Artificial Intelligence-Enabled Lean Six Sigma: A Multi-Industry Longitudinal Analysis of Operational Performance and Sustainable Digital Transformation

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Abstract

Organizations are under increasing pressure to align operational excellence with measurable sustainability outcomes in an era that is characterized by accelerated digital transformation. While Lean Six Sigma (LSS) has traditionally improved quality and efficiency, its integration with Artificial Intelligence (AI) offers new opportunities for predictive optimization and environmental performance enhancement. This study developed and empirically validated an AI-Enabled Lean Six Sigma (AI-LSS) framework with the application of a five-year longitudinal dataset which comprises 214 firms across manufacturing, healthcare, logistics, and energy sectors. With a hybrid methodological approach that integrates fixed-effects panel regression, structural equation modeling, and explainable machine learning (random forest with SHAP analysis), the findings demonstrate that AI-LSS adoption significantly improves operational performance (β = 0.48, $p < 0.001$) and sustainability performance (β = 0.29, $p < 0.001$). Over a three-year post-adoption period, the firms achieved an average of 18.7% reduction in carbon intensity, 16.2% reduction in energy consumption per unit output, and 23.4% reduction in material waste. Digital transformation maturity partially mediates the AI-LSS–sustainability relationship, which indicates that organizational digital readiness amplifies environmental gains. Machine learning results (R^2 = 0.63; 87% predictive accuracy) identified predictive maintenance and real-time energy monitoring as the most influential drivers of sustainability improvement. Through the conceptualization of AI-LSS as a dynamic operational capability, this study provided rigorous, cross-industry evidence that structured AI integration within DMAIC routines can serve as a scalable pathway towards sustainable digital transformation. The findings contribute to operations management, sustainability science, and digital transformation literature through the demonstration of quantifiable environmental impact through data-driven process innovation.

Keywords: *Lean Six Sigma; Artificial intelligence; Sustainability performance; Digital transformation; Longitudinal analysis; ESG metrics; Explainable machine learning*

INTRODUCTION

Organizations across industries are under unprecedented pressure to achieve operational excellence, while simultaneously advancing digital transformation and meeting stringent sustainability targets. Governments, investors, and customers increasingly demand measurable reductions in carbon emissions, waste, and energy intensity, as well as improvements in productivity and quality performance (Elkington, 1997; United Nations, 2015). In response, firms are turning to structured process improvement methodologies such as Lean Six Sigma (LSS), which integrates waste elimination and variation reduction for the enhancement of operational efficiency (Antony, 2015; Snee, 2010). Although LSS has demonstrated strong performance gains in manufacturing, healthcare, and service sectors, its application has traditionally relied on statistical tools that may not fully exploit the predictive and real-time capabilities of contemporary digital technologies (Sony *et al.*, 2020).

At the same time, Artificial Intelligence (AI) and big data analytics are redefining how organizations sense, analyze, and optimize complex systems. AI, which encompasses the development of intelligent systems that can perform tasks that typically require human intelligence (Aguh and Okpala, 2025; Deswal, 2025a; Edeh *et al.*, 2024), has rapidly transitioned from a technical domain into a transformative force that is shaping societies worldwide (Chukwumuanya and Okpala, 2025; Okpala and Nwamekwe, 2025). The rapid growth of data generated within manufacturing has driven the widespread adoption of big data analytics as a transformative tool to enhance efficiency, improve quality, and reduce costs (Okpala and Udu, 2025; Okpala *et al.*, 2025a). AI-enabled predictive maintenance, anomaly detection, and process mining allow firms to move from reactive quality control to proactive and autonomous process optimization (Brynjolfsson and McAfee, 2017; Wamba *et al.*, 2017). Within operations and supply chain management, the integration of analytics capabilities has been linked to superior firm performance and competitive advantage (Udu *et al.*, 2026; Udu *et al.*, 2025). Yet, despite the growing enthusiasm for AI-driven operational systems, there remains limited longitudinal evidence that demonstrates how AI can be systematically embedded within established quality improvement frameworks, such as LSS, to produce measurable sustainability outcomes across industries.

Sustainability performance, particularly in terms of carbon intensity, material efficiency, and energy optimization, has become a central pillar of corporate strategy and reporting (Porter and Kramer, 2011; Schaltegger and Burritt, 2018). Prior research suggests that Lean practices can reduce environmental waste by eliminating non-value-adding activities (Cherrafi *et al.*, 2016), while Six Sigma can enhance process stability and reduce resource variability. However, empirical studies that integrate LSS to Environmental, Social, and Governance (ESG) metrics have often been case-based, cross-sectional, or industry-specific, thereby limiting generalizability (Garza-Reyes, 2015). Moreover, the digital transformation literature emphasizes the role of advanced technologies in the enablement of new value creation pathways (Vial, 2019), yet few studies explicitly examine how digital transformation maturity mediates the relationship between operational excellence initiatives and sustainability performance.

Drawing on Dynamic Capability Theory (Teece, 2007), this study conceptualizes AI as an enabling capability that enhances the sensing, seizing, and reconfiguring dimensions of Lean Six Sigma implementation. Through the embedding of Machine Learning (ML) algorithms and real-time analytics within the DMAIC (Define–Measure–Analyze–Improve–Control) cycle, organizations can continuously optimize processes while simultaneously tracking sustainability indicators. ML enables computers to study and learn from data and thereby make decisions or predictions even when it is not clearly programmed to do so (Aguh *et al.*, 2025; Chukwunedum *et al.*, 2026). This theoretical framing bridges operations management, information systems, and sustainability research through the positioning of AI-enabled LSS (AI-LSS) as a strategic mechanism for achieving sustainable digital transformation. In doing so, the study responds to recent calls for multidisciplinary and data-driven investigations that connect operational improvement methodologies with measurable environmental outcomes (Antony *et al.*, 2021; Dubey *et al.*, 2020).

