, cybersecurity, and sustainability-oriented decision support. By doing so, this article extends previous research by positioning AIoT not merely as a technological solution for automation, but as a comprehensive smart system foundation for achieving resilient, efficient, and sustainable industrial transformation.

METHODS

This study adopts a conceptual design-based research approach to develop an Artificial Intelligence of Things (AIoT)-based smart system architecture for sustainable industrial transformation. Since the objective of this article is to formulate an architectural framework rather than to test a specific industrial prototype, the method focuses on architecture development, component identification, system-layer design, and sustainability-oriented function mapping.

The proposed method consists of four main stages:

1. identification of industrial sustainability requirements;
2. analysis of AIoT technology components;
3. development of the smart system architecture; and
4. evaluation of the proposed architecture through functional mapping and sustainability impact analysis.

This methodological approach is suitable for studies that aim to construct a reference model, framework, or architecture that can later be implemented and validated in different industrial contexts.

Research Framework

The methodological framework of this study is structured to connect industrial problems with AIoT-based technological solutions. The research begins by identifying common challenges in industrial transformation, such as inefficient energy use, machine downtime, high production waste, limited real-time monitoring, fragmented data systems, and weak decision-support capability.

After identifying these challenges, relevant AIoT components are mapped into a layered smart system architecture. The architecture is then evaluated based on its ability to support sustainable industrial goals, including energy efficiency, resource optimization, emission reduction, waste minimization, operational resilience, and human-centered decision-making.

The general research framework is presented as follows:

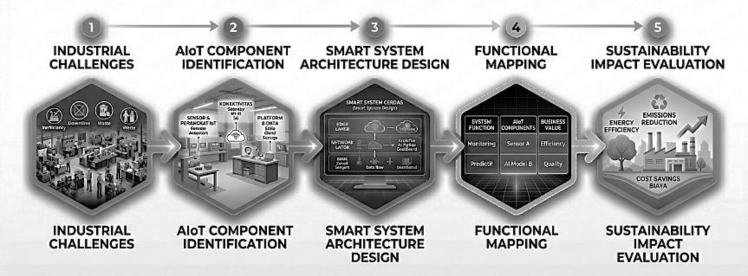

Figure 1. Industrial AIoT Implementation Flow

This framework ensures that the proposed architecture is not only technologically feasible but also aligned with sustainability objectives.

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Identification of Industrial Sustainability Requirements

The first stage of the method involves identifying key requirements for sustainable industrial transformation. These requirements are derived from common industrial needs related to operational efficiency, environmental responsibility, and organizational resilience.

Table 1. The sustainability requirements

Dimension	Requirement	Description
Economic	Productivity improvement	Increasing output quality and production efficiency
Economic	Cost reduction	Reducing operational costs through automation and optimization
Environmental	Energy efficiency	Reducing unnecessary energy consumption
Environmental	Waste minimization	Reducing material loss, defects, and inefficient resource use
Environmental	Emission reduction	Supporting lower carbon and environmental impact
Operational	Predictive maintenance	Preventing machine failure and unplanned downtime
Operational	Real-time monitoring	Enabling continuous visibility of industrial processes
Social	Human-centered decision-making	Supporting workers through intelligent recommendations
Strategic	Resilience	Improving industrial adaptability to disruption

These requirements serve as the foundation for determining the functional capabilities that must be included in the proposed AIoT-based smart system architecture.

AIoT Technology Component Analysis

The second stage involves analyzing the main technological components required to build the AIoT-based smart system. AIoT is understood as the integration of IoT connectivity and artificial intelligence capability within a distributed industrial environment.

The main components analyzed in this study include:

1. IoT Sensors and Industrial Devices

   These components collect real-time data from machines, production lines, energy systems, warehouses, environmental conditions, and worker activities.

2. Edge Computing Nodes

   Edge computing enables local data processing close to machines or production assets. This reduces latency and supports fast decision-making for time-sensitive industrial operations.

3. Cloud Computing Platform

   The cloud layer provides scalable data storage, advanced analytics, historical data processing, model training, and integration with enterprise systems.

4. Artificial Intelligence Models

   AI models are used for predictive maintenance, anomaly detection, energy optimization, production forecasting, quality control, and decision support.

