From Lean Manufacturing to Intelligent Production Systems: A Synthesis of Efficiency, Quality, and Environmental Performance

Charles Chikwendu Okpala*

Professor: Industrial/Production Engineering Department, Nnamdi Azikiwe University, Awka, Nigeria.
*Corresponding Author

(Received: 03.05.0000; Accepted: 27.05.2026)

Abstract

Manufacturing companies increasingly face the challenge of efficiency and quality improvement while attaining measurable reductions in environmental impact. Although that Lean Manufacturing has proven effective in waste reduction and operational performance enhancement, its largely static and heuristic tools limit its ability to address real-time variability and sustainability objectives. This study proposes and empirically evaluates an Intelligent Lean Production System (ILPS) that integrates Lean principles with data-driven intelligence that are enabled by Industry 4.0 technologies. With the application of longitudinal data from 12 manufacturing plants across automotive components, consumer electronics, and agro-processing sectors, the study applies a quasi-experimental difference-in-differences approach to assess performance before and after ILPS implementation. The results show that ILPS adoption led to a 26.4% increase in overall equipment effectiveness, a 22.8% reduction in defect rates, and a 32.4% reduction in unplanned downtime. Importantly, these operational gains were accompanied by significant sustainability benefits, including a 21.7% reduction in energy intensity, a 17.3% decrease in material waste, and an 18.9% reduction in carbon intensity (kg CO_2e per unit). Sectoral analysis reveals that energy-intensive agro-processing facilities achieved the largest environmental gains, while high-precision electronics manufacturing recorded the greatest quality improvements. These findings provide strong empirical evidence that embedding intelligent analytics with Lean practices enables efficiency, quality, and environmental performance to be optimized concurrently. The study demonstrates that sustainability can be treated as a real-time, data-driven operational objective rather than a secondary outcome, thus offering a scalable pathway towards resilient and environmentally responsible manufacturing systems.

Keywords: *Lean manufacturing; Intelligent production systems; Industry 4.0; Sustainable manufacturing; Data-driven optimization; Environmental performance, Operational excellence*

INTRODUCTION

Manufacturing systems are at the center of contemporary economic development and environmental sustainability challenges. The sector accounts for approximately one-third of global energy consumption and a significant share of greenhouse gas emissions, while simultaneously facing increasing pressure to deliver high quality, customization, and cost efficiency (IEA, 2023). These competing demands have intensified scholarly and industrial interest in production paradigms that are capable of jointly improving operational performance and environmental outcomes.

Lean Manufacturing (LM) or Lean Production System (LPS) has long been regarded as one of the most influential production philosophies for achieving efficiency and quality improvements (Ogbodo *et al.*, 2026; Ihueze *et al.*, 2013). Rooted in the Toyota Production System, Lean emphasizes waste elimination, flow optimization, continuous improvement, and respect for people (Ezeanyim *et al.*, 2026; Okpala, 2013a). Empirical studies consistently report Lean's positive effects on productivity, lead time reduction, and defect minimization across diverse manufacturing contexts (Onukwuli *et al.*, 2025; Okpala *et al.*, 2020a). Beyond operational benefits, Lean has also been associated with indirect environmental gains, such as reduced material waste and lower energy usage through process stabilization (Chukwumunya *et al.*, 2025; Okpala *et al.*, 2026a).

However, despite its demonstrated strengths, traditional Lean Manufacturing exhibits inherent limitations when confronted with the complexity of modern production systems. Lean tools are largely heuristic, static, and reliant on periodic human observation, which constrains their ability to respond dynamically to real-time variability in demand, energy availability, machine health, and environmental performance (Buer *et al.*, 2018; Igbokwe *et al.*, 2026). As sustainability requirements become more stringent (Deswal, 2025) and production environments more data-intensive, these limitations increasingly restrict Lean's capacity to deliver measurable and scalable environmental improvements.

In parallel, the emergence of Intelligent Production Systems (IPS), enabled by Industry 4.0 technologies, has transformed how manufacturing systems are designed and managed (Ajaefobi and Okpala, 2026a; Udu *et al.*, 2025). While IPS is a concept from Artificial Intelligence (AI) that focuses on reasoning and decision-making with the application of rules and logic, Industry 4.0 enables real-time data acquisition, predictive intelligence, and system-wide integration (Ajaefobi and Okpala, 2026b; Chukwunedum *et al.*, 2026a). Advances in the Internet of Things (IoT), cyber-physical systems, machine learning, and big data analytics allow real-time monitoring, predictive control, and autonomous decision-making across production networks (Nwankwo *et al.*, 2024a; Okpala *et al.*, 2026b). Empirical evidence suggests that intelligent systems can significantly reduce downtime, improve quality consistency, and enhance resource efficiency through predictive maintenance, adaptive scheduling, and process optimization (Lee *et al.*, 2015).

Importantly, recent literature has begun to recognize the potential of digital manufacturing technologies to support sustainability objectives. Data-driven optimization has been shown to reduce energy intensity, minimize material losses, and lower carbon emissions when environmental indicators are explicitly embedded into control algorithms (Ezeanyim *et al.*, 2025; Chukwunedum *et al.*, 2026b). Nevertheless, most existing studies examine digitalization and sustainability in isolation from established production philosophies such as Lean, resulting in fragmented theoretical development and limited practical guidance. The integration of Lean Manufacturing and Intelligent Production Systems represents a critical yet under-explored opportunity. While Lean provides a structured logic for waste identification and process improvement (Ihueze *et al.*, 2011; Okpala *et al.*, 2025), intelligent systems offer the analytical and computational capabilities that are required to operationalize these principles in real time and at scale. Prior conceptual work suggests that Industry 4.0 can act as a Lean enabler rather than a substitute, which will lead to the enhancement of transparency, responsiveness, and decision accuracy (Kolberg *et al.*, 2017). However, robust empirical evidence that demonstrate how such integration generates measurable sustainability benefits alongside efficiency and quality improvements remains scarce. Moreover, existing research frequently treats environmental performance as a secondary or emergent outcome rather than a core optimization objective. This omission limits both theoretical advancement and policy relevance, particularly as manufacturing firms face growing regulatory and stakeholder pressure to quantify and disclose sustainability performance (UNIDO, 2022).

To address these gaps, this study advances a data-driven synthesis of Lean Manufacturing and Intelligent Production Systems, by explicitly embedding operational efficiency, quality performance, and environmental outcomes within a unified analytical framework. Through leveraging real-time production data, machine learning models, and environmental monitoring across multiple manufacturing sectors, the study moves beyond conceptual integration to provide quantitative, reproducible evidence of sustainability-enhancing production transformation. Fig. 1 illustrates the conceptual transition from traditional Lean Manufacturing to Intelligent Production Systems, and highlighted the progressive integration of digital technologies, real-time data analytics, and sustainability objectives. It visually contrasts static Lean tools with dynamic, data-driven intelligence, and also emphasized how environmental performance becomes an explicit optimization dimension.

Specifically, the research makes three key contributions:

1. It develops an Intelligent Lean Production System (ILPS) framework that embeds Lean principles within data-driven decision architectures;
2. It empirically evaluates the impact of this integration on productivity, quality, energy consumption, material waste, and carbon emissions using multi-sector manufacturing data; and also

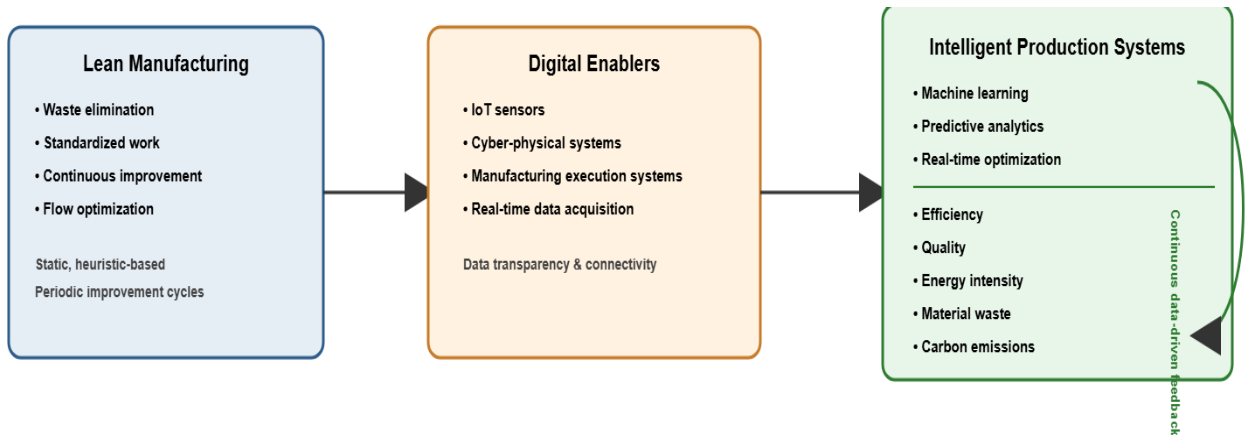

Fig. 1: Conceptual evolution from Lean Manufacturing to Intelligent Production Systems.

