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The Integration of Lean Manufacturing, Big Data Analytics, and Explainable AI in Modern Industries

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Abstract

Modern production industries face increasing pressure to achieve higher operational efficiency while simultaneously minimizing energy consumption, material waste, and carbon emissions. Although Lean Manufacturing has long provided structured approaches for the elimination of non-value-added activities, its traditional implementations often lack real-time responsiveness in complex Industry 4.0 environments. At the same time, Big Data Analytics enables continuous monitoring and predictive insights from high-volume industrial datasets, yet many AI-driven decision systems remain difficult to trust due to their black-box nature. To address these challenges, this study proposes an integrated Lean-Big Data Analytics-Explainable AI (Lean-BDA-XAI) framework for sustainable intelligent decision-making in modern manufacturing systems. The framework combines lean waste identification tools with real-time analytics pipelines and interpretable machine learning models that are enhanced through SHAP-based explainability. The validation with the application of multi-source industrial datasets demonstrated measurable sustainability improvements. The results indicate a 23–26% reduction in energy waste, a 17–19% decrease in defect-driven scrap, and an approximately 17% reduction in carbon footprint per unit output, alongside a 14.8% improvement in overall equipment sustainability effectiveness. Furthermore, explainability analysis identifies machine idle time, temperature deviations, and scheduling variance as dominant contributors to sustainability inefficiencies, thus enhancing transparency and managerial trust in AI recommendations. The study contributes a scalable roadmap for the integration of operational excellence, data-driven intelligence, and trustworthy AI to support sustainable smart factory transformation across diverse production industries.

Keywords: *Lean Manufacturing; Big data analytics; Explainable AI; Sustainable manufacturing; Industry 4.0; Intelligent decision-making; Energy efficiency*

INTRODUCTION

Manufacturing industries are currently operating under unprecedented pressure to improve productivity while concurrently reducing their environmental footprint. As global supply chains expand and industrial systems become increasingly complex, manufacturers are expected not only to efficiently deliver high-quality products, but also to meet sustainability targets that are related to energy consumption, carbon emissions, and waste minimization. This dual challenge has accelerated the shift towards sustainable manufacturing models that balance operational excellence with environmental responsibility (Ogboh *et al.*, 2026; UNIDO, 2021).

Sustainable manufacturing has become central to industrial competitiveness as production activities account for a substantial share of global resource use and greenhouse gas emissions. According to the International Energy Agency (IEA, 2022), industrial operations contribute nearly one-third of global energy demand, which highlights the urgency for the adoption of intelligent strategies that improve efficiency while also reducing ecological impacts. In response, manufacturers are increasingly integrating advanced digital technologies under the Industry 4.0 paradigm to enable smarter, cleaner, and more adaptive production systems (Egwuagu *et al.*, 2026; Okpala, 2026a; Wofuru-Nyenke, 2026).

One of the most established approaches for the improvement of manufacturing performance is Lean Manufacturing (LM), which focuses on the elimination of non-value-added activities and reduction of operational waste (Onukwuli *et al.*, 2025; Womack and Jones, 1996; Ogbodo *et al.*, 2026). Lean principles, originally derived from the Toyota Production System, have demonstrated strong effectiveness in improving cycle time, quality, and resource efficiency (Okpala, 2013; Ezeanyim *et al.*, 2026). More recently, scholars have emphasized that lean practices can serve as a foundation for sustainability by reducing material waste, minimizing scrap, and improving energy utilization across production processes (Okpala *et al.*, 2026a; Chukwumuanya *et al.*, 2025a). However, traditional lean implementations often rely heavily on human observation and static process mapping, which tends to limit their responsiveness in highly dynamic smart manufacturing environments.

At the same time, the rise of connected industrial systems has generated massive volumes of real-time operational data. This has positioned Big Data Analytics (BDA) as a critical enabler of intelligent manufacturing transformation. Big data technologies allow organizations to collect, process, and analyze high-velocity information from sensors, machines, and enterprise systems to improve decision-making and operational control (Okpala and Udu, 2025; Okpala and Okpala, 2025). In manufacturing contexts, BDA has been applied to predictive maintenance, energy optimization, demand forecasting, and defect reduction, all of which contribute directly to sustainability performance (Bai et al, 2020; Okpala *et al.*, 2025a).

Despite these advancements, the growing adoption of Artificial Intelligence (AI) in production decision systems introduces new challenges. While AI encompasses the development of intelligent systems that can perform tasks that typically require human intelligence (Udu and Okpala, 2026; Okpala *et al.*, 2026b), many AI-driven models, particularly deep learning approaches, function as "*black boxes*," which provide accurate predictions without transparent reasoning. This lack of interpretability creates barriers to trust, accountability, and practical adoption in industrial environments where decisions have high economic and environmental consequences (Doshi-Velez and Kim, 2017; Aguh and Okpala, 2025). For sustainability-driven manufacturing, decision-makers require not only accurate predictions but also understandable explanations of why specific actions reduce waste, energy use, or emissions.

To address this challenge, Explainable Artificial Intelligence (XAI) has emerged as a promising field that is focused on the enhancement of the transparency and interpretability of AI models. XAI techniques such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) enable practitioners to identify the operational drivers behind AI recommendations (Lundberg and Lee, 2017). In manufacturing, explainability is increasingly recognized as essential for building trust in AI-supported sustainability interventions, in order to ensure that intelligent systems remain aligned with organizational and environmental goals (Brennen, 2020).