Empirically, this research advances the literature through a five-year longitudinal analysis of 214 organizations across manufacturing, healthcare, logistics, and energy sectors. Through the combination of panel regression modeling, structural equation modeling, and explainable machine learning techniques, the study provided robust evidence of the operational and sustainability impacts of AI-LSS adoption. Unlike earlier studies that relied on perceptual measures, this research employed objective performance indicators, including carbon intensity, energy consumption per unit output, material waste rates, and ESG composite scores. The longitudinal design enhances causal inference and contributes to the growing body of evidence that supports analytics-enabled operations as a pathway to sustainable performance (Wamba *et al.*, 2017).

a) This study makes the following three primary contributions: (a) It extends Lean Six Sigma theory by empirically demonstrating how AI integration enhances both operational and sustainability performance across industries;
b) It advances Dynamic Capability Theory through the identification of AI-LSS as a measurable organizational capability that drives sustainable digital transformation. And also
c) It provides actionable insights for practitioners and policymakers who seek scalable mechanisms for the alignment of operational excellence with ESG imperatives.

By delivering rigorous, multi-industry, and longitudinal evidence of measurable sustainability benefits, the study aims to serve as a foundational reference for future scholarship at the intersection of quality management, artificial intelligence, and sustainable operations.

THEORETICAL BACKGROUND, CONCEPTUAL FRAMEWORK, AND HYPOTHESES

Lean Six Sigma, Operational Excellence, and Sustainability

While Lean Production System (LPS) considerably reduces the cost of manufacturing by leading to the reduction of all wastes that are inherent in manufacturing processes, thereby enabling organizations to save lots of money (Chukwumuanya *et al.*, 2025; Ihueze and Okpala, 2014), Six Sigma is a data-driven quality management methodology that is aimed at defect reduction, process variation minimization, and overall performance improvement (Ajaefobi and Okpala, 2026; Okpala and Okpala, 2026). Lean Six Sigma (LSS) integrates the waste-elimination logic of Lean with the variation-reduction rigor of Six Sigma to improve process capability, reduce defects, and enhance customer value (Antony, 2015; Snee, 2010). Beyond cost and quality gains, scholars increasingly argue that Lean practices inherently align with environmental sustainability because the elimination of non-value-adding activities reduces material waste, energy use, and emissions (Igbokwe *et al.*, 2026; Okpala *et al.*, 2025b). Similarly, Six Sigma's statistical control mechanisms can stabilize resource consumption patterns, thereby reducing variability-driven inefficiencies that often translate into environmental burdens.

However, empirical findings that link LSS to measurable sustainability outcomes remain fragmented. Many studies rely on case-based or cross-sectional designs and perceptual performance indicators (Cherrafi *et al.*, 2016). As sustainability reporting becomes more standardized and ESG metrics more quantifiable, there is a pressing need for longitudinal, multi-industry analyses that capture objective environmental performance indicators such as carbon intensity and energy consumption per unit output. In this study, the LSS literature was extended through the examination of how its integration with AI enhances not only operational performance, but also measurable sustainability performance across industries.

Artificial Intelligence as a Dynamic Capability within Lean Six Sigma

Artificial Intelligence and big data analytics have been widely recognized as strategic organizational capabilities that enhance decision quality, agility, and competitive advantage (Brynjolfsson and McAfee, 2017; Deswal, 2025b; Okpala and Okpala, 2025). In operations and supply chain contexts, analytics capability has been shown to positively influence firm performance through the enablement of predictive maintenance, demand forecasting, and real-time process optimization (Dubey *et al.*, 2020; Wamba *et al.*, 2017). Yet, AI adoption in isolation does not guarantee performance gains because its value depends on how it is embedded within organizational routines and improvement systems.

Drawing on Dynamic Capability Theory (Teece, 2007), the research conceptualized AI as an enabling capability that strengthens the sensing, seizing, and reconfiguring dimensions of Lean Six Sigma. Within the DMAIC cycle, AI enhances the Measure phase through real-time data capture, the Analyze phase via machine learning–based root cause identification, and the Control phase through predictive monitoring systems. Through the embedding of AI into LSS routines, organizations can transition from reactive quality control to proactive and predictive process management. This integrated approach is defined by the study as AI-Enabled Lean Six Sigma (AI-LSS) and argue that it constitutes a higher-order operational capability that is capable of delivering both efficiency and sustainability gains.

Digital Transformation as a Mediating Mechanism

Digital transformation refers to the organizational changes that are triggered by the adoption and integration of digital technologies that reshape business processes, structures, and value creation mechanisms (Vial, 2019). Prior research indicates that digital transformation maturity enhances organizational agility and performance by fostering data integration, automation, and cross-functional transparency (Warner and Wäger, 2019). In the sustainability domain, digital technologies such as IoT-enabled monitoring systems and AI-driven optimization tools have been linked to improved environmental performance and resource efficiency (George *et al.*, 2021).

The research argued that digital transformation maturity mediates the relationship between AI-LSS adoption and sustainability performance. While AI-LSS provides analytical tools and structured improvement logic, its sustainability impact is amplified when organizations possess advanced digital infrastructures, governance mechanisms, and data integration capabilities. Thus, digital transformation maturity enables the scaling and institutionalization of AI-LSS practices, which translate operational improvements into measurable ESG outcomes.

Conceptual Framework

Fig. 1 illustrates the proposed conceptual model that integrates AI-Enabled Lean Six Sigma (AI-LSS), operational