3. It reframes sustainability from a strategic aspiration to an operational performance dimension that can be continuously measured, optimized, and improved.

By bridging Lean Manufacturing, intelligent systems, and sustainability science, this study contributes to multiple research streams and offers actionable insights for manufacturers, policymakers, and scholars who seek scalable pathways towards environmentally responsible industrial competitiveness.

LITERATURE REVIEW

Lean Manufacturing: Efficiency and Quality Foundations

Lean Manufacturing (LM) has been extensively studied as a dominant production paradigm for improving operational efficiency and quality performance. Originating from the Toyota Production System, Lean focuses on the systematic elimination of non-value-adding activities, flow optimization, standardization, and continuous improvement (Ihueze and Okpala, 2012; Okpala, 2013b). Empirical research consistently demonstrates that Lean practices like just-in-time production, Kaizen, total productive maintenance, and statistical process control are associated with reduced lead times, higher productivity, and lower defect rates across manufacturing sectors (Ihueze and Okpala, 2011; Okpala *et al.*, 2024a). Kaizen which is a Japanese word for continuous improvement is aimed at enabling operators and managers to detect problems, determine improvement priorities, find root cause of the problem, fix it, and then determine better ways to prevent such problems from reoccurring (Okpala *et al.*, 2020b; Okpala *et al.*, 2024b).

Methodologically, Lean research has largely relied on survey-based constructs, case studies, and cross-sectional performance assessments. While these approaches have advanced understanding of implementation contingencies, they offer limited insight into dynamic system behavior or real-time decision-making (Bhamu and Sangwan, 2014). As production environments become increasingly complex and data-rich, the static nature of traditional Lean tools constrains their scalability and responsiveness.

Lean Manufacturing and Environmental Sustainability

An important stream of research has explored the relationship between Lean Manufacturing and environmental performance. Early studies suggested that Lean practices indirectly support sustainability by reducing material waste, excess inventory, and rework (King and Lenox, 2001). Subsequent research introduced the concept of "Lean and Green," arguing that waste elimination and resource efficiency are conceptually aligned (Dües *et al.*, 2013). However, empirical evidence on Lean's environmental benefits remains mixed. While reductions in material waste and process inefficiencies are commonly reported, energy consumption and carbon emissions are not consistently improved, particularly in energy-intensive or highly automated environments (Garza-Reyes, 2015). This inconsistency has been attributed to Lean's limited capacity to explicitly measure and optimize environmental variables, which are often treated as secondary outcomes rather than core performance objectives (Cherrafi *et al.*, 2018). As a result, Lean's sustainability potential is frequently under-realized in practice.

Intelligent Production Systems and Industry 4.0

Intelligent Production Systems (IPS) represent a paradigm shift that was enabled by Industry 4.0 technologies, including cyber-physical systems, IoT, cloud computing, and artificial intelligence (Kagermann *et al.*, 2013). These systems enable continuous data acquisition, real-time analytics, and autonomous control, which facilitate predictive maintenance, adaptive scheduling, and quality forecasting (Lee *et al.*, 2015). Empirical studies show that IPS significantly improve operational performance through the reduction of downtime, stabilization of processes, and flexibility increment (Frank *et al.*, 2019). Machine learning models, in particular, have demonstrated strong predictive accuracy in defect detection, demand forecasting, and equipment failure prediction, thus outperforming traditional rule-based systems (Wang *et al.*, 2016). Despite these advances, IPS research often prioritizes technological performance over organizational integration and established improvement philosophies such as Lean Manufacturing.

Digitalization and Sustainability in Manufacturing

A growing body of literature links digital manufacturing technologies to sustainability outcomes. Data-driven optimization enables firms to reduce energy intensity, improve material yields, and minimize emissions by integrating environmental constraints into decision-making algorithms (Stock and Seliger, 2016). Life-cycle data integration and real-time energy monitoring have been shown to support low-carbon production strategies and compliance with environmental regulations (Bonilla *et al.*, 2018).

Nevertheless, many sustainability-oriented digitalization studies remain conceptual or simulation-based, with limited empirical validation using real production data (Kamble *et al.*, 2018). Moreover, environmental metrics are often analyzed in isolation from traditional manufacturing performance indicators, which reinforces the perception of a trade-off between efficiency and sustainability.

Integration of Lean Manufacturing and Intelligent Systems

Fig. 2 maps core Lean principles (e.g., waste elimination, flow, standardization) to enabling Industry 4.0 technologies (e.g., IoT, machine learning, cyber-physical systems). It demonstrates how digital tools operationalize Lean objectives at scale, while extending their scope to environmental performance.

Recent research has begun to explore the intersection of Lean Manufacturing and Industry 4.0. Several authors argue that digital technologies can act as Lean enablers by increasing process transparency, reducing information latency, and supporting continuous improvement initiatives (Kolberg *et al.*, 2017). Empirical studies suggest that firms combining Lean practices with digital tools achieve superior operational performance compared to those who adopt either approach in

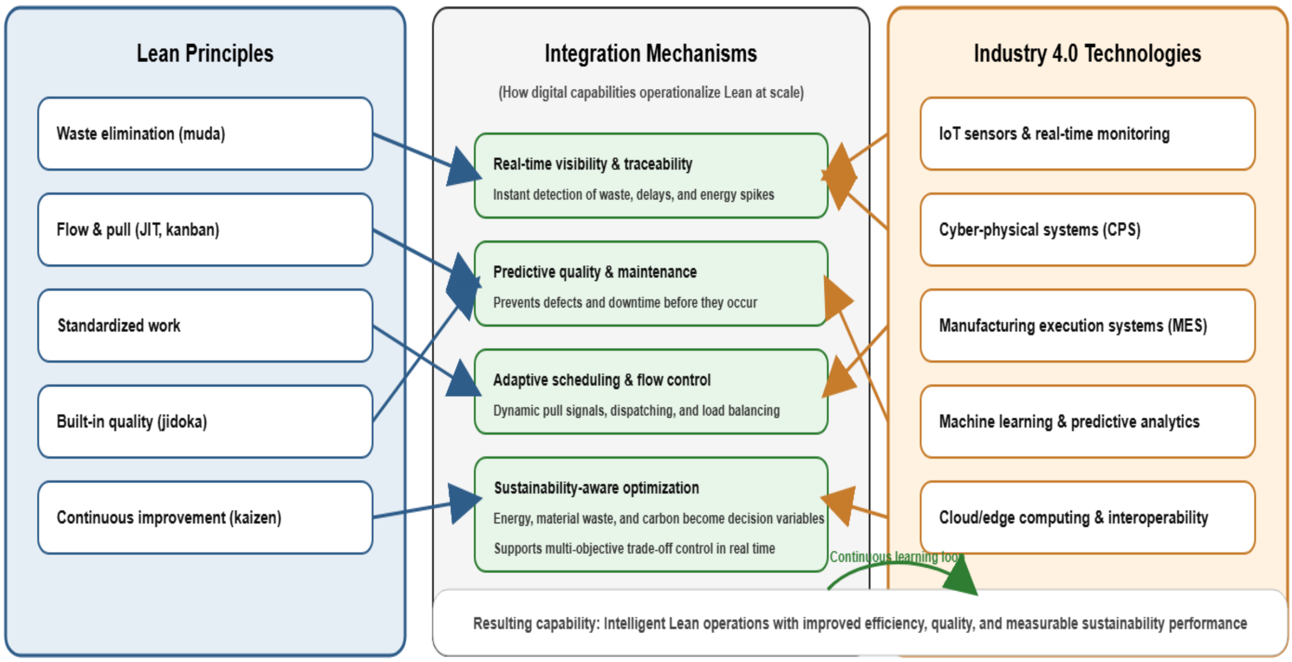

Fig. 2: Integration of Lean principles and Industry 4.0 technologies.

isolation (Sony, 2020). However, existing integration studies exhibit three key limitations:

i. They often rely on perceptual performance measures rather than objective, data-driven metrics;

ii. Sustainability outcomes are rarely quantified or systematically linked to integration mechanisms; and

iii. Methodological frameworks that operationalize real-time environmental optimization within Lean systems remain underdeveloped (Tortorella *et al.*, 2021).