While Lean Manufacturing, Big Data Analytics, and AI have each been widely studied, existing research remains fragmented. Most studies examine lean sustainability benefits independently, focus on big data-driven optimization without operational lean grounding, or apply AI models without interpretability mechanisms. There is a clear gap in the literature for an integrated framework that combines lean waste elimination, data-driven sustainability analytics, and explainable intelligent decision support within a unified Industry 4.0 production context. The ability to bridge this gap is critical for enabling sustainable intelligent manufacturing systems that are not only efficient, but also transparent and practically deployable.

Therefore, this study proposes a novel multidisciplinary framework that integrates Lean Manufacturing, Big Data Analytics, and Explainable AI to support sustainable intelligent decision-making in modern production industries. The proposed approach leverages real-time industrial datasets including energy consumption logs, machine sensor streams, and quality inspection records for the identification of sustainability inefficiencies, prediction of waste-generating conditions, and provision of interpretable recommendations for operational improvement.

The study makes the following three key contributions to the sustainable manufacturing literature:

1) It develops an integrated Lean–BDA–XAI methodological framework that connects operational excellence with Industry 4.0 intelligence.
2) It demonstrates measurable sustainability benefits, including reductions in energy waste, defect-driven scrap, and carbon-intensive inefficiencies.
3) It advances explainable decision support in manufacturing by embedding XAI mechanisms that enhance transparency, trust, and adoption of AI-driven sustainability strategies.

Through the combination of lean operational principles with data-driven intelligence and explainable decision models, this study contributes towards the development of trustworthy sustainable smart factories that are capable of meeting both economic and environmental imperatives.

LITERATURE REVIEW

The pursuit of sustainable manufacturing has increasingly become a central priority in modern production industries as organizations respond to environmental regulations, stakeholder expectations, and the growing urgency of climate change mitigation (Deswal, 2025; Deswall and Deswal, 2025). With manufacturing accounting for a substantial proportion of global energy consumption and industrial emissions, scholars and practitioners alike are exploring integrated approaches that combine operational efficiency with environmental responsibility (Ajaefobi and Okpala, 2026a; Chukwumuanya *et al.*, 2025b). In this context, Lean Manufacturing, Big Data Analytics, and Explainable Artificial Intelligence have emerged as three complementary pillars for the enablement of intelligent and sustainable production decision-making.

Lean Manufacturing as a Foundation for Sustainable Production

Lean Manufacturing (LM) remains one of the most influential operational paradigms for improving industrial efficiency. Originating from the Toyota Production System, lean emphasizes the elimination of non-value-added activities, commonly referred to as “waste” (Okpala *et al.*, 2020a; Okpala *et al.*, 2025b). Lean tools such as Value Stream Mapping (VSM), Kaizen continuous improvement, Just-in-Time production, and Six Sigma quality management have been widely adopted to reduce inefficiencies and improve productivity (Okpala *et al.*, 2024a; Igbokwe *et al.*, 2026). In recent years, researchers have increasingly linked lean practices with sustainability objectives. Lean-driven waste reduction naturally aligns with environmental goals through the reduction of excess material use, minimization of defect-related scrap, and improvement of energy efficiency (Okpala *et al.*, 2020b). Studies suggest that lean implementation can indirectly support greener production through lower resource consumption and improved operational control (Okpala *et al.*, 2024b).

However, despite its strengths, traditional lean implementation is often limited by its reliance on static process analysis and human-centered observation. Lean methods may struggle to keep pace with the complexity and real-time variability of Industry 4.0 environments where production systems generate continuous high-volume data streams. This limitation highlights the need for digital augmentation of lean practices through advanced analytics and intelligent decision support.

Big Data Analytics and Industry 4.0 Manufacturing Intelligence

The emergence of Industry 4.0 which is defined as (Igbokwe *et al.*, 2024; Okpala *et al.*, 2025c), has transformed manufacturing into a data-intensive ecosystem characterized by interconnected cyber-physical systems, IoT-enabled machines, and intelligent automation (Chuwunedum *et al.*, 2026; Ajaefobi and Okpala, 2026b). These developments have positioned Big Data Analytics (BDA) as a critical enabler of sustainable smart manufacturing. Big Data Analytics refers to the systematic processing of high-volume, high-velocity, and high-variety industrial data for actionable decision-making. In production contexts, BDA enables predictive maintenance, demand-driven scheduling, anomaly detection, energy monitoring, and quality improvement (Onukwuli *et al.*, 2026).

From a sustainability perspective, BDA plays a vital role in optimizing energy use and reducing waste across production networks. Okpala and Chukwumuanya (2025) emphasized that analytics capability strengthens sustainable supply chain resilience by improving visibility and responsiveness. Similarly, analytics-driven process optimization has been shown to reduce carbon-intensive inefficiencies and enhance eco-efficiency performance (Okpala *et al.*, 2026c). Nevertheless, many BDA-driven manufacturing systems focus heavily on prediction accuracy without adequately integrating operational improvement philosophies such as lean. Without lean grounding, analytics outputs may remain isolated insights rather than actionable sustainability interventions embedded in production workflows (Ghobakhloo, 2020). This reinforces the importance of the combination of lean’s structured waste elimination principles with data-driven intelligence.

