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Explainable AI-Based Decision Support Systems for Sustainable Industrial Automation

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Abstract: The rapid emergence of Industry 4.0 and the transition toward Industry 5.0 have transformed manufacturing systems into highly interconnected, data-driven, and intelligent ecosystems. Artificial Intelligence (AI) has become a fundamental enabler of industrial automation through predictive maintenance, process optimization, quality assurance, resource allocation, and autonomous decision-making. However, many industrial AI models operate as black-box systems, limiting transparency, interpretability, and trust among stakeholders. This challenge is particularly significant in safety critical industrial environments where decision reliability directly influences operational efficiency, sustainability, and economic performance. Explainable Artificial Intelligence (XAI) has emerged as a promising solution to enhance transparency and accountability in automated decision making systems. This study proposes an Explainable AI-Based Decision Support System (XAIDSS) for sustainable industrial automation. The proposed framework integrates machine learning algorithms, explainability mechanisms, industrial Internet of Things (IIoT) infrastructures, and sustainability assessment modules to improve operational efficiency while ensuring interpretability. The study develops a conceptual architecture for industrial decision support and evaluates its potential impact on predictive maintenance, energy optimization, production scheduling, and fault diagnosis. Results indicate that incorporating explainability mechanisms significantly improves decision confidence, regulatory compliance, and human-machine collaboration. The proposed framework contributes to the development of transparent, sustainable, and resilient industrial ecosystems capable of supporting next-generation intelligent manufacturing environments.

Keywords: Renewable Energy, Hybrid Systems, Solar-Wind Microgrid, Optimization, Artificial Intelligence

1. Introduction

Industrial automation has undergone substantial transformation over the past decade owing to advances in artificial intelligence, machine learning, cloud computing, and industrial Internet of Things technologies. Modern manufacturing systems increasingly rely on autonomous decision-making mechanisms to improve productivity, reduce downtime, optimize energy consumption, and enhance operational sustainability [1].

The transition from traditional automation systems to intelligent automation has resulted in unprecedented levels of data generation. Sensors embedded within industrial machines continuously monitor temperature, pressure, vibration, power consumption, production quality, and environmental conditions. Such data streams enable predictive analytics and automated decision-making systems capable of identifying operational inefficiencies before they escalate into costly failures [2].

Despite significant advancements, a major challenge remains associated with the interpretability of artificial intelligence models. Deep learning architectures and ensemble machine learning algorithms often achieve high predictive accuracy but fail to provide understandable explanations regarding their decisions. Industrial managers, operators, regulators, and engineers frequently hesitate to rely entirely on black-box systems because critical operational decisions require transparency and accountability [3].

Explainable Artificial Intelligence (XAI) addresses this challenge by providing human-understandable explanations for machine-generated decisions. XAI techniques enhance trustworthiness by enabling users to understand how input variables influence outcomes. Such transparency is essential for industrial applications involving predictive maintenance, fault detection, supply chain optimization, energy management, and safety-critical control systems [4].

Sustainability has emerged as another critical consideration in industrial environments. Manufacturing industries account for substantial energy consumption and greenhouse gas emissions globally. Sustainable industrial automation seeks to balance economic productivity, environmental responsibility, and social well-being through intelligent resource management and optimized production strategies [5].

The convergence of explainable AI and sustainable automation creates opportunities for developing transparent decision support systems capable of improving operational efficiency while reducing environmental impact. Such systems can assist organizations in meeting sustainability objectives without compromising productivity or profitability [6].

This paper proposes an Explainable AI-Based Decision Support System (XAIDSS) designed specifically for sustainable industrial automation. The study examines current developments in XAI and industrial intelligence, identifies existing challenges, and develops a conceptual framework for integrating explainable decision-making mechanisms into industrial environments.

2. Background and Motivation

The increasing complexity of industrial systems has led to a growing dependence on AI-driven decision-making technologies. Modern manufacturing facilities operate through interconnected cyber-physical systems where machines communicate autonomously and generate vast volumes of operational data [7].

While machine learning algorithms provide substantial benefits in forecasting equipment failures and optimizing manufacturing processes, the inability to explain decisions remains a significant barrier to adoption. Industrial stakeholders often require justification before implementing recommendations generated by AI systems. This requirement becomes even more important in regulated industries such as aerospace, pharmaceuticals, automotive manufacturing, and energy production [8].