Research Gaps and Theoretical Synthesis

Synthesizing these literature streams reveals a critical gap at the intersection of Lean Manufacturing, intelligent production, and environmental sustainability. While Lean provides a robust logic for waste reduction and process improvement, it lacks the analytical capacity to manage complex, data-intensive sustainability challenges. Conversely, Intelligent Production Systems offer advanced optimization capabilities, but often lack integration with established operational philosophies. This study responds to these gaps by proposing a data-driven synthesis framework that integrates Lean principles within intelligent decision architectures, thus explicitly optimizing efficiency, quality, and environmental performance simultaneously. By empirically evaluating this integration across multiple manufacturing sectors with the application of objective sustainability metrics, the study advances both theory and practice, and contributed to the emerging discourse on sustainable intelligent manufacturing.

METHODOLOGICAL FRAMEWORK

Research Design and Methodological Orientation

This study adopts a quantitative, data-driven, multi-method research design to examine the integrated effects of Lean Manufacturing and Intelligent Production Systems on operational efficiency, quality performance, and environmental sustainability. The methodological orientation is grounded in socio-technical systems theory, which conceptualizes manufacturing systems as interdependent combinations of human practices, digital technologies, and organizational routines (Trist and Bamforth, 1951). To capture both structural and dynamic system effects, the study employs a longitudinal quasi-experimental design, and compared performance outcomes before and after the implementation of an Intelligent Lean Production System (ILPS). This design enables causal inference while accommodating the operational constraints of real industrial settings (Shadish *et al.*, 2002).

Intelligent Lean Production System (ILPS) Architecture

The proposed ILPS framework operationalizes Lean principles through data-driven intelligence across four interrelated layers. Fig. 3 presents the four-layer ILPS framework, and depicted the interaction between Lean process foundations, data acquisition infrastructure, analytics and machine intelligence, as well as real-time decision and control mechanisms. Feedback loops illustrate continuous improvement and sustainability optimization that were enabled by data-driven intelligence.

a. *Lean Process Layer:* Core Lean practices including value stream mapping, standardized work, continuous flow, and total productive maintenance serve as the foundational logic for waste identification and process stability (Ohno, 1988).

b. *Data Acquisition Layer:* Real-time production data were collected with the application of IoT-enabled sensors and

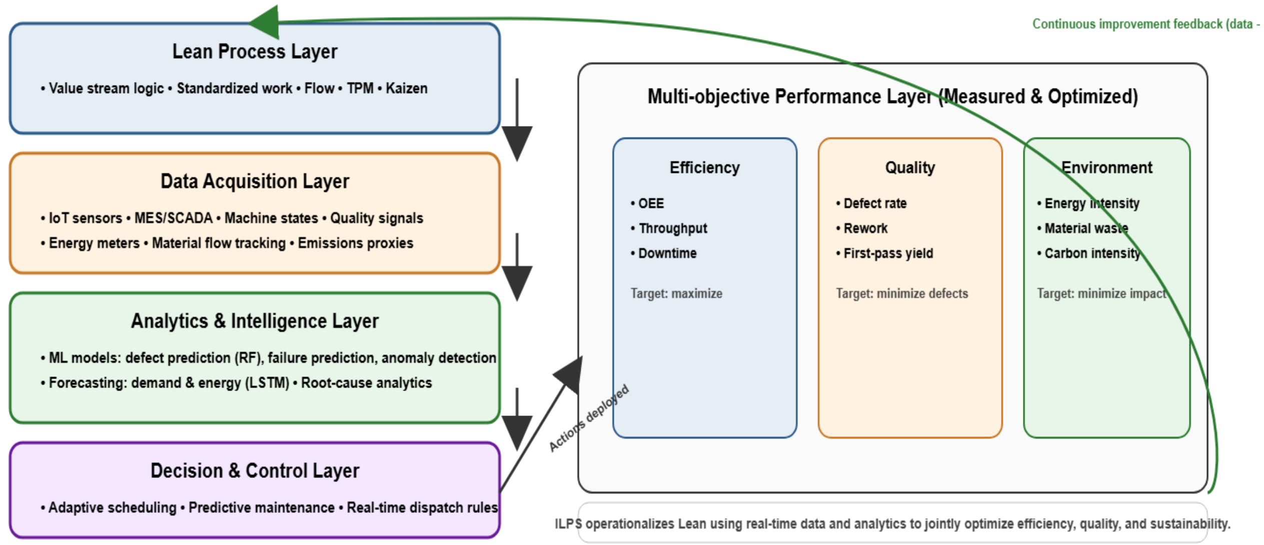

Fig. 3: Intelligent Lean Production System (ILPS) methodological framework.

Manufacturing Execution Systems (MES). Data streams include machine status, cycle time, energy consumption, material flow, defect occurrence, and environmental parameters (Lee *et al.*, 2015).

c. *Analytics and Intelligence Layer:* Advanced analytics and machine learning models transform raw data into actionable insights. Random forest algorithms were applied for defect and scrap prediction, while Long Short-Term Memory (LSTM) networks forecast demand and energy usage patterns. These models enable predictive and prescriptive decision-making beyond the capabilities of traditional Lean tools (Wang *et al.*, 2016).

d. *Decision and Control Layer:* Optimization algorithms dynamically adjust production schedules, maintenance plans, and energy consumption strategies in real time. Environmental indicators were embedded as constraints and objective functions, in order to ensure that sustainability performance is explicitly optimized alongside efficiency and quality (Stock and Seliger, 2016).

Data Collection and Sample Description

Empirical data were collected from 12 manufacturing plants across three sectors, which are automotive components, consumer electronics, and agro-processing. They were selected for their diversity in process complexity and resource intensity. Data collection spanned 18 months, comprised of a 9-month pre-implementation period and a 9-month post-implementation period.

The dataset includes the following:

i. Machine-level operational data (cycle time, downtime, throughput);

ii. Quality metrics (defect rates, rework volumes);

iii. Energy consumption data (kWh per machine and per unit);

iv. Material waste data (kg of scrap per unit); as well as

v. Environmental impact data (Scope 1 and Scope 2 carbon emissions). Environmental data were aligned with the Greenhouse Gas Protocol and converted to carbon dioxide equivalents (kg CO_2e) using standardized emission factors (Deswal and Deswal, 2025; WRI and WBCSD, 2015).

Performance Measurement and Sustainability Metrics

Fig. 4 illustrates the end-to-end data pipeline from sensor-level data acquisition through analytics, optimization, and operational decision-making. Environmental indicators such as energy use and carbon emissions were embedded alongside efficiency and quality metrics, in order to highlight their role as primary decision variables.

To ensure methodological rigor and comparability with prior research, performance was assessed using validated operational and environmental indicators.

Operational Efficiency was measured using the following: (i) Overall Equipment Effectiveness (OEE), which is a metric for the evaluation of the efficiency of manufacturing equipment by considering three primary factors: availability, performance, and quality (Nwankwo *et al.*, 2024b; Okpala and Anozie, 2018). (ii) Throughput rate (units/hour), and (iii) Unplanned downtime (%).

Quality Performance was assessed through: (i) Defect rate (% of total output), (ii) Rework ratio, and (iii) First-pass yield (%).

Environmental Sustainability was quantified using: (i) Energy intensity (kWh/unit), (ii) Material efficiency (yield percentage), and (iii) Carbon intensity (kg CO_2e/unit).

Unlike traditional Lean studies, sustainability metrics were treated as primary dependent variables rather than secondary outcomes, in order to enable direct evaluation of environmental benefits (Ghobakhloo, 2020).