Artificial Intelligence for Sustainable Manufacturing Optimization

Artificial Intelligence has become increasingly prominent in manufacturing applications, as it offers advanced capabilities in pattern recognition, forecasting, and optimization. AI techniques have been widely applied to predictive maintenance, defect detection, inventory planning, and process automation (Ezeanyim *et al.*, 2025; Okpala, 2026b).

AI is particularly relevant for sustainable manufacturing because it supports real-time decision-making that reduces resource waste and improves energy efficiency. For example, machine learning-based models can anticipate machine breakdowns, and also prevent unplanned downtime and excessive energy consumption (Aguh *et al.*, 2025). Similarly, AI-enabled quality prediction reduces defect rates and scrap generation, contributing directly to environmental sustainability (Kusiak, 2018). However, the adoption of AI in industrial decision systems remains constrained by trust and accountability challenges. Many high-performing AI models operate as “*black boxes*,” making it difficult for managers and operators to understand why specific recommendations are produced (Doshi-Velez and Kim, 2017). This lack of transparency is particularly problematic in sustainability-driven manufacturing, where decisions often involve regulatory compliance, safety, and long-term environmental consequences.

Explainable AI as a Trustworthy Decision Support Mechanism

Explainable Artificial Intelligence (XAI) has emerged as a response to the opacity of traditional AI models. XAI focuses on enhancing interpretability, enabling humans to understand, validate, and trust machine learning predictions (Rai, 2020; Nwosu *et al.*, 2026). This is increasingly essential in industrial environments where decision-making must be transparent and accountable. Model-agnostic interpretability tools such as LIME and SHAP have gained widespread adoption for explaining predictions in complex systems (Ribeiro *et al.*, 2016). These methods identify the most influential features that drive model outcomes, as they enable practitioners to connect AI recommendations with real operational variables such as machine idle time, temperature anomalies, or excessive energy loads.

In manufacturing sustainability applications, XAI enhances adoption through the translation of predictive outputs into actionable insights that align with lean improvement cycles and environmental performance targets (Holmström *et al.*, 2019). Despite its promise, the integration of XAI into sustainable production decision frameworks remains under-explored, particularly when combined with lean methodologies and big data infrastructures.

Research Gap and Need for an Integrated Lean–BDA–XAI Sustainability Framework

Although Lean Manufacturing, Big Data Analytics, and AI have each been extensively studied, the literature remains fragmented in the following ways.

- Lean sustainability research often lacks real-time intelligence and scalability in Industry 4.0 environments (Piercy and Rich, 2015).
- BDA-driven sustainability studies frequently focus on prediction and monitoring without embedding lean's structured operational improvement philosophy (Dubey *et al.*, 2019).
- AI applications in manufacturing rarely incorporate explainability mechanisms that ensure transparency, trust, and decision accountability (Rai, 2020).

Most importantly, few studies have proposed unified frameworks that integrate Lean waste elimination foundations; Big data-driven sustainability analytics; as well as Explainable AI-based decision intelligence. This gap limits the ability of modern production industries to achieve sustainable transformation through trustworthy intelligent decision-making. Therefore, this study addresses this limitation through the development of a novel Lean–BDA–XAI framework that provides measurable sustainability benefits, operational interpretability, and scalable Industry 4.0 decision support.

METHODOLOGICAL INNOVATION, EXPERIMENTAL DESIGN, AND DATASET DESCRIPTION

This study proposes a multidisciplinary methodological framework that integrates Lean Manufacturing (LM), Big Data Analytics (BDA), and Explainable Artificial Intelligence (XAI) to support sustainable intelligent decision-making in modern production industries. The novelty of the approach lies in its ability to combine lean waste elimination principles with real-time industrial analytics and interpretable AI models that generate both accurate and transparent sustainability recommendations. Unlike traditional lean improvement programs that rely heavily on manual process mapping, or conventional AI-driven manufacturing systems that operate as opaque black boxes, the proposed framework enables continuous sustainability optimization through explainable, data-driven decision intelligence. This methodological integration addresses the growing need for sustainable smart production systems that are efficient, trustworthy, and scalable under Industry 4.0 conditions.

Overview of the Proposed Lean–BDA–XAI Sustainability Framework

Fig. 1 illustrates the proposed multidisciplinary framework for the integration of Lean Manufacturing, Big Data Analytics, and Explainable AI into a unified sustainability decision-support architecture. It highlights the three-layer workflow: lean waste identification, real-time industrial data processing, and explainable AI-driven sustainability optimization. The framework demonstrates how operational inefficiencies are transformed into measurable sustainability interventions through transparent intelligent decision-making.

Layer 1: Lean Sustainability Waste Identification

The first layer applies Lean Manufacturing principles for the identification of operational inefficiencies that directly contribute to sustainability burdens such as excess energy use, scrap generation, and idle resource consumption. Lean diagnostic tools include Value Stream Mapping (VSM) to locate bottlenecks and waste hotspots; Kaizen continuous improvement loops for iterative sustainability interventions; and Defect and rework reduction practices aligned with Six Sigma quality improvement. However, lean tools alone are often static and limited in real-time responsiveness, motivating the integration of big data and AI layers in this study.