The motivation for integrating explainable AI into industrial decision support systems stems from four primary factors:

First, transparency improves trust among human operators. Second, explainability enhances compliance with emerging AI governance regulations. Third, interpretable recommendations facilitate faster problem diagnosis and resolution. Finally, transparent systems support sustainable manufacturing initiatives by clearly identifying resource inefficiencies and environmental impacts [9].

Consequently, explainable decision support systems have become an important research area within Industry 5.0, which emphasizes human-centric, resilient, and sustainable industrial development [10].

3. Literature Review

Recent studies have highlighted the growing significance of explainable AI in industrial applications. Adadi and Berrada [11] emphasize that explainability is essential for ensuring transparency in machine learning systems deployed within critical environments. Their study identifies interpretability as a key factor influencing trust and adoption.

Arrieta et al. [12] provide a comprehensive review of explainable AI techniques and classify explanation methods into intrinsic and post-hoc categories. Their findings indicate that explainability significantly enhances decision reliability in high-risk environments.

Rai [13] argues that organizations increasingly demand interpretable machine learning models due to ethical, legal, and operational concerns. Explainability allows stakeholders to understand model behavior and identify potential biases.

In industrial environments, predictive maintenance represents one of the most successful applications of machine learning. Carvalho et al. [14] demonstrate how AI-driven predictive maintenance reduces equipment downtime and maintenance costs. However, the study notes that maintenance engineers often struggle to interpret black-box predictions.

Similarly, Tao et al. [15] highlight the role of digital twins in intelligent manufacturing systems. Their work suggests that integrating explainable AI with digital twin technologies can improve operational transparency and support sustainable decision-making.

Sustainability-focused studies emphasize the importance of AI in reducing industrial energy consumption. Zhang et al. [16] report that intelligent energy management systems can achieve substantial efficiency improvements through predictive optimization techniques.

Despite these advancements, existing research reveals a lack of comprehensive frameworks that integrate explainability, sustainability, and industrial decision support into a unified architecture. The present study seeks to address this gap.

Table 1. Comparison of Conventional AI and Explainable AI in Industrial Automation

Parameter	Conventional AI	Explainable AI
Decision Accuracy	High	High
Transparency	Low	High
Interpretability	Limited	Extensive
Regulatory Compliance	Challenging	Enhanced
User Trust	Moderate	High
Sustainability Insights	Limited	Strong
Human-AI Collaboration	Restricted	Improved
Industrial Adoption Potential	Moderate	High

Table 2. Major Industrial Applications of Explainable AI

Application Area	Industrial Benifit	Sustainability Impact
Predictive Maintenance	Reduced downtime	Reduced resource waste
Quality Inspection	Improved product quality	Reduced material losses
Energy Management	Lower power consumption	Reduced emissions
Supply Chain Optimization	Efficient logistics	Lower transportation
Production Scheduling	Better resource utilization	Improved sustainability
Fault Diagnosis	Faster issue detection	Reduced operational losses

Table 3. Key Challenges in Sustainable Industrial Automation

Challenge	Description	Potential XAI Solution
Black-Box Decisions	Lack of transparency	Explainable models
Data Complexity	Large-scale sensor data	Feature importance analysis
Regulatory Compliance	AI governance requirements	Transparent decision trails
Human Trust	Resistance to automation	Interpretable recommendations
Energy Consumption	Inefficient resource use	Sustainability-focused analytics
System Reliability	Unexpected failures	Explainable predictive maintenance

4. Research Gap

Although existing studies have investigated explainable AI, industrial automation, predictive analytics, and sustainability independently, few studies have integrated these domains into a comprehensive decision support framework. Most current systems prioritize predictive accuracy while neglecting interpretability and sustainability metrics. Furthermore, industrial stakeholders require actionable explanations that can be directly incorporated into operational workflows.

The identified research gap therefore lies in the development of an integrated Explainable AI-Based Decision Support System capable of simultaneously addressing transparency, operational efficiency, and sustainability objectives within Industry 5.0 environments.

5. Research Objectives

The primary objective of this research is to develop an explainable decision support framework for sustainable industrial automation.

Specific objectives include:

1. To investigate existing explainable AI approaches applicable to industrial environments.
2. To design an integrated XAIDSS architecture.
3. To evaluate the role of explainability in enhancing trust and decision quality.
4. To assess sustainability benefits associated with explainable industrial intelligence.
5. To identify future research directions for Industry 5.0 automation systems.
6. Proposed Explainable AI-Based Decision Support System (XAIDSS)

6.1 Conceptual Framework

The proposed Explainable AI-Based Decision Support System (XAIDSS) is designed to support sustainable industrial automation by integrating Industrial Internet of Things (IIoT), machine learning, explainable artificial intelligence, sustainability assessment mechanisms, and human-centered decision-making modules.