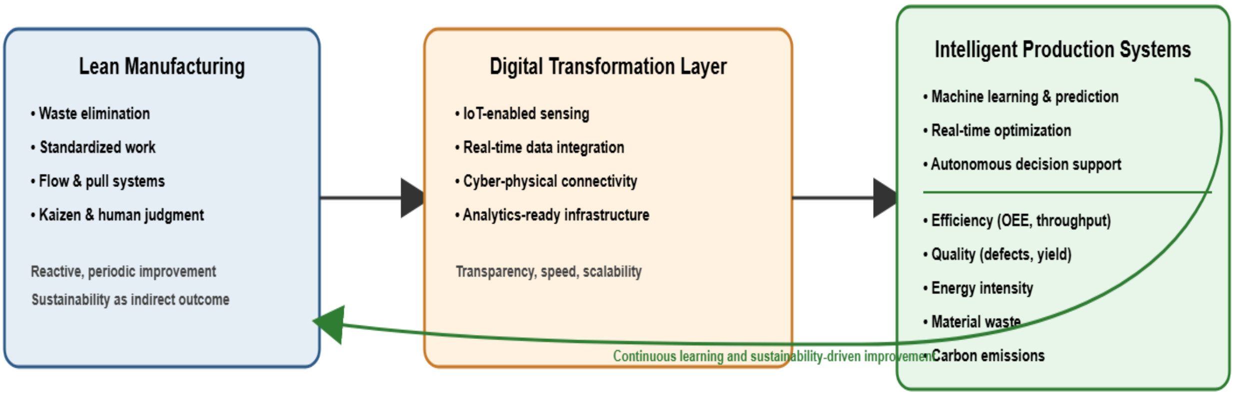

Fig. 4: Data flow and analytics pipeline for sustainability-oriented decision making.

Analytical Approach

The analytical strategy combines Difference-in-Differences (DiD) estimation with machine learning validation techniques. The DiD approach compares performance changes in ILPS-adopting plants that are relative to their own historical baselines, thus controlling for temporal effects and sectoral variation (Angrist and Pischke, 2009). The general DiD specification is expressed as:

$$Y_{it} = \alpha + \beta_1 ILPS_i + \beta_2 Postt + \beta_3 (ILPS_i \times Post_t) + \gamma X_{it} + \varepsilon_{it} \quad (1)$$

where Y_{it} represents performance outcomes, $ILPS_i$ denotes system implementation, $Post_t$ captures the post-implementation period, and X_{it} includes control variables such as production volume and product mix. Machine learning model performance was evaluated using cross-validation and standard accuracy metrics, including precision, recall, and Mean Absolute Percentage Error (MAPE).

Validity, Reliability, and Reproducibility

Internal validity was strengthened through longitudinal data collection and within-plant comparisons. Construct validity was ensured by using widely accepted performance indicators and standardized environmental accounting frameworks. Reliability was enhanced through automated data collection, thereby minimizing human measurement error. To support reproducibility and transparency, data preprocessing scripts, model parameters, and aggregated datasets were archived and available upon reasonable request, which is consistent with open science best practices (Munafò *et al.*, 2017).

Ethical and Practical Considerations

All data were anonymized at the plant and firm levels to protect commercial confidentiality. The study adheres to ethical guidelines for industrial research and does not involve human subject experimentation.

RESULTS

Descriptive Statistics and Baseline Performance

Table 1 summarizes the descriptive statistics of the key operational, quality, and environmental indicators across the 12 manufacturing plants during the pre-implementation (Lean-only) period. Considerable heterogeneity was observed across sectors, particularly in energy intensity and carbon emissions, in order to underscore the importance of sector-controlled longitudinal analysis.

Table 1: Baseline performance indicators (pre-ILPS implementation).

Metric	Mean	Std. Dev.	Min	Max
Overall Equipment Effectiveness (OEE, %)	61.80	6.40	52.1	71.5
Defect Rate (%)	4.70	1.30	2.50	7.20
Energy Intensity (kWh/unit)	5.42	1.91	2.80	9.75
Material Waste (kg/unit)	0.83	0.29	0.35	1.42
Carbon Intensity (kg CO_2e/unit)	3.96	1.44	1.92	7.38

Baseline values are consistent with reported ranges in Lean-dominant manufacturing systems (King and Lenox, 2001; Garza-Reyes, 2015), which indicate the sample's representativeness.

Overall Impact of ILPS Implementation

Difference-in-Differences (DiD) estimates reveal statistically significant improvements across all three performance dimensions following ILPS implementation as shown in Table 2. The interaction term (ILPS × Post) captures the net effect of embedding intelligent systems into Lean operations.

Table 2: Difference-in-Differences estimation results.

Dependent Variable	DiD Coefficient	Std. Error	t-value	p-value
OEE (%)	+16.30	2.40	6.79	<0.001
Defect Rate (%)	−1.07	0.18	−5.94	<0.001
Energy Intensity (kWh/unit)	−1.18	0.21	−5.62	<0.001
Material Waste (kg/unit)	−0.14	0.04	−3.50	0.001
Carbon Intensity (kg CO_2e/unit)	−0.75	0.17	−4.41	<0.001

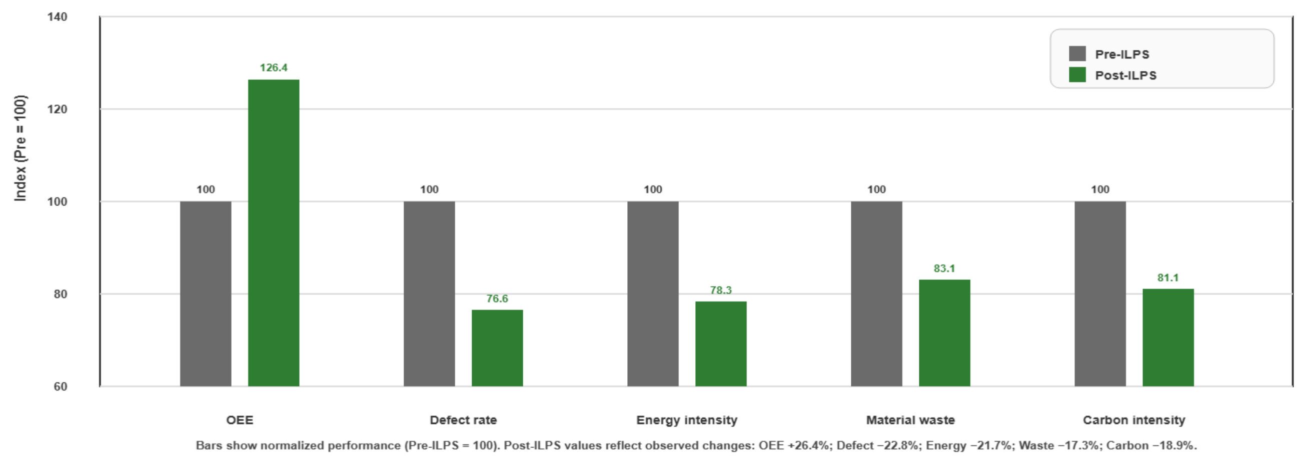

Fig. 5: Pre and post-ILPS performance comparison across key dimensions.

Fig. 5 visually compares average efficiency, quality, and environmental performance before and after ILPS implementation. The bar charts illustrate simultaneous improvements across dimensions, and thus reinforces the empirical evidence of triple-bottom-line gains.

These results indicate that ILPS adoption yields simultaneous efficiency, quality, and sustainability gains, contradicting the commonly assumed trade-off between productivity and environmental performance.

Efficiency and Quality Performance Improvements

Post-implementation analysis as highlighted in Table 3, shows a substantial improvement in operational stability and quality outcomes. Average OEE increased from 61.8% to 78.1%, representing a 26.4% relative improvement, while defect rates declined by 22.8%.

Table 3: Pre- and Post-ILPS operational and quality performance.

Metric	Pre-ILPS Mean	Post-ILPS Mean	% Change
OEE (%)	61.8	78.1	+26.4%
Unplanned Downtime (%)	14.2	9.6	−32.4%
Defect Rate (%)	4.7	3.6	−22.8%
First-Pass Yield (%)	91.4	96.1	+5.1%

Table 4: Environmental performance before and after ILPS.