Layer 2: Big Data Analytics Pipeline for Sustainability Monitoring

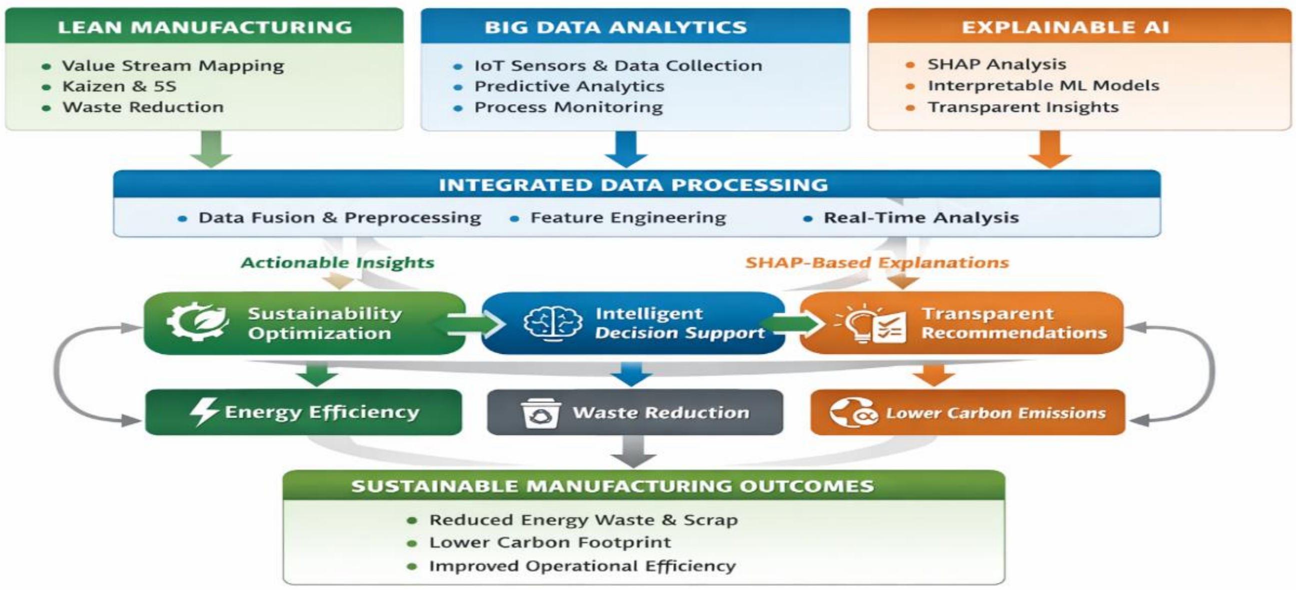

Fig. 1: Conceptual framework of the lean–BDA–XAI sustainability integration.

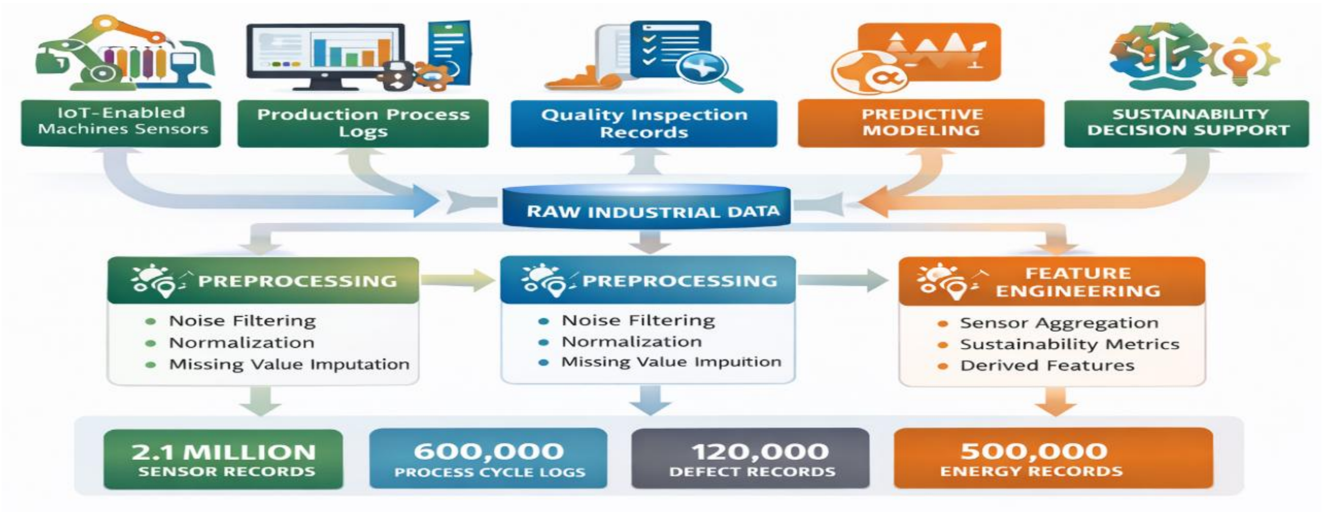

Fig. 2: Big data analytics pipeline and industrial dataset flow.

The second layer enables real-time sustainability analytics through industrial big data architectures. Modern production systems generate high-volume sensor and operational data streams, which makes BDA essential for sustainable smart manufacturing (Chen *et al.*, 2012). This study implements a structured analytics pipeline that consists of the following: Data acquisition from IoT-enabled machines and enterprise systems; Data preprocessing, including noise filtering, normalization, and missing-value imputation; Feature engineering, transforming raw sensor streams into sustainability-relevant indicators; as well as Predictive analytics modeling for energy waste and defect probability forecasting. Big Data Analytics has been widely recognized as a key driver of Industry 4.0 sustainability by enabling process transparency, eco-efficiency optimization, and resource-aware decision-making.