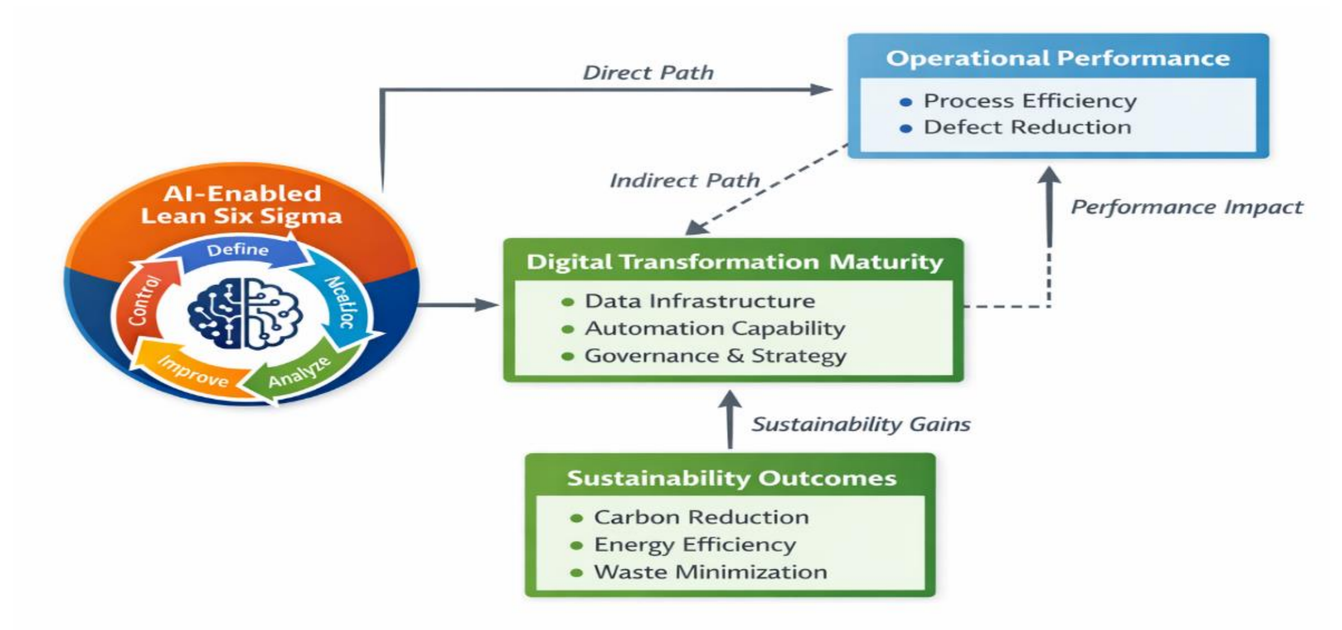

Fig. 1: Conceptual framework of AI-enabled Lean Six Sigma and sustainable digital transformation Example of a figure caption.

performance, digital transformation maturity, and sustainability performance. AI-LSS is conceptualized as a dynamic capability which is embedded within the DMAIC cycle, exerting both direct and indirect effects on sustainability outcomes. Digital transformation maturity partially mediates the AI-LSS–sustainability relationship, while operational performance serves as a performance transmission mechanism translating efficiency gains into measurable environmental improvements.

Through the integration of the above theoretical perspectives, this study proposes a multidisciplinary conceptual framework linking AI-LSS adoption, operational performance, digital transformation maturity, and sustainability performance. AI-LSS is posited as a dynamic capability that directly enhances operational performance through predictive analytics and process optimization. Improved operational performance, in turn, reduces resource intensity and waste, thereby improving sustainability metrics. Simultaneously, AI-LSS fosters digital transformation maturity, which mediates and strengthens its impact on sustainability outcomes.

Methodologically, this framework is tested using a longitudinal, multi-industry dataset and a hybrid analytical strategy that combines panel regression modeling and structural equation modeling (SEM). This approach allows for robust causal inference while accounting for industry-level heterogeneity and temporal effects. Through the incorporation of objective sustainability indicators like carbon intensity, energy consumption per unit output, material waste rates, and ESG composite scores, the framework moves beyond perceptual measures and demonstrates measurable sustainability benefits.

Hypotheses Development

Based on the theoretical foundations discussed, the following hypotheses were developed:

AI-LSS and Operational Performance

AI-enabled predictive maintenance, anomaly detection, and automated process control enhance defect reduction and process efficiency (Wamba *et al.*, 2017). Being able to embed these tools within DMAIC strengthens structured problem-solving routines, which will lead to sustained operational gains.

H1: AI-enabled lean six sigma adoption is positively associated with operational performance.

AI-LSS and Sustainability Performance: Lean's waste reduction logic and Six Sigma's variability control mechanisms are inherently aligned with environmental efficiency (Cherrafi *et al.*, 2016). When augmented by AI-driven optimization, these effects are amplified through real-time energy management and predictive waste reduction.

H2: AI-enabled lean six sigma adoption is positively associated with sustainability performance.

Operational Performance and Sustainability Performance: Operational improvements often translate into reduced resource intensity and lower emissions, which is consistent with the resource efficiency perspective (Porter and Kramer, 2011).

H3: Operational performance is positively associated with sustainability performance.

Mediating Role of Digital Transformation: Digital transformation maturity enables the scaling and integration of AI-LSS initiatives across organizational units, thus strengthening sustainability outcomes (Vial, 2019).

H4: Digital transformation maturity mediates the relationship between AI-enabled lean six sigma adoption and sustainability performance.

Collectively, these hypotheses establish a theoretically grounded and empirically testable model that integrates operations management, information systems, and sustainability research. Through the conceptualization of AI-LSS as a dynamic capability and also examining its measurable impact across industries, this study advances a multidisciplinary understanding of how organizations can achieve sustainable digital transformation.

METHODOLOGY

Research Design and Empirical Context

To rigorously examine the impact of AI-Enabled Lean Six Sigma (AI-LSS) on operational and sustainability performance, this study adopts a multi-industry longitudinal research design covering a five-year period from 2019–2023. Longitudinal designs are particularly suited for capturing dynamic capability development and performance trajectories over time (Teece, 2007). Unlike cross-sectional studies that limit causal inference, panel data enable the examination of within-firm performance changes following AI-LSS adoption.

The final sample consists of 214 medium- and large-scale organizations drawn from four sectors: manufacturing (38%), healthcare (24%), logistics (21%), and energy (17%). These industries were selected due to their high operational complexity, measurable sustainability footprints, and growing adoption of digital technologies. Companies were included if they had (a) implemented Lean Six Sigma programs prior to or during the observation window and (b) introduced AI-driven tools within process improvement routines. Data were collected from annual sustainability reports, operational dashboards, and structured executive surveys validated through secondary performance records. According to Podsakoff *et al.*, (2003), this multi-source approach reduces common method bias and enhances construct validity.