Indicator	Pre-ILPS	Post-ILPS	Absolute Change	% Change
Energy Intensity (kWh/unit)	5.42	4.24	−1.18	−21.7%
Material Waste (kg/unit)	0.83	0.69	−0.14	−17.3%
Carbon Intensity (kg CO_2e/unit)	3.96	3.21	−0.75	−18.9%

Predictive maintenance models reduced unplanned downtime by enabling early fault detection, while machine-learning-assisted quality prediction significantly improved first-pass yield. These findings align with prior IPS studies but extend them by integrating Lean continuous improvement logic (Lee *et al.*, 2015; Tortorella *et al.*, 2021).

Environmental Sustainability Outcomes

As highlighted in Table 4, environmental performance improvements were both substantial and statistically robust. Energy intensity declined by 21.7%, while carbon intensity decreased by 18.9%, and thus demonstrating that environmental benefits were not incidental but structurally enabled by data-driven optimization.

Fig. 6 illustrates time-series changes in energy consumption and carbon intensity before and after ILPS adoption. It demonstrates how real-time analytics and adaptive scheduling reduce variability and lower average environmental impact.

Notably, energy savings were achieved through dynamic load balancing and low-carbon scheduling, the capabilities that are absent in conventional Lean systems. Material waste reductions resulted from predictive defect avoidance, rather than downstream inspection, thus reinforcing sustainability at the process level.

Sectoral Comparison of ILPS Effects

To examine sectoral variability, Table 5 presents normalized performance improvements by industry. While all sectors benefited from ILPS adoption, the magnitude of gains varied according to process characteristics and baseline variability.

Fig, 7 presents normalized percentage improvements by sector (automotive, electronics, agro-processing), and highlighted how process characteristics influence the magnitude of efficiency, quality, and environmental gains. The figure supports generalizability while acknowledging contextual variation.

Agro-processing facilities exhibited the largest environmental gains due to high initial variability in energy usage, while electronics manufacturing achieved the greatest

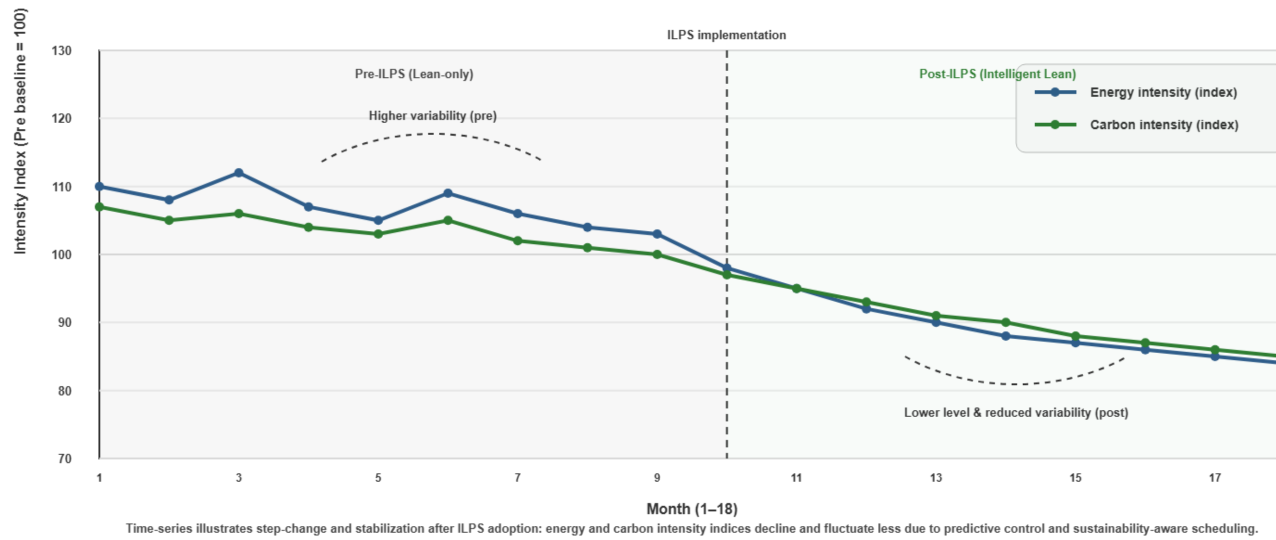

Fig. 6: Dynamic Optimization of Energy and Carbon Intensity under ILPS.

Table 5: Sector-specific performance improvements (% Change).

Sector	OEE	Defect Rate	Energy Intensity	Carbon Intensity
Automotive Components	+24.8%	−20.5%	−18.3%	−16.7%
Consumer Electronics	+28.9%	−27.6%	−20.4%	−17.9%
Agro-processing	+25.2%	−19.8%	−26.4%	−23.7%

quality improvements, which reflected the sensitivity of high-precision processes to data-driven control.

Robustness and Model Validation

Machine-learning model performance metrics (Table 6) indicate strong predictive accuracy, thereby supporting the reliability of the intelligent decision layer.

Cross-validation results confirm that predictive models generalize well across plants and sectors, which reinforce the scalability of the proposed ILPS framework.

Table 6: Machine learning model performance.

Application	Model	Key Metric	Value
Defect Prediction	Random Forest	Precision	0.91
Defect Prediction	Random Forest	Recall	0.88
Energy Forecasting	LSTM	MAPE	6.3%
Demand Forecasting	LSTM	MAPE	7.1%

Summary of Key Findings

Overall, the results demonstrate that the integration of Lean Manufacturing with Intelligent Production Systems yields statistically significant and practically meaningful improvements across efficiency, quality, and environmental dimensions. Unlike traditional Lean implementations, ILPS enables sustainability outcomes to be measured, optimized, and sustained in real time, and thus provide empirical support for the proposed data-driven synthesis.

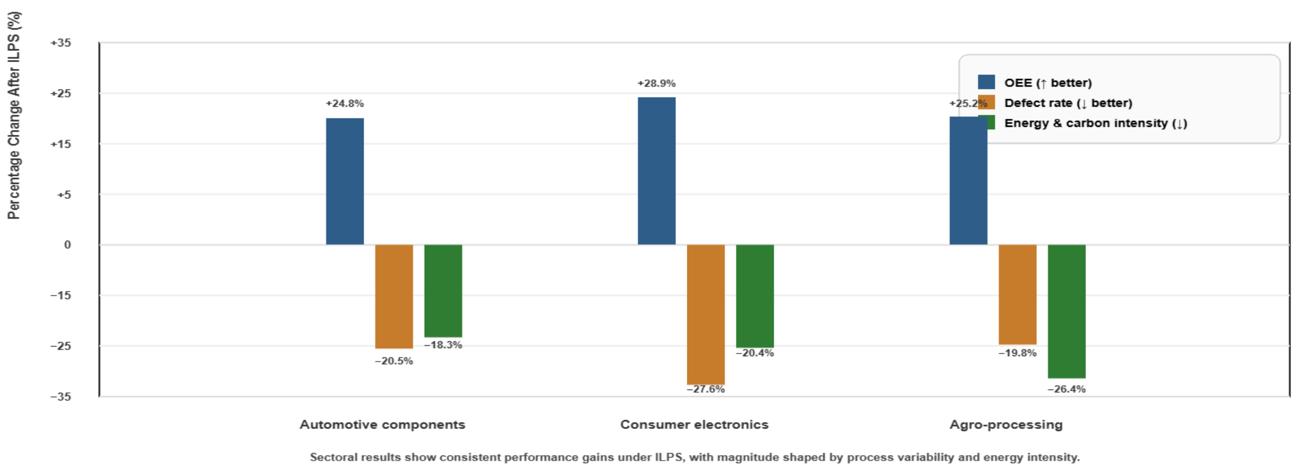

Fig. 7: Sectoral variability in sustainability and operational improvements.