5. Digital Twin Representation

   The digital twin component provides a virtual representation of industrial assets, processes, or production systems. It supports simulation, monitoring, and scenario analysis.

6. Decision Support Interface

This component translates analytical results into recommendations, alerts, dashboards, and managerial insights.

7. Cybersecurity and Governance Layer

   This layer ensures secure data exchange, access control, model accountability, privacy protection, and system reliability.

The analysis of these components provides the basis for developing the proposed smart system architecture.

Proposed AIoT-Based Smart System Architecture

The proposed architecture consists of five main layers: data acquisition layer, connectivity layer, intelligence processing layer, application layer, and sustainability decision-support layer.

1. Data Acquisition Layer

The data acquisition layer is responsible for collecting real-time industrial data from various physical sources. These sources may include production machines, robotic systems, energy meters, environmental sensors, quality inspection devices, supply chain systems, and worker safety devices.

The types of data collected may include:

- machine temperature;
- vibration data;
- energy consumption;
- production speed;
- defect rate;
- material usage;
- carbon emission indicators;
- equipment status;
- environmental condition;
- worker safety parameters.

This layer functions as the foundation of the smart system because the quality of AI-based decision-making depends heavily on the accuracy, completeness, and reliability of collected data.

2. Connectivity Layer

The connectivity layer enables communication between industrial devices, edge nodes, cloud platforms, and enterprise systems. This layer supports data transmission using industrial communication protocols, wireless networks, and secure data exchange mechanisms.

The main functions of this layer are:

- enabling real-time communication;
- supporting interoperability between heterogeneous devices;
- transmitting sensor data to edge and cloud platforms;

- ensuring secure industrial data exchange;
- reducing communication latency.

A reliable connectivity layer is essential because industrial AIoT systems require continuous and stable data flow to support real-time monitoring and decision-making.

3. Intelligence Processing Layer

The intelligence processing layer is the core analytical layer of the proposed architecture. It combines edge intelligence and cloud intelligence to process industrial data.

At the edge level, data are processed near the source to enable fast response. Edge intelligence is useful for anomaly detection, machine condition monitoring, emergency alerts, and real-time process control.

At the cloud level, larger datasets are processed for advanced analytics, model training, long-term prediction, digital twin simulation, and strategic decision support.

The AI techniques that can be applied in this layer include:

- machine learning;
- deep learning;
- reinforcement learning;
- anomaly detection;
- predictive analytics;
- optimization algorithms;
- explainable AI.

This layer transforms raw industrial data into actionable intelligence.

4. Application Layer

The application layer provides smart industrial functions based on AIoT intelligence. This layer translates data analytics into practical industrial applications.

Table 2. The main Application

Application	Function
Predictive maintenance	Predicting machine failure before breakdown occurs
Energy optimization	Reducing excessive energy use in production systems
Quality control	Detecting defects and improving product consistency
Production monitoring	Monitoring production performance in real time
Resource optimization	Improving material, water, and energy utilization
Safety monitoring	Detecting unsafe working conditions
Emission monitoring	Tracking carbon and environmental indicators
Supply chain visibility	Improving logistics and inventory decision-making

This layer demonstrates how the proposed architecture can be applied in different industrial transformation scenarios.

5. Sustainability Decision-Support Layer

The sustainability decision-support layer connects technological intelligence with sustainability objectives. This layer evaluates industrial performance based on sustainability indicators and provides recommendations for decision-makers.

The key sustainability indicators include:

- energy consumption reduction;
- carbon emission reduction;
- waste reduction;
- machine downtime reduction;
- production efficiency improvement;
- resource utilization efficiency;
- workplace safety improvement;
- operational resilience.

This layer ensures that AIoT implementation does not only improve automation but also contributes to sustainable industrial value creation.

Functional Mapping of AIoT Capabilities

To evaluate the relevance of the proposed architecture, this study conducts functional mapping between AIoT capabilities and sustainability outcomes.