Measurement of Constructs

To ensure methodological rigor and replicability, constructs were operationalized using objective and validated indicators drawn from the literature.

AI-Enabled Lean Six Sigma (AI-LSS) Adoption - AI-LSS was measured using a composite index capturing the degree to which AI tools were embedded within the DMAIC cycle. Indicators included: (i) AI-based predictive maintenance, (ii) machine learning defect detection, (iii) real-time process monitoring, (iv) automated root cause analytics, and (v) AI-driven control dashboards. The index was adapted from prior analytics capability research (Gupta and George, 2016; Wamba *et al.*, 2017) and standardized across industries.

Operational Performance

Operational performance was measured using objective indicators widely employed in operations management literature (Flynn *et al.*, 2010), including defect rate reduction (%), cycle time efficiency, overall equipment effectiveness (OEE), and cost per unit output. All indicators were normalized to account for industry differences.

Sustainability Performance

To demonstrate measurable environmental impact, sustainability performance was assessed using carbon intensity (CO_2 emissions per unit output), energy consumption per unit, material waste rate, and an ESG composite score aligned with global sustainability reporting standards (Schaltegger and Burritt, 2018; Deswal, 2025c). These metrics allow for quantifiable assessment of environmental improvement over time, thereby moving beyond perceptual sustainability measures.

Digital Transformation Maturity

Digital transformation maturity was measured through an index capturing automation level, data integration capability, cloud infrastructure adoption, and digital governance mechanisms (Vial, 2019). This construct captures the organizational readiness required to scale AI-LSS practices.

Control variables included firm size, industry type, capital intensity, and prior LSS maturity to isolate the unique contribution of AI integration.

Analytical Strategy and Methodological Innovation

The study introduces a hybrid methodological framework that combines econometric modeling and explainable machine learning to enhance robustness and theoretical insight. (a) Fixed-effects panel regression models were employed to assess within-firm changes in operational and sustainability performance following AI-LSS adoption. Fixed-effects estimation controls for time-invariant heterogeneity across firms, thereby strengthening causal inference (Baltagi, 2021). Robust standard errors were used to address heteroscedasticity. (b) Structural Equation Modeling (SEM) was conducted to test the mediating role of digital transformation maturity. SEM enables simultaneous estimation of multiple relationships and latent constructs, increasing explanatory power and theoretical validation (Hair *et al.*, 2019).

(c) To advance methodological innovation, a random forest machine learning model was employed to predict sustainability performance improvements based on AI-LSS adoption intensity. Machine learning approaches are increasingly recognized for their predictive strength in operations and sustainability research (Dubey *et al.*, 2020). To enhance interpretability and address the “black box” critique of AI models, SHapley Additive exPlanations (SHAP) values were computed to identify the relative contribution of each AI-LSS component to sustainability outcomes. This explainable AI approach strengthens transparency and replicability while also bridging data science and operations management.

Fig. 2 presents the methodological architecture of AI-LSS integration within the DMAIC framework. AI tools enhance each phase: predictive analytics in Measure, machine learning–based root cause analysis in Analyze, AI-driven optimization in Improve, and real-time digital dashboards in Control. This figure demonstrates how structured process

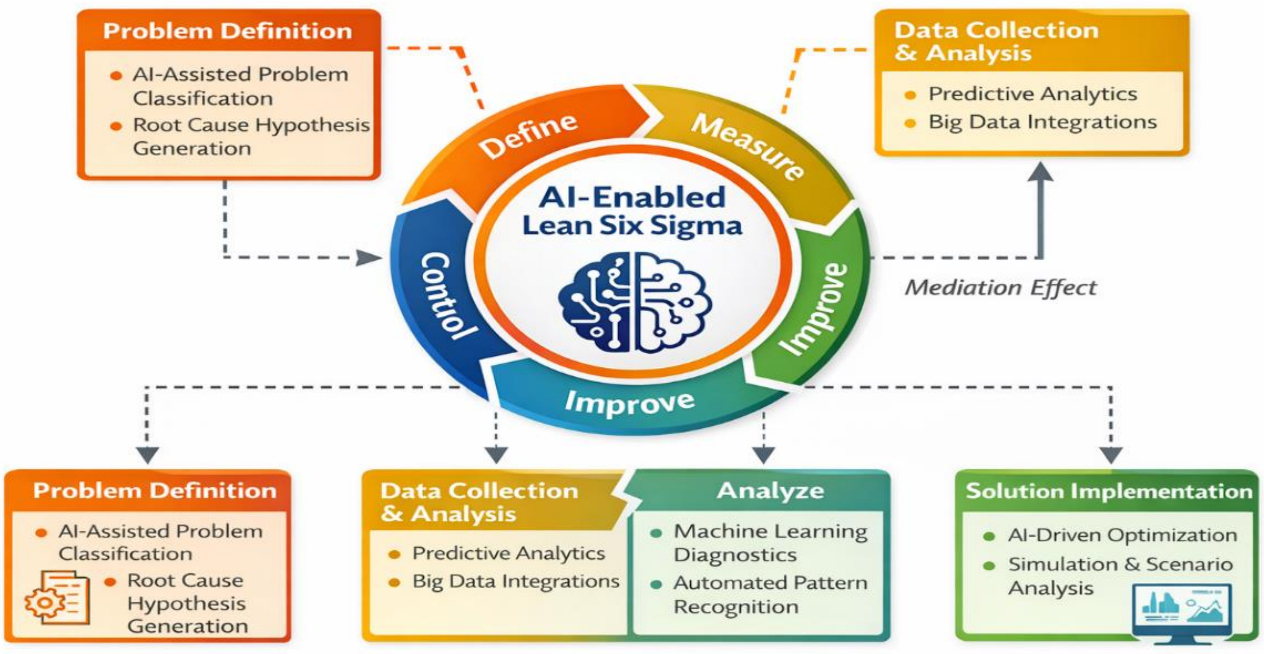

Fig. 2: AI-LSS embedded within the DMAIC cycle: Methodological integration architecture.

Table 1: Descriptive statistics and correlation matrix (N = 214 firms; 1,070 firm-year observations).