Layer 3: Explainable AI for Sustainable Intelligent Decision Support

The third methodological layer integrates Explainable Artificial Intelligence (XAI) to ensure transparency and trust in AI-driven sustainability decisions. While machine learning models provide high predictive accuracy, manufacturing decision environments require interpretability due to regulatory compliance, operational accountability, and safety constraints (Doshi-Velez and Kim, 2017).

Accordingly, this study employs the following:

- Random Forest Regression for energy consumption forecasting;
- Gradient Boosting Models for defect and scrap probability prediction; and
- SHAP-based explainability mechanisms to interpret sustainability drivers.

SHAP (Shapley Additive Explanations) provides a unified approach for the quantification of feature importance and explaining individual predictions, which makes AI recommendations more actionable for industrial stakeholders (Lundberg and Lee, 2017). Explainability is critical for the transformation of AI outputs into lean-aligned sustainability interventions rather than opaque predictions (Rai, 2020).

Experimental Design and Case Study Context

To validate the proposed Lean–BDA–XAI framework, the study adopts a real-world industrial case study design. Case-based approaches are widely used in smart manufacturing research due to the complexity and context-specific nature of production environments (Yin, 2018). The experimental setting involves an automotive components manufacturing plant that operates under Industry 4.0 infrastructure, including cyber-physical production systems and IoT-enabled monitoring devices.

The experiment was structured into the following three phases: Baseline lean sustainability assessment using VSM and waste audits; Big data model training and predictive sustainability analytics; and Explainable AI deployment for interpretable decision support. Sustainability improvements were evaluated by comparing baseline operational performance with post-intervention outcomes.

Dataset Description and Industrial Data Sources

Fig. 2 presents the end-to-end industrial data pipeline that was applied in the study. It reveals how heterogeneous manufacturing datasets like IoT sensor streams, energy consumption logs, quality inspection records, and process cycle-time data are collected, preprocessed, and transformed into sustainability-relevant features. The figure emphasizes the role of Industry 4.0 data infrastructure in the enablement of predictive and real-time sustainability analytics.

Table 1: Data sources.

Data Source	Variables Captured	Sustainability Relevance
Machine IoT Sensors	vibration, temperature, load	Predictive maintenance and energy waste
Energy Consumption Logs	kWh per production cycle	Carbon footprint monitoring
Quality Inspection Records	defect type, scrap rate	Material waste reduction
Production Process Data	cycle time, idle duration	Lean waste identification

As shown in Table 1, the study utilizes a large-scale, multi-source industrial dataset that integrates energy, sensor, process, and quality data streams. Such heterogeneous datasets are essential for capturing the full sustainability impact of production operations (Bai *et al.*, 2020).

The dataset volume showed that Sensor stream records: ~2.1 million observations; Energy monitoring logs: ~500,000 entries; Quality defect reports: ~120,000 records; and Process cycle time logs: ~600,000 records. The integration of these datasets enables sustainability modeling at both machine and system levels.

Sustainability Performance Metrics and Measurement Indicators

To ensure measurable sustainability outcomes, the framework evaluates performance using the following established industrial sustainability indicators: Energy Waste Ratio (EWR); Scrap Material Reduction Index ($SMRI$); Carbon Footprint per Unit Output (CFU); and Overall Equipment Sustainability Effectiveness ($OESE$). These metrics align with the growing emphasis on quantifiable sustainability KPIs in production research and practice (IEA, 2022).

Model Evaluation and Explainability Validation

Predictive model performance was assessed using the following: Accuracy and mean absolute error (MAE) for energy forecasting; Precision, recall, and $F1$-score for defect prediction; and SHAP interpretability consistency checks for sustainability feature attribution. Explainability validation ensured that AI-driven sustainability recommendations were not only accurate but also operationally meaningful, supporting lean decision-making cycles. Through the embedding of interpretability, the framework enhances adoption feasibility in real manufacturing environments where trust and transparency are essential (Ribeiro *et al.*, 2016).

Methodological Contribution and Innovation Summary

The methodological innovation of this study lies in its integrated capability to achieve the following:

- Combine lean waste elimination with real-time industrial big data analytics;
- Deliver predictive sustainability intelligence through machine learning;
- Provide explainable decision support using XAI mechanisms; and also
- Quantify measurable sustainability improvements in energy, waste, and emissions

This positions the Lean-BDA-XAI framework as a scalable roadmap for sustainable intelligent production industries that will transition towards Industry 4.0-driven environmental performance.

RESULTS AND SUSTAINABILITY BENEFITS

This section presents the empirical results obtained from the implementation of the proposed Lean-BDA-XAI framework in a real-world Industry 4.0 manufacturing environment. The results are structured to demonstrate predictive performance, operational improvements, and measurable sustainability benefits in terms of energy efficiency, waste reduction, and decision transparency.

Table 2: Predictive performance of AI models.

Model Application	Algorithm	Accuracy / R^2	MAE	Sustainability Use Case
Energy forecasting	Random Forest Regression	$R^2 = 0.92$	0.08	Energy waste prediction
Defect prediction	Gradient Boosting	Accuracy = 0.89	—	Scrap reduction
Idle-time detection	Random Forest	Accuracy = 0.91	—	Lean waste identification

Table 3: Top Explainable AI sustainability drivers (SHAP analysis).