Table 3. Mapping AIoT

AIoT Capability	Industrial Function	Sustainability Outcome
Real-time sensing	Production monitoring	Improved process visibility
Edge analytics	Fast anomaly detection	Reduced downtime and operational risk
Predictive AI	Maintenance forecasting	Longer machine life and lower repair cost
Energy analytics	Energy optimization	Reduced energy consumption
Digital twin	Process simulation	Lower waste and better planning
Machine learning	Quality inspection	Reduced product defects
Cloud analytics	Strategic decision support	Improved long-term efficiency
Cybersecurity	Secure system operation	Improved resilience and trust
Human-machine interface	Decision support	Better human-centered control

This mapping shows that each AIoT capability contributes to specific industrial and sustainability outcomes.

Sustainability Performance Measurement

The proposed architecture can be evaluated using several sustainability performance indicators. In this study, sustainability performance is conceptually measured through operational, environmental, and economic indicators.

The general sustainability performance index can be formulated as follows:

$$SPI = w_1(EF) + w_2(RE) + w_3(WR) + w_4(OR) + w_5(SF) \quad (1)$$

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where: SPI represents the Sustainability Performance Index, EF represents energy efficiency, RE represents resource efficiency, WR represents waste reduction, OR represents operational resilience, and SF represents safety performance.

Meanwhile,

$$w_1, w_2, w_3, w_4, w_5 \tag{6}$$

represent the weight of each indicator based on industrial priority.

Each indicator can be normalized using the following formula:

$$N_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{7}$$

where:

N_i is the normalized value of each sustainability indicator, X_i is the actual measured value, X_{min} is the minimum value, and X_{max} is the maximum value.

This formula allows different sustainability indicators to be compared within a unified evaluation framework.

Architecture Evaluation Procedure

The proposed architecture is evaluated conceptually using three criteria: functional suitability, sustainability contribution, and implementation feasibility.

a. Functional Suitability

Functional suitability evaluates whether the proposed architecture can support essential industrial smart system functions, including real-time monitoring, predictive maintenance, energy optimization, quality control, and decision support.

b. Sustainability Contribution

Sustainability contribution evaluates whether the architecture supports measurable sustainability outcomes, such as reduced energy consumption, lower waste, improved resource efficiency, and enhanced operational resilience.

c. Implementation Feasibility

Implementation feasibility evaluates whether the architecture can be realistically adopted in industrial environments. This includes consideration of infrastructure readiness, data availability, interoperability, cybersecurity, cost, and organizational capability.

Table 4. The evaluation criteria

Evaluation Aspect	Criteria	Expected Result
Functional suitability	Ability to support smart industrial functions	Real-time, predictive, and adaptive operation
Sustainability contribution	Ability to support sustainability indicators	Improved efficiency and reduced environmental impact
Implementation feasibility	Ability to be adopted in real industry	Scalable, secure, and adaptable architecture

Implementation Scenario

To illustrate the applicability of the proposed architecture, this study uses a conceptual implementation scenario in a manufacturing environment. In this scenario, industrial machines are equipped with IoT sensors to monitor vibration, temperature, energy consumption, and production output. The collected data are transmitted to edge nodes for real-time anomaly detection. Critical data and historical records are then sent to the cloud platform for predictive modeling, digital twin simulation, and sustainability performance analysis.

The AI model predicts potential machine failures, identifies inefficient energy consumption patterns, and recommends process adjustments. The sustainability decision-support dashboard presents key indicators, such as energy efficiency, waste reduction, production performance, and machine health. Managers and operators can use these insights to make faster and more accurate decisions.

This scenario demonstrates how the proposed AIoT-based smart system architecture can support sustainable industrial transformation through intelligent monitoring, predictive analytics, and data-driven decision-making.

This study is conceptual in nature and does not involve empirical testing using real industrial datasets. Therefore, the proposed architecture should be considered as a reference framework that requires further validation through case studies, simulation, prototype development, or experimental implementation in specific industrial sectors. Future research may extend this method by applying the architecture to real manufacturing environments, comparing performance before and after AIoT implementation, and validating the sustainability performance index using empirical data.