The framework consists of five interconnected layers. The first layer comprises industrial sensing and data acquisition systems. Smart sensors continuously collect operational information related to machine health, energy consumption, production throughput, environmental conditions, vibration patterns, temperature fluctuations, and equipment utilization.

The second layer focuses on data management and preprocessing. Raw industrial data are filtered, normalized, and transformed into machine-readable formats suitable for advanced analytics. Data cleaning procedures remove noise and inconsistencies that may negatively influence prediction performance.

The third layer contains the AI analytics engine. Machine learning algorithms perform predictive maintenance, fault diagnosis, quality inspection, demand forecasting, and production optimization tasks. Deep learning and ensemble learning models generate highly accurate predictions based on historical and real-time industrial data.

The fourth layer incorporates explainability mechanisms. Explainable AI methods such as SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-Agnostic Explanations), feature importance ranking, counterfactual analysis, and decision rule extraction provide transparent explanations for AI-generated recommendations.

The final layer consists of a decision support interface through which managers, operators, engineers, and policymakers interact with the system. Recommendations are presented alongside explanatory information, confidence levels, sustainability metrics, and risk assessments.

The integration of these layers creates a transparent industrial intelligence ecosystem capable of supporting sustainable manufacturing objectives while maintaining human oversight.

6.2 System Architecture

The proposed architecture follows a hierarchical structure.

Industrial machines, robotic systems, and smart sensors generate operational data. These data streams are transmitted through IIoT communication networks to cloud-based or edge-computing platforms.

Machine learning models process incoming data and generate predictive outputs. The explainability engine then interprets model decisions and identifies key variables influencing outcomes.

Decision recommendations are subsequently transmitted to production managers and industrial operators. Human experts retain authority to approve, modify, or reject system-generated suggestions.

This human-in-the-loop architecture aligns with Industry 5.0 principles emphasizing collaboration between intelligent systems and human expertise [17].

6. Methodology

The methodology adopted in this study follows a five-stage framework.

The first stage involves industrial data collection from interconnected sensors deployed across manufacturing facilities.

The second stage focuses on data preprocessing and feature engineering. Variables associated with equipment condition, operational efficiency, and sustainability performance are extracted.

The third stage employs machine learning techniques including Random Forest, XGBoost, Support Vector Machines, Artificial Neural Networks, and Long Short-Term Memory networks.

The fourth stage introduces explainability mechanisms. SHAP values quantify feature contributions, while LIME generates local explanations for individual predictions.

The final stage evaluates sustainability performance using environmental, economic, and operational indicators.

Table 4. Methodological Stages of the Proposed XAIDSS

Stage	Description	Expected Outcome
Data Collection	Acquisition of industrial sensor data	Real-time operational visibility

Data Processing	Cleaning and transformation	High-quality datasets
AI Modeling	Predictive analytics and optimization	Accurate predictions
Explainability Analysis	Interpretation of model decisions	Transparent recommendations
Sustainability Evaluation	Environmental and operational assessment	Sustainable decision-making

7. Mathematical Formulation

The predictive maintenance component estimates equipment failure probability using machine learning models.

The prediction function may be expressed as:

[Y = f(X_1, X_2, X_3, ..., X_n)]

where:

Y represents equipment condition prediction,

X_1 , X_2 , X_3 ,...X_n represent operational features such as vibration, temperature, pressure, energy consumption, and machine utilization.

Feature contribution through SHAP values can be represented as:

[f(x)=\phi_0+\sum_{i=1}^{n}\phi_i]

where:

(\phi_0) denotes the baseline prediction and

(\phi_i) represents the contribution of feature i.

Sustainability performance can be evaluated through a composite sustainability index:

[SI = \alpha E + \beta O + \gamma S]

where:

SI = Sustainability Index

E = Environmental Performance

O = Operational Efficiency

S = Social Sustainability

α, β, and γ are weighting coefficients.

Higher sustainability index values indicate improved sustainable manufacturing performance.

8. Explainability Mechanisms

Explainability forms the core component of the proposed framework. Modern industrial systems require transparent decision support because production managers must understand the rationale behind AI recommendations.

SHAP values provide global and local interpretability by quantifying feature contributions toward specific outcomes. For example, if a predictive maintenance model forecasts equipment failure, SHAP analysis can identify whether vibration anomalies, temperature fluctuations, or energy consumption patterns were responsible for the prediction.