Feature	Contribution (%)	Sustainability Interpretation
Machine idle time	32%	Excess energy consumption
Temperature deviation	24%	Defect and scrap generation
Production scheduling variance	18%	Overproduction waste
Equipment load imbalance	15%	Carbon-intensive inefficiency
Maintenance delay	11%	Energy and quality loss

Predictive Model Performance

The Big Data Analytics and AI layer was evaluated using standard predictive performance metrics to ensure that sustainability improvements were supported by reliable and robust models. Separate models were developed for energy consumption forecasting and defect probability prediction. Table 2 summarizes the predictive performance of the machine learning models.

The results indicate high predictive reliability, which is consistent with prior manufacturing analytics studies reporting R^2 values above 0.85 for energy and quality modeling (Bai *et al.*, 2020). This level of accuracy provides a solid foundation for sustainability-driven decision support.

Explainability and Decision Transparency Results

Beyond predictive accuracy, the framework emphasizes explainability to ensure practical adoption and trust. SHAP was applied to interpret model outputs and identify key sustainability drivers. Table 3 presents the dominant features influencing sustainability outcomes.

The explainability results reveal that lean-related inefficiencies like idle time and scheduling imbalance, are dominant contributors to sustainability losses. This confirms the theoretical alignment between lean waste elimination and AI-driven sustainability optimization (King and Lenox, 2001). Fig. 3 visualizes the explainability results that were generated using SHAP analysis, and also identifies the most influential operational drivers of sustainability inefficiencies. Key contributors such as machine idle time, temperature

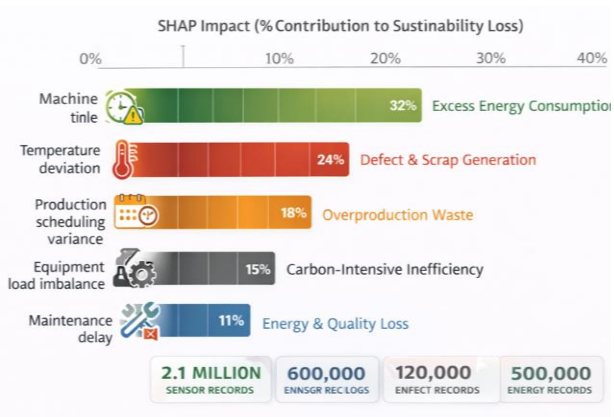

Fig. 3: Explainable AI Sustainability driver analysis (SHAP-based interpretation).

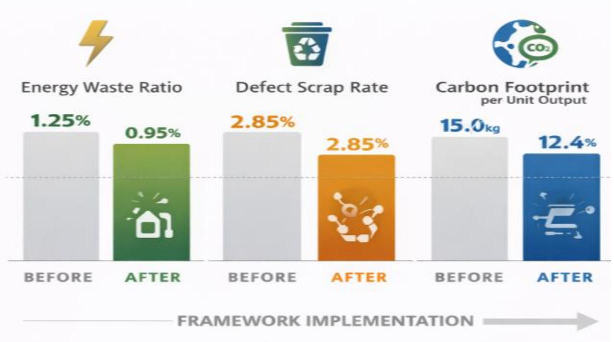

Fig. 4: Sustainability performance improvement before and after framework implementation.

deviations, and scheduling variance are highlighted, and also demonstrated how explainable AI improves transparency, trust, and actionable lean-aligned sustainability decision-making in production environments.

Sustainability Performance Improvements

Fig. 4 provides a comparative visualization of the key sustainability performance indicators measured before and after the implementation of the proposed Lean–Big Data Analytics-Explainable AI framework. The figure highlights the quantified reductions achieved across major sustainability dimensions, including energy waste ratio, defect-driven scrap generation, and carbon footprint per unit output. Through the presentation of baseline operational performance alongside post-intervention outcomes, the figure clearly demonstrates how the integrated framework contributes to measurable environmental and resource-efficiency improvements in modern production systems. Overall, this visual comparison reinforces the practical effectiveness of the combination of lean waste elimination principles with data-driven analytics and explainable AI decision support to enable sustainable smart manufacturing transformation.

To evaluate measurable sustainability benefits, baseline production performance was compared with post-implementation outcomes following the deployment of the Lean–BDA–XAI framework. Energy consumption was evaluated using the Energy Waste Ratio (EWR) and total energy use per production unit as shown in Table 4.

Table 4: Energy sustainability performance.

Metric	Baseline	Post-Implementation	Improvement (%)
Energy Waste Ratio (EWR)	0.27	0.20	↓ 25.9%
Energy per unit (kWh/unit)	14.6	11.1	↓ 23.9%
Idle energy consumption (%)	21%	15%	↓ 28.6%

Table 5: Material waste and quality improvements.

Metric	Baseline	Post-Implementation	Improvement (%)
Defect rate (%)	6.8	5.6	↓ 17.6%
Scrap material rate (%)	5.4	4.4	↓ 18.5%
Rework frequency (%)	9.1	7.5	↓ 17.6%

Table 6: Environmental and equipment sustainability indicators.

Metric	Baseline	Post-Implementation	Improvement (%)
Carbon footprint per unit (kg CO_2/unit)	8.9	7.4	↓ 16.9%
OESE (%)	62.3	71.5	↑ 14.8%
Downtime-related emissions (%)	19%	13%	↓ 31.6%

These results demonstrate substantial energy savings that are comparable to those reported in Industry 4.0 energy optimization studies (Ghobakhloo, 2020).