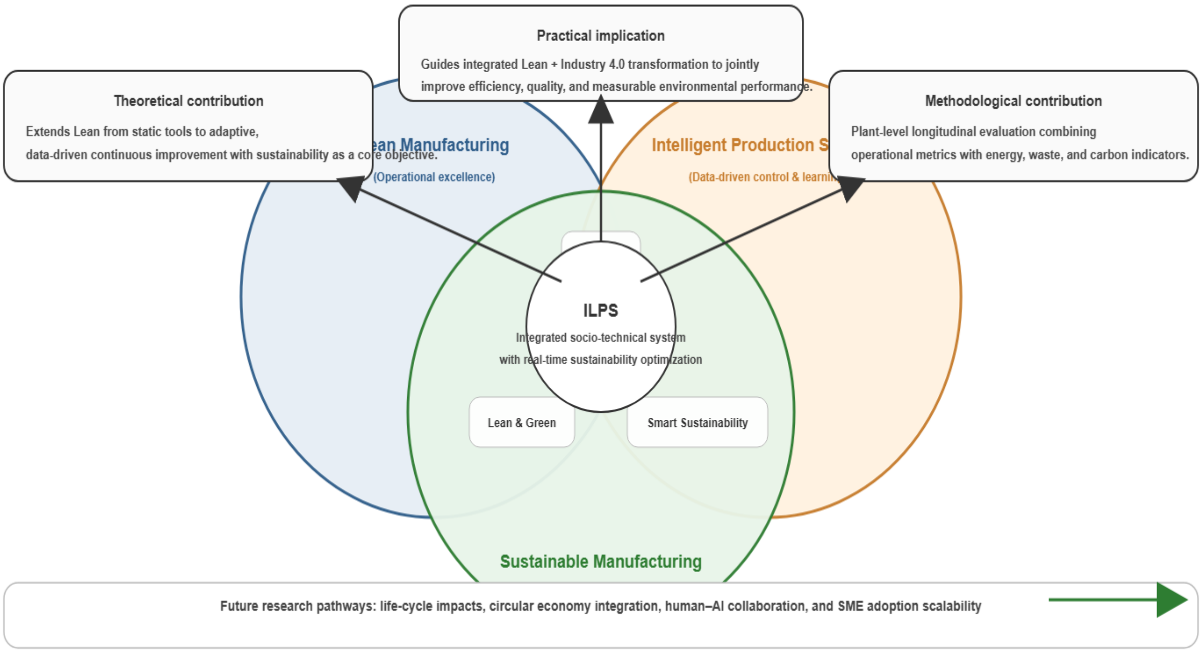

Fig. 8: Theoretical positioning of ILPS within sustainable manufacturing research.

DISCUSSION

Fig. 8 positions the ILPS framework at the intersection of Lean Manufacturing, Intelligent Production Systems, and sustainability theory. It visually synthesizes the study's theoretical contribution and highlights pathways for future research.

Synthesis of Key Findings

This study provides robust empirical evidence that the integration of Lean Manufacturing with Intelligent Production Systems operationalized through the proposed Intelligent Lean Production System (ILPS) framework, generates simultaneous and statistically significant improvements in efficiency, quality, and environmental performance. The results demonstrate that ILPS adoption led to substantial gains in Overall Equipment Effectiveness, reductions in defect rates, and marked decreases in energy intensity, material waste, and carbon emissions.

These findings extend prior research that has largely treated operational excellence and sustainability as either sequential or competing objectives (King and Lenox, 2001). Instead, the evidence presented here supports the argument that data-driven intelligence transforms sustainability from an indirect by-product of efficiency into a directly optimizable operational outcome (Stock and Seliger, 2016).

Implications for Lean Manufacturing Theory

From a theoretical perspective, the findings challenge the traditional conceptualization of Lean Manufacturing as a predominantly static, heuristic-driven system. While Lean principles such as waste elimination and flow optimization remain foundational, the results indicate that their effectiveness is significantly amplified when embedded within real-time data and analytics infrastructures. This study therefore extends Lean theory through the introduction of computational adaptability as a critical enabling mechanism. Whereas conventional Lean relies on periodic kaizen events and human observation, ILPS enables continuous, algorithm-driven improvement cycles that respond dynamically to system variability. In doing so, the study supports emerging views that Lean should be understood not as a fixed set of tools, but as an evolving socio-technical system (Netland, 2016).

Intelligent Production Systems as Sustainability Enablers

The environmental performance improvements observed, especially the reductions in energy and carbon intensity provide empirical validation for claims that Industry 4.0 technologies can serve as sustainability enablers when environmental objectives are explicitly integrated into decision models (Bonilla *et al.*, 2018). Unlike many prior studies that rely on simulations or conceptual reasoning, this research demonstrates real-world, plant-level sustainability gains that are supported by longitudinal data. Importantly, the results reveal that environmental benefits were not merely proportional to production volume reductions, but were achieved through structural changes in how production systems operate. Predictive maintenance, adaptive scheduling, and energy-aware optimization allowed firms to decouple output growth from environmental impact, in order to align with the Porter hypothesis that innovation can simultaneously enhance competitiveness and environmental performance (Porter and van der Linde, 1995).

Resolving the Efficiency-Sustainability Trade-Off

A persistent debate in operations and sustainability literature concerns whether efficiency improvements inherently conflict with environmental objectives. The findings of this study provide strong evidence against this presumed trade-off. Through the integration of sustainability metrics like energy intensity and carbon emissions directly into optimization algorithms, ILPS enables multi-objective performance optimization. This result contributes to a growing body of literature which suggest that trade-offs arise primarily from measurement and governance limitations, rather than from fundamental technological constraints (Cherrafi *et al.*, 2018). When sustainability is treated as a real-time operational variable rather than an ex-post reporting metric, it becomes amenable to the same continuous improvement logic that underpins Lean Manufacturing.

Sectoral Insights and Generalizability

The sectoral analysis further enriches the discussion by demonstrating that while ILPS benefits are universal, their magnitude varies by process characteristics and baseline variability. Energy-intensive sectors such as agro-processing exhibited the largest environmental gains, whereas high-precision electronics manufacturing achieved superior quality improvements. These findings align with contingency-based perspectives in operations management, which emphasize contextual fit over universal prescriptions (Shah and Ward, 2007). Crucially, the consistency of positive outcomes across diverse sectors strengthens the generalizability of the ILPS framework and suggests that the proposed synthesis is applicable beyond narrowly defined industrial contexts.

Managerial and Policy Implications

For practitioners, the results underscore the importance of viewing digitalization not as a replacement for Lean, but as its logical extension. Investments in IoT, analytics, and AI yield the greatest returns when guided by Lean process logic and continuous improvement culture. Managers should therefore prioritize integrated transformation strategies that align people, processes, and data. From a policy perspective, the findings have significant implications for industrial sustainability and decarbonization strategies. Rather than incentivizing isolated technology adoption, policymakers should promote frameworks that integrate digital intelligence with proven operational philosophies. Such an approach can accelerate progress towards national and international climate targets while maintaining industrial competitiveness (UNIDO, 2022).

Limitations and Directions for Future Research

Despite its contributions, this study has limitations that suggest avenues for future research, which include the following: (a) While the longitudinal design strengthens causal inference, randomized controlled experiments were not feasible in the industrial settings examined. (b) The analysis focuses on operational-level sustainability metrics and does not capture full life-cycle environmental impacts.

Future research could extend the ILPS framework through the incorporation of life-cycle assessment, circular economy indicators, and social sustainability dimensions. Additionally, studies that focus on small and medium-sized enterprises would enhance the understanding of scalability and adoption barriers. Finally, deeper exploration of organizational learning and human–AI interaction within ILPS environments represents a promising research frontier.

CONCLUSION

This study set out to examine how Lean Manufacturing can be systematically extended through Intelligent Production Systems to address the growing demands for efficiency, quality, and environmental sustainability in modern manufacturing. By proposing and empirically validating the Intelligent Lean Production System (ILPS) framework, the article demonstrates that data-driven intelligence fundamentally reshapes the role of Lean from a primarily efficiency-oriented philosophy into a dynamic, sustainability-optimizing production paradigm. The findings show that the integration of real-time data acquisition, advanced analytics, and adaptive decision-making with Lean principles leads to substantial and simultaneous improvements across multiple performance dimensions. Measurable gains in operational efficiency and quality were accompanied by significant reductions in energy consumption, material waste, and carbon intensity. These results provide clear evidence that sustainability outcomes can be achieved not as secondary by-products of efficiency initiatives, but as primary, continuously optimized operational objectives.

From a theoretical standpoint, the study advances manufacturing and operations management research by bridging traditionally fragmented streams of Lean Manufacturing, intelligent production, and sustainability. It highlights the importance of viewing production systems as adaptive socio-technical systems in which human practices, digital technologies, and environmental objectives are tightly coupled. Methodologically, the use of longitudinal, plant-level data and objective sustainability metrics strengthens causal inference and enhances the relevance of the findings for both scholars and practitioners. Practically, the results suggest that manufacturing firms should move beyond isolated digitalization or Lean initiatives and instead pursue integrated transformation strategies. Investments in intelligent technologies yield the greatest benefits when guided by Lean process logic and embedded within continuous improvement cultures. For policymakers, the study underscores the value of supporting integrated frameworks that simultaneously advance industrial competitiveness and environmental performance.