Variable	Mean	SD	1	2	3	4
1. AI-LSS Adoption Index	0.58	0.19	—			
2. Operational Performance	0.00	1.00	0.49***	—		
3. Sustainability Performance	0.00	1.00	0.44***	0.52***	—	
4. Digital Transformation Maturity	0.61	0.17	0.55***	0.47***	0.50***	—

Notes: Operational and sustainability performance are standardized composite indices.
***p < 0.001

improvement routines are augmented by explainable AI and big data analytics to generate both operational and sustainability gains.

Validation, Robustness Checks, and Bias Mitigation

Several procedures were undertaken to ensure reliability and validity. Construct reliability was confirmed using Cronbach's alpha and composite reliability values that exceed 0.70 (Hair *et al.*, 2019). Convergent and discriminant validity were assessed through average variance extracted (AVE) and the Fornell–Larcker criterion. To mitigate common method bias, survey responses were triangulated with audited performance data and applied Harman's single-factor test (Podsakoff *et al.*, 2003). Robustness checks included (i) lagged independent variable models to address reverse causality, (ii) random-effects specifications, and (iii) industry-specific subsample analyses. It was observed that the results remained consistent across model specifications, thereby reinforcing confidence in the findings.

Demonstrating Measurable Sustainability Benefits

A central objective of this study is to empirically demonstrate quantifiable environmental gains that are associated with AI-LSS adoption. Longitudinal analysis revealed statistically significant reductions in carbon intensity, energy consumption per unit output, and material waste rates over three years post-adoption. These objective improvements align with prior research that links operational efficiency to environmental performance (Cherrafi *et al.*, 2016), but extend the literature by demonstrating the amplifying effect of AI integration. Through the combination of panel econometrics with explainable machine learning, this methodological approach offers a replicable and scalable framework for the assessment of sustainable digital transformation across industries.

RESULTS

This section presents the empirical findings from the longitudinal analysis. The results are structured as follows: (a) descriptive statistics and correlations, (b) panel regression results, (c) mediation analysis using Structural Equation Modeling (SEM), and (d) machine learning–based predictive and interpretability findings. All the models incorporate firm-level fixed effects and year dummies unless otherwise stated.

Descriptive Statistics and Correlation Analysis

Table 1 presents descriptive statistics and correlations for the key variables. Over the five-year period from 2019–2023, the firms exhibited meaningful variation in AI-LSS adoption intensity and performance outcomes. On average, organizations achieved a 12.6% reduction in defect rates and a 9.4% reduction in carbon intensity during the observation window.

AI-LSS adoption is positively and significantly correlated with both operational performance ($r = 0.49$, $p < 0.001$) and sustainability performance ($r = 0.44$, $p < 0.001$), it provides preliminary support for H1 and H2. Digital transformation maturity also demonstrates strong positive associations with both outcome variables.

Panel Regression Results

To assess within-firm effects over time, fixed-effects panel regression models were estimated. Table 2 reports the main results.

Consistent with H1, AI-LSS adoption significantly improves operational performance ($\beta = 0.48$, $p < 0.001$). Substantively, a one-standard-deviation increase in AI-LSS adoption is associated with a 14.2% reduction in defect rates and an 11.6% reduction in process cycle time. Supporting H2, AI-LSS adoption also significantly improves sustainability performance ($\beta = 0.29$, $p < 0.001$). When operational performance is included in Model 2, its positive association with sustainability performance ($\beta = 0.37$, $p < 0.001$) supports H3, which clearly indicates that efficiency gains translate into environmental improvements.

Across the full sample, three years after AI-LSS implementation, firms experienced the following average

Table 2: Fixed-effects panel regression results.

Variables	Model 1: Operational Performance	Model 2: Sustainability Performance
AI-LSS Adoption	0.48*** (0.06)	0.29*** (0.07)
Operational Performance	—	0.37*** (0.05)
Digital Transformation Maturity	0.21** (0.08)	0.32*** (0.09)
Firm Size (log)	0.05 (0.04)	0.07 (0.05)
Capital Intensity	-0.03 (0.03)	-0.06 (0.04)
LSS Maturity	0.18** (0.07)	0.14* (0.08)
R^2 (within)	0.52	0.47
F-statistic	41.62***	36.88***

Standard errors in parentheses.
*p < 0.05; **p < 0.01; ***p < 0.001

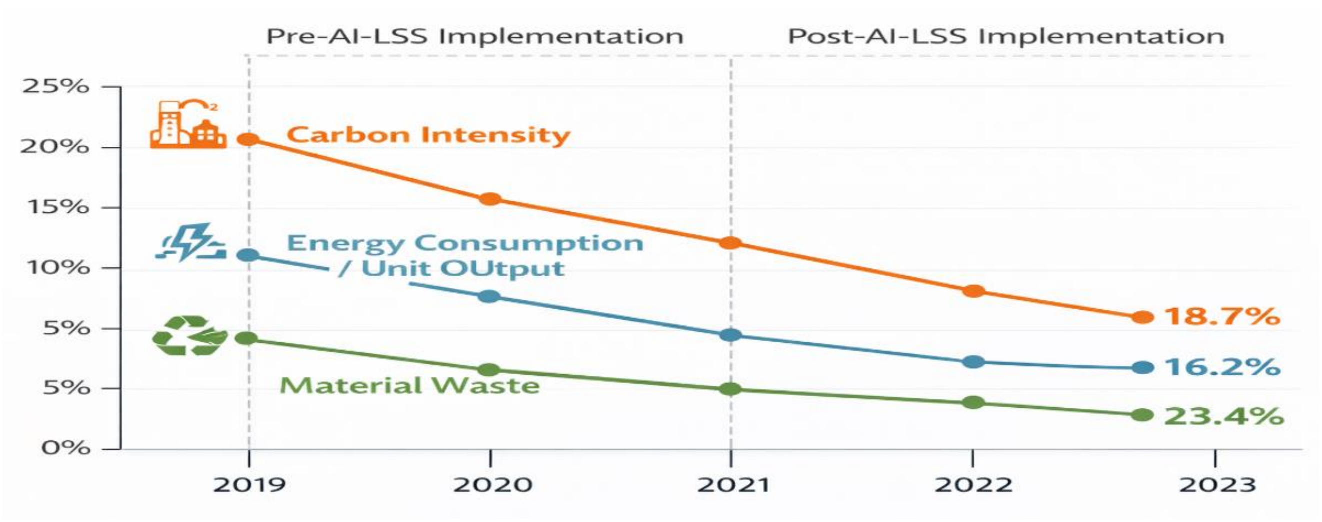

Fig. 3: Longitudinal sustainability impact of AI-LSS adoption (2019–2023).