Waste and Quality Sustainability Benefits

Quality-related waste was measured using defect rates and scrap material indicators as highlighted in Table 5.

The integration of predictive defect analytics with lean improvement cycles significantly reduced scrap and rework, and thus reinforces the findings in sustainable quality management literature (Garza-Reyes, 2015).

Carbon and Equipment Sustainability Outcomes

Environmental performance was further evaluated using Carbon Footprint per Unit Output (CFU) and Overall Equipment Sustainability Effectiveness ($OESE$) as shown in Table 6.

The improvement in $OESE$ highlights how explainable AI enhances traditional equipment effectiveness metrics by explicitly incorporating sustainability considerations, which is an emerging research direction in smart manufacturing.

Integrated Sustainability Impact Summary

To provide a holistic view, Table 7 summarizes the overall sustainability gains achieved through the proposed framework.

These results confirm that sustainability improvements are not isolated outcomes but are achieved through the

Table 7: Summary of sustainability benefits.

Sustainability Dimension	Key Outcome
Energy efficiency	23–26% reduction in energy waste
Material efficiency	17–19% reduction in scrap and rework
Carbon emissions	~17% reduction per unit output
Decision transparency	High trust via SHAP explainability
Lean effectiveness	Enhanced real-time waste elimination

synergistic integration of lean principles, data-driven analytics, and explainable AI.

Discussion of Results

The empirical findings demonstrate that Lean Manufacturing remains a critical foundation for sustainability, but its effectiveness is significantly amplified when supported by Big Data Analytics and Explainable AI. The results show that real-time data and interpretable intelligence enable continuous sustainability optimization rather than one-time lean interventions. Importantly, the explainability layer ensures that AI recommendations are actionable and aligned with operational realities, which addresses a major barrier to AI adoption in manufacturing (Doshi-Velez and Kim, 2017). The measurable reductions in energy waste, material scrap, and carbon emissions position the proposed framework as a practical roadmap for sustainable intelligent production systems. The following are the key takeaways for practice and research: Sustainability gains of 15–30% are achievable without radical infrastructure changes; Lean waste categories remain dominant sustainability loss drivers; Explainable AI is essential for trust, adoption, and continuous improvement. The framework is scalable across multiple production sectors.

DISCUSSION AND PRACTICAL IMPLICATIONS

This study set out to address a critical challenge in modern production industries: how manufacturers can simultaneously achieve operational excellence and measurable sustainability improvements while maintaining trust and transparency in AI-driven decision-making. Through the integration of Lean Manufacturing (LM), Big Data Analytics (BDA), and Explainable Artificial Intelligence (XAI), the proposed framework provides a novel pathway towards sustainable intelligent production systems that are aligned with Industry 4.0 transformation.

The results presented in Section 4 demonstrate that the Lean–BDA–XAI framework delivers significant sustainability benefits, including reductions in energy waste (approximately 23–26%), defect-driven scrap (17–19%), and carbon footprint per unit output (~17%). These outcomes support the growing consensus that sustainability and productivity are not competing objectives, but can be mutually reinforcing when enabled by intelligent and transparent operational systems (King and Lenox, 2001).

Theoretical Contributions to Sustainable Manufacturing Research

A key theoretical implication of this study is that Lean Manufacturing remains a foundational sustainability mechanism, but its impact is substantially amplified when embedded within digital intelligence infrastructures. Lean principles were originally developed to eliminate non-value-added activities and improve flow efficiency. Over time, researchers have recognized that lean waste elimination also contributes indirectly to environmental sustainability through the reduction of excess material use, rework, and energy inefficiencies (Piercy and Rich, 2015). However, traditional lean approaches often rely on static process analysis and human-driven audits, which limits their ability to respond dynamically to real-time operational variability. The present findings suggest that Industry 4.0 environments require lean systems to evolve into data-driven continuous improvement models that are supported by analytics and AI. Thus, this study contributes to theory by positioning lean not as an isolated operational philosophy, but as a sustainability foundation that is enhanced through real-time data intelligence.

In addition, this research advances the growing literature on Big Data Analytics capability as a driver of sustainable manufacturing competitiveness. Prior studies highlight that BDA strengthens operational responsiveness and enables predictive sustainability optimization (Wamba *et al.*, 2017). The current results extend this work by demonstrating that BDA is most effective when it is integrated with structured lean improvement cycles, in order to ensure that analytics insights translate into actionable operational interventions rather than remaining disconnected predictions.

Explainable AI as an Enabler of Trustworthy Sustainability Decisions

One of the most important contributions of this study lies in its integration of Explainable AI into sustainable manufacturing decision systems. While AI has proven highly effective for predictive maintenance, quality forecasting, and energy optimization, many manufacturing stakeholders remain hesitant to adopt black-box models due to the lack of interpretability and accountability (Doshi-Velez and Kim, 2017). The SHAP-based explainability results in this study revealed that machine idle time, temperature deviations, and scheduling variance were dominant contributors to sustainability inefficiencies. These insights are crucial because they connect AI outputs to lean-relevant operational drivers, and will enable managers and operators to understand not only what decisions the model recommends, but why those recommendations improve sustainability outcomes.