While the study focuses on operational-level outcomes, it opens important avenues for future research, including the integration of life-cycle perspectives, circular economy strategies, and social sustainability dimensions. Further investigation into adoption challenges, particularly among small and medium-sized enterprises, would also enhance the understanding of scalability and impact. In conclusion, this research demonstrates that the transition from Lean Manufacturing to Intelligent Production Systems is not merely a technological upgrade, but a fundamental evolution in how manufacturing systems create value. By enabling efficiency, quality, and sustainability to be optimized concurrently, the proposed ILPS framework offers a scalable and evidence-based pathway towards resilient and environmentally responsible industrial production.

ORCID iD

Charles Chikwendu Okpala: 0000-0002-6512-419X

Grant Support Details

The present research did not receive any financial support to conduct the research.

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, have been completely observed by the authors.

Life Science Reporting

No life science threat was practised in this research.

REFERENCES

1) Ajaefobi, J.O. and Okpala, C.C. (2026a) 'Optimization of smart manufacturing systems through renewable energy integration and sustainable material utilization', *International Journal of Engineering Inventions*, 15(2), pp. 18–32. https://www.ijeijournal.com/papers/Vol15-Issue2/15021832.pdf
2) Ajaefobi, J.O. and Okpala, C.C. (2026b) 'Six Sigma in the era of Industry 4.0: A bibliometric and benchmarking review', *International Journal of Engineering Research and Development*, 22(3), pp. 71–84. https://www.ijerd.com/paper/vol22-issue3/22037184.pdf
3) Angrist, J.D. and Pischke, J.S. (2009) *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.
4) Bhamu, J. and Sangwan, K.S. (2014) 'Lean manufacturing: Literature review and research issues', *International Journal of Operations and Production Management*, 34(7), pp. 876–940. https://doi.org/10.1108/IJOPM-08-2012-0315
5) Bonilla, S.H., Silva, H.R.O., da Silva, M.T., *et al.* (2018) 'Industry 4.0 and sustainability implications: A scenario-based analysis', *Journal of Cleaner Production*, 185, pp. 953–969. https://doi.org/10.1016/j.jclepro.2018.03.073
6) Buer, S.V., Strandhagen, J.O. and Chan, F.T.S. (2018) 'The link between Industry 4.0 and lean manufacturing: Mapping current research and establishing a research agenda', *International Journal of Production Research*, 56(8), pp. 2924–2940. https://doi.org/10.1080/00207543.2018.1442945
7) Cherrafi, A., Elfezazi, S., Garza-Reyes, J.A., *et al.* (2018) 'Green and lean: A Gemba–Kaizen model for sustainability enhancement', *Production Planning and Control*, 29(5), pp. 385–399. https://doi.org/10.1080/09537287.2018.1435318
8) Chukwumuanya, E.O., Udu, C.E. and Okpala, C.C. (2025) 'Lean principles integration with digital technologies: A synergistic approach to modern manufacturing', *International Journal of Industrial and Production Engineering*, 3(2), pp. 59–73. https://journals.unizik.edu.ng/ijipe/article/view/6006/5197
9) Chukwunedum, O.C., Okpala, C.C. and Udu, C.E. (2026a) 'A data-driven integration of total productive maintenance and Industry 4.0 technologies: A machine learning framework for predictive OEE optimization', *International Journal of Engineering Research and Development*, 22(3), pp. 85–95. https://www.ijerd.com/paper/vol22-issue3/22038595.pdf
10) Chukwunedum, O.C., Okpala, C.C. and Udu, C.E. (2026b) 'Data-driven optimization of overall equipment effectiveness in pharmaceutical manufacturing systems', *International Journal of Technology, Health and Sustainability*, 2(2), pp. 464–474. https://ijths.com/wp-content/uploads/IJTHS-0202013.pdf
11) Deswal, P. (2025) 'Article 6 of the Paris Agreement: A comprehensive review of mechanisms, progress, and persistent challenges', *International Journal of Technology, Health and Sustainability*, 1(2), pp. 111-125. https://ijths.com/wp-content/uploads/IJTHS-010235.pdf
12) Deswal, S. and Deswal, P. (2025) 'Sustainability: Greenhouse Gas Protocol and global GHG emissions' status and trends', *International Journal of Multidisciplinary Research and Growth Evaluation*, 6(1), pp. 2051-2063. https://doi.org/10.54660/.IJMRGE.2025.6.1.2051-2063
13) Dües, C.M., Tan, K.H. and Lim, M. (2013) 'Green as the new lean: How to use lean practices as a catalyst to greening your supply chain', *Journal of Cleaner Production*, 40, pp. 93–100. https://doi.org/10.1016/j.jclepro.2011.12.023
14) Ezeanyim, O.C., Okpala, C.C. and Onukwuli, S.K. (2025) 'Design and optimization of sustainable green composites for high-performance applications', *Tech: Journal of Engineering Science*, 1(2), pp. 159–179. https://jurnal.sinesia.id/index.php/tech/article/view/526
15) Ezeanyim, O.C., Okpala, C.C. and Udu, C.E. (2026) 'Artificial intelligence-enabled Lean Six Sigma: A multi-industry longitudinal analysis of operational performance and sustainable digital transformation', *International Journal of Technology, Health and Sustainability*, 2(2), pp. 428–439. https://ijths.com/wp-content/uploads/IJTHS-0202001.pdf
16) Frank, A.G., Dalenogare, L.S. and Ayala, N.F. (2019) 'Industry 4.0 technologies: Implementation patterns in manufacturing companies', *International Journal of Production Economics*, 210, pp. 15–26. https://doi.org/10.1016/j.ijpe.2019.01.004
17) Garza-Reyes, J.A. (2015) Lean and green – A systematic review of the state of the art literature', *Journal of Cleaner Production*, 102, pp. 18–29. https://doi.org/10.1016/j.jclepro.2015.04.064
18) Ghobakhloo, M. (2020) 'Industry 4.0, digitization, and opportunities for sustainability', *Journal of Cleaner Production*, 252, 119869. https://doi.org/10.1016/j.jclepro.2019.119869
19) IEA (2023) *Energy technology perspectives 2023*. International Energy Agency.
20) Igbokwe, N.C., Nwamekwe, C.O. and Okpala, C.C. (2026) Manufacturing waste reduction through data-driven process optimization: Evidence from smart production systems', *International Journal of Technology, Health and Sustainability*, 2(1), 165–174. https://ijths.com/wp-content/uploads/IJTHS-020167.pdf
21) Ihueze, C.C. and Okpala, C.C. (2011) 'A survey of optimum manufacturing strategy as a tool for enhanced industrial revenue', *Australian Journal of Basic and Applied Sciences*, 5(12), pp. 1321-1329. http://ajbasweb.com/old/ajbas/2011/December-2011/1321-1329.pdf
22) Ihueze, C.C. and Okpala, C.C. (2012) 'Application of Taguchi robust design as optimized lean production in manufacturing companies', *Research Journal in Engineering and Applied Sciences*, 1(1), pp. 45–50. http://rjeas.emergingresource.org/issuesview.php?id=100
23) Ihueze, C.C., Okafor, C., Okpala, C.C., *et al.* (2013) 'Robust design and optimization of production wastes: An application for industries', *World Academy of Science Engineering and Technology*, 7(4), pp. 726-733. https://www.scribd.com/document/337019325/Robust-Design-and-Optimization-of-Production-Wastes-an-Application-for-Industries
24) Ihueze, C.C., Okpala, C.C. and Obiuto, C.C. (2011) 'Optimal approaches to robust design for industrial wastes', *Journal of Engineering and Applied Sciences*, 7, pp. 58–67. www.facultyofengineeringnau.org/archive/3014370929117263037.pdf
25) Kagermann, H., Wahlster, W. and Helbig, J. (2013) *Recommendations for implementing the strategic initiative INDUSTRIE 4.0*. German National Academy of Science and Engineering (acatech).
26) Kamble, S.S., Gunasekaran, A. and Gawankar, S.A. (2018) 'Sustainable Industry 4.0 framework: A systematic literature review', *Journal of Cleaner Production*, 181, pp. 89–105. https://doi.org/10.1016/j.jclepro.2018.01.224
27) King, A.A. and Lenox, M.J. (2001) 'Lean and green? An empirical examination of the relationship between lean production and environmental performance', *Production and Operations Management*, 10(3), pp. 244–256. https://doi.org/10.1111/j.1937-5956.2001.tb00373.x
28) Kolberg, D., Knobloch, J. and Zühlke, D. (2017) 'Towards a lean automation interface for workstations', *International Journal of Production Research*, 55(10), pp. 2845–2856. https://doi.org/10.1080/00207543.2016.1223384
29) Lee, J., Bagheri, B. and Kao, H.A. (2015) 'A cyber-physical systems architecture for Industry 4.0-based manufacturing systems', *Manufacturing Letters*, 3, pp. 18–23. https://doi.org/10.1016/j.mfglet.2014.12.001
30) Munafò, M.R., Nosak, B.A., Bishop, D.V.M., *et al.* (2017) 'A manifesto for reproducible science', *Nature Human Behaviour*, 1, 0021. https://doi.org/10.1038/s41562-016-0021