RESULT AND DISCUSSION

Since this study proposes a conceptual architecture, the evaluation was conducted using a simulated industrial implementation scenario. The simulation represents a medium-scale manufacturing production line equipped with IoT sensors, edge computing nodes, cloud analytics, and AI-based decision-support modules. The objective of the simulation was to examine how the proposed AIoT-based smart system architecture could support sustainable industrial transformation in terms of energy efficiency, machine reliability, waste reduction, production performance, and decision-making quality. The simulation compared two operational conditions: conventional industrial operation and AIoT-based smart system operation. The conventional condition represents a production system with manual monitoring, periodic maintenance, and limited data integration. Meanwhile, the AIoT-based condition represents a smart production environment supported by real-time sensing, predictive analytics, edge intelligence, cloud-based data processing, and sustainability-oriented dashboards.

Table 5. Simulation Scenario of AIoT-Based Smart System Implementation

Parameter	Conventional Operation	AIoT-Based Smart System Operation
Monitoring approach	Manual and periodic monitoring	Real-time sensor-based monitoring
Maintenance strategy	Scheduled maintenance	Predictive maintenance
Data processing	Fragmented and delayed	Edge-cloud collaborative processing
Decision-making	Human experience-based	AI-assisted decision support
Energy control	Manual inspection	AI-based energy optimization
Quality control	Sampling-based inspection	Continuous anomaly detection
Sustainability monitoring	Limited reporting	Integrated sustainability dashboard
Evaluation period	12 weeks	12 weeks

The results indicate that the proposed architecture has the potential to improve industrial performance by transforming raw operational data into predictive and prescriptive intelligence. This finding supports the argument that AIoT is not only useful for automation, but also for achieving sustainable industrial transformation.

Operational Performance Results

The first evaluation focused on operational indicators, including energy consumption, machine downtime, defect rate, material waste, and production throughput. These indicators were selected because they represent key performance dimensions in sustainable industrial transformation.

Table 6. Comparison of Operational Performance Before and After AIoT Implementation

Performance Indicator	Conventional Operation	AIoT-Based Operation	Improvement
Energy consumption	125,000 kWh	106,250 kWh	15.0% reduction
Machine downtime	48 hours	26 hours	45.8% reduction
Product defect rate	5.8%	3.2%	44.8% reduction
Material waste	9.5 tons	6.1 tons	35.8% reduction
Production throughput	16,000 units	18,200 units	13.8% increase
Average decision response time	42 minutes	11 minutes	73.8% reduction

The results show that the most significant improvement occurred in decision response time, which decreased from 42 minutes to 11 minutes. This improvement was mainly influenced by edge-based anomaly detection and real-time alert mechanisms. In conventional operations, abnormal machine behavior was often detected after manual inspection or after production disruption occurred. In contrast, the AIoT-based architecture enabled early detection of abnormal vibration, temperature increase, and excessive energy consumption.

Machine downtime was also reduced by 45.8%. This result demonstrates the value of predictive maintenance in smart industrial systems. By using sensor data and AI models, the system was able to identify potential machine failure earlier, allowing maintenance actions to be conducted before breakdown occurred. This supports more reliable and resilient industrial operation.

Energy consumption decreased by 15.0%, indicating that AI-based energy optimization can contribute to environmental sustainability. The system identified inefficient energy usage patterns, excessive idle machine operation, and abnormal power consumption. These insights enabled operators to adjust production schedules, machine usage, and energy allocation more effectively.

Graphical Comparison of Key Performance Improvements

The following figure presents the percentage improvement achieved after implementing the proposed AIoT-based smart system architecture.