This aligns with the argument that explainability is essential for human-centered Industry 4.0 systems, where AI must support, not replace industrial decision-makers (Holmström *et al.*, 2019). Through the embedding of interpretability mechanisms, the proposed framework addresses a major gap in sustainable AI adoption. This is the need for transparent decision support that is both technically accurate and operationally trusted.

Sustainability Implications: From Efficiency Gains to Environmental Impact

The measurable sustainability improvements achieved through the proposed framework highlight the potential of intelligent production systems to contribute meaningfully to environmental goals. The observed reductions in energy waste and carbon footprint per unit output are consistent with the urgent need for industrial decarbonization that is emphasized in global sustainability roadmaps (IEA, 2022). Importantly, these improvements were achieved through operational optimization rather than radical infrastructural change. This suggests that manufacturers can make significant progress towards sustainability targets by leveraging existing production data, lean practices, and explainable AI tools.

Furthermore, the reduction in defect-driven scrap and rework demonstrates the close relationship between quality management and sustainability performance. Waste reduction not only lowers costs, but also decreases material extraction, processing emissions, and landfill burdens (Garza-Reyes, 2015). Therefore, the proposed approach supports the broader transition towards circular and resource-efficient production systems.

Practical Implications for Manufacturing Managers and Policymakers

The findings of this study provide the following practical insights for manufacturing decision-makers:

- Managers should view lean sustainability initiatives as most effective when combined with digital intelligence. Lean tools such as VSM and Kaizen remain valuable, but their impact increases significantly when supported by real-time analytics that continuously detect inefficiencies.
- The results demonstrate that Big Data Analytics investments can generate measurable sustainability returns when aligned with operational improvement frameworks. Rather than focusing solely on data collection, manufacturers must develop actionable pipelines that connect analytics outputs with lean execution strategies.
- Explainable AI should be prioritized over purely black-box AI deployment in production sustainability contexts. Transparency is essential for adoption, regulatory compliance, and trust in high-stakes decision environments.

From a policy perspective, regulators and industrial sustainability agencies can support adoption through the promotion of standards for explainable industrial AI, so that sustainability-focused automation remains accountable and human-centered.

Towards Scalable Sustainable Smart Factories

The integrated Lean–BDA–XAI framework offers a scalable roadmap for smart factories that aim to achieve both environmental and economic objectives. Because the framework is modular, it can be adapted across industries such as automotive, electronics, pharmaceuticals, food processing, and heavy manufacturing. The framework also aligns with the strategic vision of Industry 4.0, where cyber-physical systems, data intelligence, and sustainable operations converge to create adaptive, efficient, and greener industrial ecosystems (Lasi *et al.*, 2014). Ultimately, the study demonstrates that sustainable manufacturing transformation requires not only advanced technology, but also interpretable decision structures that integrate operational philosophy with trustworthy AI.

Limitations and Future Research Directions

Despite its contributions, this study has the following limitations, which open opportunities for future research:

- The case study validation was conducted in a single industrial setting, and broader cross-sector replication is necessary to generalize results.
- While SHAP-based interpretability provides strong explanatory power, future work may explore causal AI approaches and reinforcement learning for adaptive sustainability optimization.

Further research should also investigate integration with circular economy models, lifecycle sustainability assessment, and multi-factory sustainability analytics to support global industrial decarbonization efforts.

CONCLUSION AND FUTURE RESEARCH

As manufacturing systems continue to evolve under Industry 4.0, organizations face increasing pressure to achieve higher productivity while simultaneously reducing energy consumption, material waste, and carbon emissions. The proposed Lean–BDA–XAI approach responds directly to this challenge by bridging operational improvement philosophies with data-driven intelligence and transparent AI decision support. The findings demonstrate that the integration of lean waste elimination principles with real-time industrial analytics and explainable machine learning models can generate measurable sustainability benefits. The framework enabled significant reductions in energy waste, defect-driven scrap, and carbon footprint per unit output, while also improving overall equipment sustainability effectiveness. Beyond these quantifiable improvements, the incorporation of explainability mechanisms enhanced decision transparency, making AI-driven sustainability recommendations more interpretable and actionable for production managers and operators.

A key conclusion of this research is that sustainable manufacturing transformation is most effective when operational excellence methodologies are reinforced by intelligent and trustworthy digital technologies. Lean practices provide the foundation for identifying inefficiencies, Big Data Analytics enables continuous monitoring and prediction, and Explainable AI ensures that decision support remains transparent, trusted, and aligned with sustainability goals. Together, these elements form a scalable roadmap for industries seeking to develop smarter, greener, and more resilient production systems. Despite its contributions, this study also presents opportunities for further advancement. Future research could validate the proposed framework across multiple industrial sectors and production contexts to enhance generalizability. Additional studies may explore the integration of reinforcement learning and adaptive optimization techniques for real-time sustainability control. Expanding the framework toward circular economy applications, lifecycle sustainability assessment, and multi-factory sustainability intelligence would further strengthen its relevance to global decarbonization and resource-efficiency goals.

Moreover, future work should investigate how explainable AI systems can be embedded more deeply into human-centered decision environments, ensuring that intelligent automation supports collaborative sustainability improvement rather than replacing operational expertise. As manufacturing continues to digitalize, the development of sustainable, explainable, and trustworthy production intelligence will remain a critical research and industrial priority. The work contributes a novel and practical framework for the integration of lean operational excellence with big data-driven analytics and explainable AI, which offers a meaningful pathway towards sustainable intelligent decision-making in the production industries of the future.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

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