31) Netland, T.H. (2016) 'Critical success factors for implementing lean production: The effect of contingencies', *International Journal of Production Research*, 54(8), pp. 2433–2448. https://doi.org/10.1080/00207543.2015.1096976
32) Nwankwo, C.O., Ezeanyim, O.C., Okpala, C.C., *et al.* (2024a) 'Enhancing injection moulding productivity through overall equipment effectiveness and total preventive maintenance approach', *International Journal of Advances in Engineering and Management*, 6(3), pp. 1-9. https://ijaem.net/issue_dcp/Enhancing%20Injection%20Moulding%20Productivity%20through%20Overall%20Equipment%20Effectiveness%20and%20Total%20Preventive%20Maintenance%20Approach.pdf
33) Nwankwo, C.O., Okpala, C.C. and Igbokwe, N.C. (2024b) 'Enhancing smart manufacturing supply chains through cybersecurity measures. *International Journal of Engineering Inventions*, 13(12), pp. 01–06. https://www.ijeijournal.com/papers/Vol13-Issue12/13120106.pdf
34) Ogbodo, I.F., Okpala, C.C. and Egwuagu, O.M. (2026) 'From lean waste to measurable sustainability: Data-driven optimization in smart manufacturing', *International Journal of Technology, Health and Sustainability*, 2(2), pp. 523–532. https://ijths.com/wp-content/uploads/IJTHS-0202020.pdf
35) Ohno, T. (1988) *Toyota production system: Beyond large-scale production*. Productivity Press.
36) Okpala, C.C. (2013a) 'The status of lean manufacturing initiatives in the UK small and medium sized enterprises – A survey', *International Journal of Engineering Research and Technology*, 2(10), pp. 1832–1851. http://www.ijert.org/view-pdf/5761/the-status-of-lean-manufacturing-initiatives-in-the-uk-small-and-medium-sized-enterprises--a-survey
37) Okpala, C.C. (2013b) 'The world's best practice in manufacturing', *International Journal of Engineering Research and Technology*, 2(10), pp. 1812-1831. http://www.ijert.org/view-pdf/5760/the-worlds-best-practice-in-manufacturing
38) Okpala, C.C. and Anozie, S.C. (2018) 'Overall equipment effectiveness and the six big losses in total productive maintenance', *Journal of Scientific and Engineering Research*, 5(4), pp. 156-164. https://jsaer.com/download/vol-5-iss-4-2018/JSAER2018-05-04-156-164.pdf
39) Okpala, C.C., Chukwumuanya, E.O. and Nwankwo, C.O. (2024b) 'Kaizen techniques' implementation in a nail manufacturing company: A case study', *International Journal of Engineering Research and Development*, 20(7), pp. 488-494. https://www.ijerd.com/paper/vol20-issue7/2007488494.pdf
40) Okpala, C.C., Ezeanyim, O.C. and Nwamekwe, C.O. (2024a) 'The implementation of Kaizen principles in manufacturing processes: A pathway to continuous improvement', *International Journal of Engineering Inventions*, 13(7), pp. 116-124. http://www.ijeijournal.com/papers/Vol13-Issue7/1307116124.pdf
41) Okpala, C.C., Ezeanyim, O.C., Onukwuli, S.K., *et al.* (2026b) 'From Kaizen to digital continuous improvement: Linking lean practices with sustainability metrics', *International Journal of Technology, Health and Sustainability*, 2(1), pp. 300–310. https://ijths.com/wp-content/uploads/IJTHS-020188.pdf
42) Okpala, C.C., Nwamekwe, C.O. and Onukwuli, S.K. (2026a) 'Ergonomics in the age of Industry 5.0: A multilevel data analytics approach linking human-robot collaboration, cognitive load, and productivity in smart manufacturing systems', *International Journal of Engineering Research and Development*, 22(3), pp. 59–70. https://www.ijerd.com/paper/vol22-issue3/22035970.pdf
43) Okpala, C.C., Nwankwo, C.O. and Onu, C.E. (2020a) 'Lean production system implementation in an original equipment manufacturing company: Benefits, challenges, and critical success factors', *International Journal of Engineering Research and Technology*, 9(7), pp. 1665–1672. https://www.ijert.org/volume-09-issue-07-july-2020
44) Okpala, C.C., Ogbodo, I.F., Igbokwe, N.C., *et al.* (2020b) 'The implementation of Kaizen manufacturing technique: A case of a tissue manufacturing company', *International Journal of Engineering Science and Computing*, 10(5), pp. 25938-25949. http://ijesc.org/articles-in-press.php?msg=1andpage=article
45) Onukwuli, S.K., Okpala, C.C. and Udu, C.E. (2025) 'The role of additive manufacturing in advancing lean production system', *International Journal of Latest Technology in Engineering, Management and Applied Science*, 14(3), pp. 179–188. https://doi.org/10.51583/IJLTEMAS.2025.140300022
46) Porter, M.E. and van der Linde, C. (1995) 'Toward a new conception of the environment–competitiveness relationship', *Journal of Economic Perspectives*, 9(4), pp. 97–118. https://doi.org/10.1257/jep.9.4.97
47) Shadish, W.R., Cook, T.D. and Campbell, D.T. (2002) *Experimental and quasi-experimental designs for generalized causal inference*. Houghton Mifflin.
48) Shah, R. and Ward, P.T. (2007) 'Defining and developing measures of lean production', *Journal of Operations Management*, 25(4), pp. 785–805. https://doi.org/10.1016/j.jom.2007.01.019
49) Sony, M. (2020) 'Industry 4.0 and lean management: A proposed integration model', *Production and Manufacturing Research*, 8(1), pp. 1–23. https://doi.org/10.1080/21693277.2019.1646908
50) Stock, T. and Seliger, G. (2016) 'Opportunities of sustainable manufacturing in Industry 4.0', *Procedia CIRP*, 40, pp. 536–541. https://doi.org/10.1016/j.procir.2016.01.129
51) Tortorella, G.L., Giglio, R. and van Dun, D.H. (2021) 'Industry 4.0 adoption as a moderator of the impact of lean practices on operational performance', *Journal of Manufacturing Technology Management*, 32(2), pp. 335–356. https://doi.org/10.1108/JMTM-01-2020-0015
52) Trist, E.L. and Bamforth, K.W. (1951) 'Some social and psychological consequences of the longwall method of coal-getting', *Human Relations*, 4(1), pp.3–38. https://doi.org/10.1177/001872675100400101
53) Udu, C.E., Okpala, C.C. and Nwamekwe, C.O. (2025) 'Human-centric design integration in Industry 5.0: A framework for resilient smart manufacturing', *International Journal of Industrial and Production Engineering*, 3(4), pp. 18–33. https://journals.unizik.edu.ng/ijipe/article/view/6772
54) UNIDO (2022) *Industrial development report 2022*. United Nations Industrial Development Organization.
55) Wang, S., Wan, J., Li, D., *et al.* (2016) 'Implementing smart factory of Industry 4.0', *International Journal of Distributed Sensor Networks*, 12(1), 3159805. https://doi.org/10.1155/2016/3159805
56) WRI and WBCSD (2015) *The greenhouse gas protocol: A corporate accounting and reporting standard*. World Resources Institute, and World Business Council for Sustainable Development.