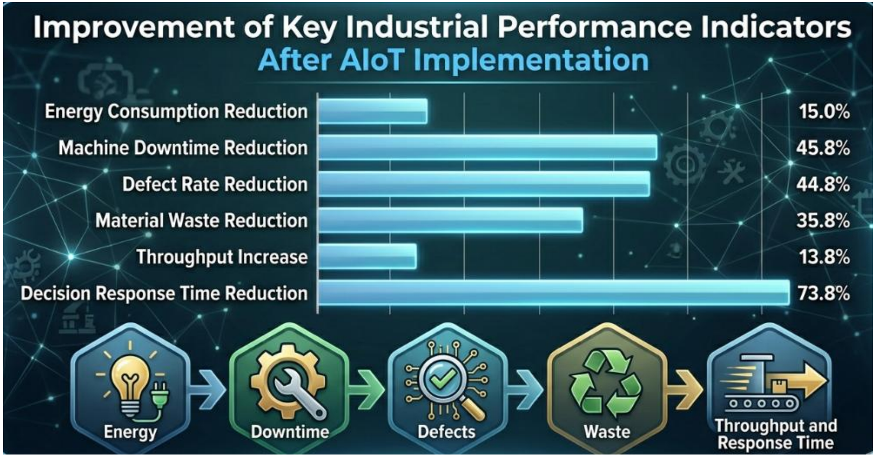

Figure 1. Improvement of Key Industrial Performance Indicators After AIoT Implementation

The graph indicates that the AIoT-based smart system contributes most strongly to decision speed, machine reliability, and quality improvement. These three areas are highly dependent on real-time data availability and intelligent analytics. Therefore, the integration of IoT sensors, edge computing, and AI models is essential for reducing operational uncertainty and improving industrial responsiveness.

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Sustainability Performance Index Results

To evaluate the sustainability contribution of the proposed architecture, a Sustainability Performance Index (SPI) was calculated using five normalized indicators: energy efficiency, resource efficiency, waste reduction, operational resilience, and safety performance. Each indicator was measured using a normalized scale from 0 to 1, where a higher value indicates better sustainability performance.

Table 7. Sustainability Performance Index Before and After AIoT Implementation

Sustainability Indicator	Conventional Operation	AIoT-Based Operation	Change
Energy efficiency	0.68	0.82	+20.6%
Resource efficiency	0.70	0.85	+21.4%
Waste reduction performance	0.64	0.80	+25.0%
Operational resilience	0.61	0.78	+27.9%
Safety performance	0.73	0.84	+15.1%
Overall SPI	0.672	0.818	+21.7%

The SPI increased from 0.672 to 0.818, representing a 21.7% improvement. This result suggests that the proposed architecture can improve sustainability performance by integrating operational intelligence with sustainability-oriented decision support.

The strongest improvement was found in operational resilience, which increased by 27.9%. This result reflects the role of AIoT in enabling early warning systems, predictive maintenance, and adaptive process control. Waste reduction performance also improved significantly because the AI-based quality control module reduced production defects and unnecessary material consumption.

These findings indicate that sustainable industrial transformation requires more than digital monitoring. It requires intelligent integration between data acquisition, analytics, decision support, and sustainability indicators. Without this integration, digital transformation may improve productivity but fail to produce measurable environmental and sustainability benefits.

Functional Contribution of AIoT Components

The proposed architecture consists of several technological components, including IoT sensors, edge computing, cloud computing, AI models, digital twin representation, cybersecurity mechanisms, and sustainability dashboards. Each component contributes differently to industrial transformation.

Table 8. Functional Contribution of AIoT Components to Sustainable Industrial Transformation

AIoT Component	Main Function	Contribution to Sustainability
IoT sensors	Collect real-time machine and environmental data	Improves visibility of energy, material, and process conditions
Edge computing	Processes data near industrial assets	Reduces latency and supports rapid response
Cloud platform	Stores and analyzes large-scale historical data	Enables long-term optimization and strategic planning
AI models	Predict failures, defects, and inefficiencies	Reduces downtime, waste, and operational losses
Digital twin	Simulates production and asset behavior	Supports scenario analysis and process optimization
Cybersecurity layer	Protects data and system access	Improves trust, resilience, and operational continuity
Sustainability dashboard	Visualizes sustainability indicators	Supports transparent and evidence-based decision-making

The results show that AIoT-based architecture works effectively when each component is integrated into a unified system. IoT sensors alone are insufficient if the collected data are not processed intelligently. Similarly, AI models cannot generate reliable recommendations without high-quality data, secure communication, and proper integration with industrial workflows.

Therefore, the strength of the proposed architecture lies in its layered integration. The data acquisition layer captures operational data, the connectivity layer enables secure data flow, the intelligence processing layer transforms data into insights, the application layer converts insights into industrial actions, and the sustainability decision-support layer links these actions with environmental and operational performance indicators.