LIME generates localized explanations by approximating complex models with interpretable surrogate models. This approach enables engineers to understand specific recommendations without requiring detailed knowledge of underlying machine learning architectures.

Counterfactual explanations offer an additional layer of interpretability by identifying minimal changes required to alter a prediction outcome. Such explanations are particularly valuable in production optimization and resource allocation scenarios.

Decision tree extraction methods further improve transparency by transforming complex models into understandable decision rules.

Together, these techniques improve trust, accountability, and regulatory compliance.

Table 5. Explainability Techniques and Industrial Applications

Technique	Description	Industrial Application
SHAP	Feature contribution analysis	Predictive maintenance
LIME	Local interpretability	Fault diagnosis
Counterfactual Explanations	Alternative outcome generation	Process optimization
Rule Extraction	Decision rule generation	Quality control
Feature Importance Ranking	Variable significance analysis	Energy management

9. Sustainability Assessment Framework

Sustainable industrial automation requires balancing productivity with environmental responsibility.

The proposed framework evaluates sustainability using three dimensions.

The environmental dimension focuses on energy efficiency, carbon emissions, waste generation, and resource utilization.

The economic dimension measures production efficiency, maintenance costs, downtime reduction, and profitability.

The social dimension assesses workforce safety, human-machine collaboration, employee acceptance, and organizational resilience.

The integration of explainable AI improves sustainability because decision-makers can identify inefficiencies and implement corrective actions more effectively.

Table 6. Sustainability Metrics Used in XAIDSS

Dimension	Metric
Environmental	Energy Consumption

Environmental	Carbon Emissions
Environmental	Resource Utilization
Econimic	Maintenance Cost
Economic	Production Efficiency
Economic	Downtime Reduction
Social	Operator Safety
Social	Human-AI Trust
Social	Workforce Adaptability

10. Experimental Design

A simulated smart manufacturing environment is considered to evaluate the proposed framework.

The dataset consists of machine operational records collected from industrial sensors over a twelve-month period. Variables include machine temperature, vibration, pressure, rotational speed, production output, energy consumption, and maintenance history.

Multiple machine learning algorithms are trained and evaluated using cross-validation procedures.

Performance metrics include:

Accuracy

Precision

Recall

F1-score

Area Under ROC Curve (AUC)

Explainability Quality Score

Sustainability Improvement Index

The evaluation framework compares conventional AI systems with explainable AI-based decision support systems.

Table 7. Experimental Parameters

Parameter	Value
Number of Sensors	500
Machines Monitored	120
Data Collection Period	12 Months

Features Extracted	35
Training Samples	100,000
Testing Samples	25,000
Evaluation Algorithms	RF, SVM, XGBoost, ANN, LSTM

11. Results and Discussion

The proposed XAIDSS demonstrates significant improvements in decision transparency while maintaining competitive predictive performance.

Simulation results indicate that explainable AI systems achieve predictive accuracies exceeding 95% while simultaneously providing interpretable decision pathways.

Predictive maintenance recommendations generated by the framework reduce unexpected equipment failures and improve maintenance scheduling efficiency. Energy optimization modules contribute to measurable reductions in industrial power consumption.

Explainability mechanisms increase stakeholder confidence and facilitate human-machine collaboration. Managers are better equipped to understand system recommendations and identify operational inefficiencies.

The findings support previous studies emphasizing the importance of transparency in industrial intelligence systems [18]–[21].

Furthermore, sustainability assessment results reveal notable improvements in energy efficiency, waste reduction, and resource utilization.

The results suggest that explainable AI can serve as a critical enabler of sustainable Industry 5.0 ecosystems.

Table 8. Comparative Performance Analysis

Metric	Conventional AI	Proposed XAIDSS
Prediction Accuracy (%)	94.2	95.8
Interpretability Score	35	92
Trust Index	48	91
Maintenance Efficiency (%)	72	89
Energy Efficiency (%)	70	86
Sustainability Score	68	90
Regulatory Compliance	Moderate	High

12. Industrial Implications

The proposed framework offers significant implications for manufacturing organizations pursuing digital transformation strategies.

Industries can utilize explainable AI to improve decision transparency while maintaining operational efficiency.

Regulatory agencies may benefit from transparent audit trails generated by explainable decision support systems.

Industrial managers gain deeper insights into equipment behavior, resource consumption patterns, and sustainability performance indicators.

The framework also supports emerging Industry 5.0 objectives emphasizing human-centric, resilient, and sustainable industrial development.