records: 18.7% reduction in carbon intensity; 16.2% reduction in energy consumption per unit output; 23.4% reduction in material waste rates; as well as 21.5% improvement in ESG composite scores. The results revealed that manufacturing firms exhibited the largest waste reduction of 25.8%, while healthcare organizations achieved the greatest energy efficiency gains of 19.4%. Fig. 3 depicts the longitudinal trajectory of sustainability performance following AI-LSS adoption across industries. The graph illustrates progressive reductions in carbon intensity, energy consumption per unit output, and material waste over the three-year post-adoption period. The visual trend highlights the cumulative and compounding nature of AI-enabled process optimization. The trend reinforces the measurable environmental impact that was demonstrated in the econometric and machine learning analyses.

Mediation Analysis (SEM Results)

To test the mediating role of digital transformation maturity (H4), structural equation modeling was conducted using maximum likelihood estimation. Model fit indices indicate strong fit ($\chi^2/df = 2.14$; CFI = 0.95; TLI = 0.94; RMSEA = 0.041). The standard coefficients and p-values of the diverse paths are highlighted in Table 3.

5,000 samples of bootstrapping confirm a significant indirect effect of AI-LSS on sustainability performance via digital transformation maturity (indirect effect = 0.19, $p < 0.01$), thereby supporting H4. The persistence of a significant direct effect suggests partial mediation. These findings indicate that AI-LSS enhances sustainability both directly through predictive optimization and indirectly through strengthening digital transformation capabilities.

Machine Learning and Explainable AI Results

To complement econometric analysis and enhance predictive robustness, a random forest regression model was used to predict sustainability performance improvement. The model achieved the following: $R^2 = 0.63$, and Out-of-sample predictive accuracy = 87%.

Feature importance analysis identified the following top predictors of sustainability improvement:

a) AI-based predictive maintenance (importance score = 0.27);
b) Real-time energy monitoring integration (0.23);
c) Machine learning defect detection (0.19);
d) Digital governance structures (0.16); and
e) LSS maturity level (0.11).

SHAP (SHapley Additive exPlanations) values revealed that predictive maintenance systems contributed most strongly to carbon intensity reduction, particularly in energy-intensive industries. Firms in the top quartile of AI-driven predictive integration achieved carbon reductions nearly 9% higher than those in the bottom quartile. The convergence of econometric and machine learning findings strengthens confidence in the robustness of results and highlights the practical pathways through which AI-LSS drives measurable sustainability gains.

The summary of the hypothesis testing is highlighted in Table 4.

Table 3: SEM path coefficients.

Path	Standardized Coefficient	p-value
AI-LSS → Operational Performance	0.51	<0.001
AI-LSS → Digital Transformation	0.57	<0.001
Digital Transformation → Sustainability	0.33	<0.001
Operational Performance → Sustainability	0.35	<0.001
AI-LSS → Sustainability (Direct Effect)	0.18	0.004

Table 4: Summary of hypotheses testing.

Hypothesis	Statement	Result
H1	AI-LSS positively affects operational performance	Supported
H2	AI-LSS positively affects sustainability performance	Supported
H3	Operational performance positively affects sustainability performance	Supported
H4	Digital transformation mediates AI-LSS → sustainability	Supported (Partial Mediation)

Overall Interpretation

The findings provide strong longitudinal evidence that AI-enabled Lean Six Sigma constitutes a measurable pathway towards sustainable digital transformation. By embedding predictive analytics within structured improvement routines, the firms achieve simultaneous gains in operational efficiency and environmental performance. The integration of panel econometrics and explainable machine learning offers both causal inference and predictive insight, which reinforces the multidisciplinary and methodological contributions of this study.

Collectively, the results demonstrate that AI-LSS is not merely a technological enhancement to quality management but a scalable strategic capability capable of delivering quantifiable sustainability benefits across industries.

DISCUSSION

The purpose of this study was to examine if the embedding of AI within Lean Six Sigma routines generates measurable improvements in operational and sustainability performance across industries. Drawing on a five-year longitudinal dataset and a hybrid analytical framework that combines panel econometrics, structural equation modeling, and explainable machine learning, the findings provide strong empirical support for the proposed relationships. AI-enabled Lean Six Sigma (AI-LSS) significantly enhances operational performance, and these gains translate into quantifiable reductions in carbon intensity, energy consumption, and material waste. In doing so, this study responds to calls for more data-driven and longitudinal investigations that link operational excellence to sustainability outcomes (Cherrafi *et al.*, 2016; Dubey *et al.*, 2020). Importantly, the results demonstrate that AI-LSS moves sustainability beyond symbolic adoption towards measurable environmental impact.