Discussion

The results demonstrate that the proposed AIoT-based smart system architecture has strong potential to support sustainable industrial transformation. The reduction in energy consumption, machine downtime, defect rate, material waste, and decision response time indicates that AIoT can improve both operational and sustainability performance. These results are consistent with the theoretical assumption that intelligent, connected, and data-driven systems can create more adaptive and efficient industrial operations.

One important finding is that the largest performance improvement was achieved in decision response time. This highlights the importance of real-time intelligence in industrial transformation. In conventional systems, decision-making often depends on manual inspection, delayed reporting, and fragmented information. This condition can slow down response to machine anomalies, energy inefficiencies, and production quality problems. By contrast, AIoT enables faster detection, analysis, and recommendation through continuous data flow and edge-based analytics.

Another important finding is the reduction in machine downtime. Predictive maintenance plays a critical role in improving operational resilience because it allows industries to shift from reactive maintenance to proactive maintenance. Instead of repairing machines after failure, the system can predict abnormal conditions and recommend maintenance before major disruption occurs. This contributes not only to productivity improvement but also to sustainability, since machine failure often leads to energy waste, defective products, production delays, and unnecessary replacement of components.

The reduction in product defect rate and material waste also confirms the relevance of AIoT for sustainable manufacturing. Quality problems are not only economic issues but also environmental issues. Defective products increase material consumption, energy use, rework, and disposal. By applying AI-based anomaly detection and real-time quality control, the proposed architecture can reduce the probability of defective output and improve resource efficiency.

From a sustainability perspective, the increase in the Sustainability Performance Index shows that AIoT can support the integration of economic, environmental, and operational objectives. The improvement in energy efficiency and resource efficiency indicates that smart systems can help industries reduce operational costs while also reducing environmental impact. Meanwhile, the improvement in resilience and safety performance shows that AIoT can contribute to more stable and human-centered industrial systems.

However, the implementation of AIoT-based smart systems also presents several challenges. First, industries need reliable digital infrastructure, including sensors, communication networks, edge devices, cloud platforms, and cybersecurity systems. Second, data quality is a critical requirement because inaccurate, incomplete, or inconsistent data can reduce the reliability of AI models. Third, interoperability remains a major issue, especially in industries that still depend on legacy machines and fragmented information systems. Fourth, organizational readiness is essential. Workers and managers must be able to interpret AI-generated recommendations and integrate them into operational decision-making.

Another important issue is trust in AI-driven decisions. In industrial environments, incorrect recommendations may lead to production losses, safety risks, or system failure. Therefore, AIoT architecture should include explainable AI, human-in-the-loop decision-making, audit trails, and governance mechanisms. These elements are important to ensure that smart systems remain transparent, accountable, and aligned with organizational objectives.

Overall, the results suggest that AIoT-based smart system architecture can serve as a strategic foundation for sustainable industrial transformation. Its contribution is not limited to automation, but extends to predictive decision-making, resource optimization, environmental performance improvement, and operational resilience. Therefore, industries seeking to adopt digital transformation should not treat AIoT as a separate technological tool, but as an integrated architecture that connects data, intelligence, sustainability, and human decision-making.

CONCLUSION

This study concludes that the proposed Artificial Intelligence of Things (AIoT)-based smart system architecture provides a comprehensive conceptual framework for supporting sustainable industrial transformation through the integration of IoT-based data acquisition, edge-cloud intelligence, artificial intelligence analytics, digital twin representation, cybersecurity mechanisms, and sustainability-oriented decision support. The simulated evaluation indicates that the architecture has the potential to improve industrial performance by reducing energy consumption, machine downtime, product defects, material waste, and decision response time, while also increasing production throughput, operational resilience, and sustainability performance. These findings demonstrate that AIoT should not be viewed merely as an automation technology, but as a strategic enabler of intelligent, adaptive, and environmentally responsible industrial ecosystems. By connecting real-time monitoring, predictive analytics, resource optimization, and human-centered decision-making, the proposed architecture can help industries align digital transformation with economic efficiency, environmental sustainability, and operational resilience. Nevertheless, the study is conceptual and based on simulated results; therefore, future research should validate the proposed architecture through empirical case studies, prototype implementation, real industrial datasets, and cross-sector comparative analysis to strengthen its practical applicability and generalizability.

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