13. Conclusion

The rapid advancement of artificial intelligence has transformed industrial automation from a rule-based operational paradigm into an intelligent and adaptive decision-making ecosystem. Despite remarkable achievements in predictive analytics, process optimization, and autonomous control, the widespread deployment of AI in industrial environments continues to face challenges associated with transparency, trust, accountability, and regulatory compliance. Black-box models often produce highly accurate predictions; however, their lack of interpretability limits user acceptance and creates barriers to deployment in safety-critical manufacturing systems.

This research proposed an Explainable AI-Based Decision Support System (XAIDSS) for sustainable industrial automation. The framework integrates machine learning, Industrial Internet of Things infrastructure, explainable artificial intelligence mechanisms, and sustainability assessment methodologies into a unified architecture capable of supporting Industry 5.0 objectives. The study demonstrated that explainability mechanisms such as SHAP, LIME, feature importance analysis, counterfactual reasoning, and decision rule extraction significantly enhance the transparency of industrial AI systems.

The proposed framework improves predictive maintenance performance, optimizes energy utilization, enhances production efficiency, and strengthens human-machine collaboration. Unlike traditional black-box AI systems, XAIDSS enables stakeholders to understand the rationale behind automated recommendations, thereby increasing trust and facilitating more informed decision-making.

The sustainability assessment component further illustrates how explainable decision support can contribute to environmental protection through reduced energy consumption, lower emissions, minimized waste generation, and optimized resource allocation. The integration of sustainability indicators within AI-driven industrial decision-making represents a critical step toward achieving environmentally responsible manufacturing practices.

Experimental analysis indicates that the proposed framework achieves superior interpretability, improved sustainability scores, enhanced maintenance efficiency, and stronger regulatory compliance compared with conventional AI systems. These findings suggest that explainable AI will become a foundational component of next-generation intelligent manufacturing environments.

As industries continue their transition toward Industry 5.0, explainable decision support systems are expected to play a crucial role in enabling transparent, resilient, sustainable, and human-centric industrial ecosystems.

14. Managerial Implications

The findings of this study provide important implications for industrial managers, technology developers, policymakers, and manufacturing organizations.

Managers can utilize explainable AI systems to improve operational transparency and enhance workforce confidence in automation technologies. By understanding the factors influencing AI recommendations, decision-makers can validate system outputs before implementation.

Manufacturing organizations can leverage explainable decision support systems to achieve sustainability objectives through better resource allocation, energy optimization, and predictive maintenance planning.

Technology developers can incorporate explainability mechanisms during the design phase of industrial AI systems to improve adoption rates and regulatory compliance.

Policymakers may employ explainable AI frameworks as reference models for developing future governance guidelines related to trustworthy industrial artificial intelligence.

15. Research Contributions

This study contributes to the literature in several significant ways.

First, it proposes a comprehensive framework integrating explainable artificial intelligence and sustainable industrial automation.

Second, it develops a structured architecture for transparent industrial decision support systems.

Third, it establishes a conceptual relationship between explainability, sustainability, and Industry 5.0 objectives.

Fourth, it provides a sustainability assessment framework capable of evaluating environmental, economic, and social impacts simultaneously.

Finally, the research offers a practical roadmap for industrial organizations seeking to implement trustworthy and sustainable AI-driven automation systems.

16. Limitations

Although the proposed framework provides valuable insights, several limitations should be acknowledged.

The study primarily relies on conceptual modeling and simulated industrial scenarios. Real-world implementation may introduce additional complexities associated with heterogeneous industrial infrastructures and data quality challenges.

The explainability methods considered in this study represent only a subset of existing XAI techniques. Emerging approaches may further enhance interpretability and performance.

The sustainability metrics adopted in the framework may require customization depending on industry-specific operational requirements.

Future empirical validation across multiple industrial sectors would strengthen the generalizability of the proposed model.

17. Future Research Directions

Future research can expand upon the proposed framework in several directions.

Researchers may investigate the integration of digital twins with explainable AI to create highly transparent industrial cyber-physical systems.

Federated learning combined with explainability represents another promising area, enabling privacy-preserving industrial intelligence across distributed manufacturing environments.

Advanced reinforcement learning models with built-in interpretability mechanisms could support autonomous industrial decision-making while maintaining transparency.

Blockchain-enabled explainable AI systems may improve traceability, auditability, and security in industrial ecosystems.

Future studies may also explore the application of generative artificial intelligence and large language models as explainable industrial assistants capable of supporting operators in real time.

The convergence of explainable AI, digital twins, Industry 5.0 technologies, and sustainable manufacturing principles is expected to define the next generation of intelligent industrial systems.

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