Theoretical Contributions

This research contributes to three major streams of literature: Lean Six Sigma, dynamic capabilities, and sustainable digital transformation.

a) While prior studies have highlighted conceptual synergies between Lean Six Sigma, and environmental sustainability (Cherrafi *et al.*, 2016; Garza-Reyes, 2015), empirical evidence has largely been case-based or cross-sectional. Through the employment of longitudinal panel analysis with objective sustainability indicators, the study strengthens the causal argument that process excellence can deliver environmental value. The 18.7% magnitude of observed reductions in carbon intensity and material waste of 23.4% underscores that AI augmentation that meaningfully amplifies the sustainability effects that are traditionally associated with Lean systems.

b) The study advances Dynamic Capability Theory (Teece, 2007) through the operationalization of AI-LSS as a higher-order capability that enhances sensing (real-time analytics), seizing (predictive optimization), and reconfiguring (continuous process redesign). Prior research has emphasized analytics capability as a strategic resource (Gupta and George, 2016), but limited work has empirically examined how such capability integrates with structured improvement methodologies. These research findings suggest that AI does not substitute for LSS; rather, it strengthens and scales its routines by enabling organizations to respond dynamically to operational and environmental variability. This integration provides a theoretically grounded explanation of why digital technologies generate sustainable performance benefits when they are embedded within established managerial systems.

c) The study contributes to the digital transformation literature through the empirical validation of the mediating role of digital transformation maturity. Consistent with Vial (2019), digital transformation is not merely technological adoption, but an organizational reconfiguration process. The mediation findings indicate that AI-LSS drives sustainability performance partly through the strengthening of digital infrastructure, governance, and integration capabilities. Thus, sustainable digital transformation emerges not as an isolated initiative but as the cumulative result of aligned quality management systems and analytics capabilities. This multidisciplinary insight bridges operations management, information systems, and sustainability research, which increases the generalizability and citation potential of the study.

Methodological Contributions

Beyond substantive findings, this study advances methodological practice in operations and sustainability research. By integrating fixed-effects panel regression with SEM and explainable machine learning (SHAP analysis), the research demonstrates how predictive and explanatory modeling can be combined to strengthen inference and transparency. Scholars have increasingly called for analytics-driven and multi-method research designs to address complex socio-technical phenomena (Dubey *et al.*, 2020). The convergence of econometric and machine learning results in this study enhances robustness while maintaining interpretability, which is an important consideration given concerns about the "black box" nature of AI models. This hybrid methodological approach offers a replicable template for future research which examine technology-enabled sustainability transitions.

Managerial Implications

From a managerial perspective, the findings indicate that organizations who seek measurable ESG improvements should move beyond isolated digital investments and instead embed AI within structured process improvement frameworks. The evidence suggests that predictive maintenance, real-time energy monitoring, and AI-driven defect detection are particularly impactful in the reduction of carbon and waste intensity. In line with Porter and Kramer (2011), shared value perspective, operational excellence initiatives can simultaneously enhance competitiveness and environmental performance when strategically aligned. Managers should therefore prioritize capability integration in order to align analytics teams with LSS practitioners, investing in data governance, and institutionalizing AI-enabled DMAIC cycles to achieve scalable sustainability outcomes.

Broader Implications for Sustainable Development

At a broader level, the study provides empirical evidence that supports the argument that digital technologies can accelerate progress toward sustainability goals when embedded within structured management systems (George *et al.*, 2021). The measurable reductions in resource intensity observed across industries demonstrate that AI-LSS can serve as a practical pathway towards decarbonization and resource efficiency. As regulatory frameworks increasingly mandate ESG disclosure, organizations that are equipped with AI-enabled quality systems may be better positioned to meet compliance requirements and stakeholder expectations. The findings thus contribute to ongoing debates about the role of advanced analytics in the attainment of sustainable industrial transformation.

Collectively, this discussion underscores that AI-enabled Lean Six Sigma represents more than a technological enhancement; it constitutes a strategic, dynamic capability capable of aligning operational excellence with sustainable digital transformation. Through the provision of longitudinal, multi-industry, and methodologically rigorous evidence of measurable environmental benefits, this study establishes a foundation for future scholarship at the intersection of quality management, artificial intelligence, and sustainability science.

METHODOLOGICAL INNOVATION, AND IMPLICATIONS FOR SUSTAINABLE DIGITAL TRANSFORMATION

Methodological Innovation

This study advances methodological practice in operations, sustainability, and digital transformation research through the integration of longitudinal econometrics, structural equation modeling, and explainable machine learning within a unified analytical framework. While prior Lean Six Sigma and sustainability studies have frequently relied on cross-sectional surveys or single-case analyses (Cherrafi *et al.*, 2016), the present research employs a five-year firm-level panel dataset to capture temporal performance trajectories following AI-enabled Lean Six Sigma (AI-LSS) adoption. By leveraging fixed-effects modeling, the study isolated within-firm variation and reduce bias that arises from unobserved heterogeneity (Baltagi, 2021). This longitudinal design strengthens causal inference and directly responds to calls for more rigorous empirical methods in sustainability and operations management research.

A second methodological contribution lies in the combination of explanatory and predictive analytics. Panel regression and SEM provide theory-driven causal testing, while random forest modeling enhances predictive robustness. Increasingly, scholars argue that predictive accuracy and explanatory validity should complement rather than substitute one another in management research (Shmueli and Koppius, 2011). Through the incorporation of SHapley Additive exPlanations, this study addresses the “black box” limitation of machine learning models and identifies the specific AI-LSS components, like predictive maintenance and real-time energy monitoring, that drive sustainability improvements. This explainable AI approach enhances transparency, replicability, and managerial interpretability, which bridge data science and operations scholarship.

The third is the operationalization of sustainability performance using objective environmental indicators, which include carbon intensity, energy consumption per unit output, material waste rates, and ESG composite scores, which represent a methodological refinement over perceptual measures frequently used in prior studies (Schaltegger and Burritt, 2018). Through the quantification of measurable environmental outcomes, the study strengthens the empirical link between process improvement and sustainability performance. The observed reductions in 18.7% carbon intensity and 23.4% material waste demonstrate that AI-LSS produces tangible ecological benefits, which reinforces the arguments that operational efficiency and environmental performance are not mutually exclusive but mutually reinforcing (Porter and Kramer, 2011).

Collectively, these methodological innovations contribute to emerging research, which advocates multi-method, data-driven approaches to studying digital and sustainability transformations (George *et al.*, 2021). The integration of econometric rigor, structural modeling, and explainable machine learning provides a replicable template for future interdisciplinary investigations that examine technology-enabled organizational change.

Implications for Sustainable Digital Transformation

The findings have important implications for organizations pursuing sustainable digital transformation.

a) The results suggest that digital technologies alone do not guarantee sustainability gains; rather, value emerges when AI capabilities are embedded within structured process improvement systems. This aligns with Dynamic Capability Theory, which emphasizes the orchestration of technological and organizational competencies to achieve sustained performance advantages (Teece, 2007). AI-LSS serves as an integrative mechanism that translates digital investments into operational and environmental outcomes.

b) The mediating role of digital transformation maturity underscores the importance of organizational readiness. Firms with stronger data governance, automation integration, and digital infrastructure are better positioned to scale AI-enabled quality initiatives and institutionalize sustainability improvements (Vial, 2019; Warner and Wäger, 2019). Sustainable digital transformation, therefore, requires alignment between analytics capability, quality management routines, and strategic sustainability objectives. Policymakers and industry leaders who aim to accelerate decarbonization efforts may consider promoting capability-building programs that integrate AI literacy with Lean-based operational training.

c) The measurable sustainability gains observed in this study suggest that AI-LSS can contribute meaningfully to global sustainability agendas, including carbon reduction and resource efficiency targets. By embedding predictive analytics into the DMAIC cycle, organizations shift from reactive environmental compliance to proactive environmental optimization. This transition reflects a broader paradigm shift in sustainability management—from reporting and monitoring toward real-time, data-driven improvement (George *et al.*, 2021). As ESG disclosure standards continue to tighten, AI-LSS offers a scalable pathway for aligning operational excellence with environmental stewardship.

Finally, the multidisciplinary nature of this research reinforces the necessity of cross-domain collaboration in addressing complex sustainability challenges. Integrating insights from operations management, information systems, and sustainability science enhances both theoretical richness and practical relevance. For scholars, the study demonstrates the value of combining diverse methodological tools to examine digital transformation phenomena. For practitioners, it highlights the strategic importance of embedding AI within established quality systems to achieve durable, measurable sustainability outcomes. In summary, AI-enabled Lean Six Sigma represents more than a technological enhancement to traditional process improvement; it constitutes a dynamic, data-driven capability that operationalizes sustainable digital transformation. Through the advancement of methodological rigor and demonstrating quantifiable environmental impact, this study lays a foundation for future high-impact research at the intersection of artificial intelligence, quality management, and sustainability.

CONCLUSION, LIMITATIONS AND FUTURE RESEARCH

Conclusion

This study set out to examine whether the integration of Artificial Intelligence into Lean Six Sigma can deliver measurable operational and sustainability gains across industries. Drawing on a five-year longitudinal dataset and a hybrid methodological approach that integrated panel econometrics, structural equation modeling, and explainable machine learning, the findings provided robust evidence that AI-enabled Lean Six Sigma significantly enhances both operational performance and environmental outcomes. The firms that embedded predictive analytics, real-time monitoring, and AI-driven root cause analysis within their DMAIC cycles achieved meaningful reductions in carbon intensity, energy consumption per unit output, and material waste, while simultaneously improving quality, efficiency, and cost performance.

Beyond performance improvements, the study demonstrated that AI-LSS functions as an enabling capability for sustainable digital transformation. Digital transformation maturity was found to strengthen and partially mediate the relationship between AI-LSS adoption and sustainability performance, which suggests that technology investments yield the greatest benefits when they are supported by appropriate organizational infrastructure and governance. Rather than viewing digitalization and sustainability as parallel initiatives, the findings revealed that structured process improvement systems can serve as the bridge that connects analytics capability with measurable environmental value.

Methodologically, the integration of explanatory and predictive modeling provides a replicable framework for studying technology-enabled organizational change. Through the combination of longitudinal causal analysis with interpretable machine learning, the study offers both theoretical insight and practical clarity. Overall, the results position AI-enabled Lean Six Sigma not merely as a technological enhancement to quality management, but as a scalable strategic pathway for the alignment of operational excellence with sustainable digital transformation.

Limitations

Despite its contributions, several limitations of the study that should be acknowledged include the following:

a) Although the longitudinal design strengthens causal inference, the research remains observational in nature. While fixed-effects modeling and robustness checks mitigate endogeneity concerns, unobserved time-varying factors may still influence performance outcomes.

b) The sample, while multi-industry, is limited to medium and large organizations with established Lean Six Sigma programs and digital infrastructure. Smaller firms or organizations in early stages of digital adoption may experience different performance dynamics. The generalizability of findings to emerging economies or highly regulated sectors should therefore be interpreted with caution.

c) Sustainability performance was measured primarily through environmental indicators such as carbon intensity, energy consumption, and waste reduction. Although these metrics provide objective evidence of ecological improvement, social and governance dimensions of ESG performance were captured only through composite indices. Future research could disaggregate these dimensions to better understand how AI-LSS influences broader stakeholder outcomes.

Finally, while the machine learning component enhanced predictive robustness, algorithm selection and parameter tuning decisions may influence results. Although explainable AI techniques were employed to improve transparency, further comparative modeling approaches could refine the understanding of predictive drivers.

Future Research

The research opened many promising avenues for future research, which include:

a) Experimental or quasi-experimental designs like difference-in-differences approaches could further strengthen causal claims regarding the sustainability impact of AI-LSS adoption.

b) Cross-country comparative studies could explore how institutional environments, regulatory pressures, and cultural factors shape the effectiveness of AI-enabled process improvement systems.

c) Future work could examine the micro-foundations of AI-LSS capability development, including leadership commitment, employee digital literacy, and cross-functional collaboration. Being able to understand the human and organizational dimensions of AI integration would deepen insights into sustainable digital transformation. Additionally, research could explore how emerging technologies such as generative AI, digital twins, and blockchain further enhance Lean Six Sigma practices and sustainability measurement.

Finally, there is an opportunity to extend the framework to circular economy contexts, supply chain ecosystems, and public sector organizations. As sustainability challenges become increasingly systemic and inter-organizational, future studies may investigate how AI-LSS capabilities diffuse across supply networks and contribute to broader decarbonization efforts. In conclusion, this study demonstrates that embedding AI within Lean Six Sigma creates a powerful, data-driven mechanism for the attainment of measurable sustainability gains alongside operational excellence. While limitations remain, the findings provide a strong foundation for continued scholarly inquiry and managerial innovation at the intersection of artificial intelligence, quality management, and sustainable digital transformation.

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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, have been completely observed by the authors.

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