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From Manufacturing Waste Reduction to Sustainable Smart Production: A Continuous Improvement Framework

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Abstract

Manufacturing firms are under growing pressure to simultaneously reduce waste, improve operational efficiency, and achieve measurable sustainability outcomes in increasingly digitalized production environments. While lean manufacturing and continuous improvement have historically delivered efficiency gains, their impact on environmental performance has often been indirect and difficult to sustain. In parallel, Industry 4.0 technologies have generated unprecedented volumes of production data, yet many organizations struggle to translate these data into actionable, sustainability-oriented improvements. This study addresses this gap by proposing and empirically validating a Chikwendu Continuous Improvement Framework (C-CIF) that systematically integrates waste reduction logic, sustainability performance measurement, and advanced data analytics within a closed-loop improvement system. Using a mixed-methods design science–oriented research approach, the framework was implemented and evaluated through multiple manufacturing case studies that represent discrete and process production contexts. The empirical analysis draws on more than four million time-stamped production and environmental data points collected over an 18-month period. Results demonstrate that C-CIF enables material waste reductions of 18–24%, energy intensity reductions of 12–19%, and process variability reductions that exceed 24%, alongside improvements in overall equipment effectiveness of more than 13 percentage points. Notably, these sustainability gains were achieved without major capital investments, which highlights the role of data-driven learning and predictive decision-making in cost-effective sustainability transformation. The study contributes to the literature through the advancement of continuous improvement theory towards predictive, sustainability-embedded decision-making and by offering a replicable framework that bridges manufacturing waste reduction and sustainable smart production. For practitioners and policymakers, the findings provide evidence that the integration of sustainability metrics directly into data-driven improvement cycles can align productivity, competitiveness, and environmental responsibility in modern manufacturing systems.

Keywords: *Sustainable manufacturing; Continuous improvement; Industry 4.0; Data analytics; Waste reduction, Smart production; Sustainability performance*

INTRODUCTION

Manufacturing systems sit at the center of the global sustainability challenge. On one hand, manufacturing drives economic growth, innovation, and employment; on the other, it accounts for a substantial share of global material consumption, energy use, and industrial emissions (IEA, 2023; UNIDO, 2022). As regulatory pressure, stakeholder expectations, and resource constraints intensify, manufacturers are increasingly expected to achieve environmental sustainability without compromising productivity, quality, or competitiveness.

Historically, manufacturing waste reduction has been pursued through lean manufacturing and Kaizen or Continuous Improvement (CI) philosophies. Lean principles like the elimination of defects, overproduction, overprocessing, waiting time, transportation, excess inventory, and unnecessary motion have delivered well-documented improvements in cost, quality, and operational efficiency (Onukwuli *et al.*, 2025; Chukwumuanya *et al.*, 2025a). Continuous improvement approaches, including Kaizen and Six Sigma, further institutionalized incremental, problem-driven learning within production systems (Okpala *et al.*, 2020; Okpala *et al.*, 2026). While these approaches have indirectly reduced environmental burdens, sustainability outcomes were rarely explicit design objectives, and performance measurement remained largely economic in nature (Garza-Reyes *et al.*, 2018).

Over the past decade, the concept of sustainable manufacturing has expanded the performance frontier through the explicit integration of environmental and social considerations alongside traditional economic metrics (Egwuagu *et al.*, 2026; Okpala *et al.*, 2025a). Indicators such as material efficiency, energy intensity, carbon emissions, and waste-to-output ratios are now widely adopted in both industry and policy contexts (Udu *et al.*, 2025a; Chukumuanya *et al.*, 2025b). However, sustainability assessments are often conducted at an aggregated or retrospective level, therefore limiting their ability to guide real-time operational decisions on the shop floor (Zhang *et al.*,2020). This disconnect between sustainability goals and day-to-day production control remains a persistent barrier to meaningful impact.

In parallel, manufacturing is undergoing a profound digital transformation driven by Industry 4.0 technologies, including industrial internet of things (IIoT), cyber–physical systems, advanced analytics, and artificial intelligence. These technologies enable continuous data collection from machines, processes, and products, creating unprecedented visibility into production behavior (Igbokwe *et al.*, 2024a; Chukwunedum *et al.*, 2026). Data-driven applications such as predictive maintenance, intelligent quality control, and digital twins have demonstrated measurable operational benefits (Ogboh *et al.*, 2026; Udu and Okpala, 2026a). Yet, much of this work remains functionally siloed, with limited integration into structured continuous improvement systems or explicit sustainability strategies (Buer *et al.*, 2018).

Recent studies have begun to explore the intersections of lean manufacturing, digitalization, and sustainability, which tend to suggest that their integration can generate synergistic benefits (Ogbodo *et al.*, 2026; Okpala, 2026a). Nevertheless, the literature remains fragmented. Many contributions focus on conceptual alignment rather than operational implementation, while empirical evidence that demonstrates measurable sustainability outcomes enabled by data-driven continuous improvement remains limited (Moyano-Fuentes *et al.*, 2021). In particular, there is a lack of practical, scalable frameworks that translate large volumes of production data into continuous, sustainability-oriented improvement actions. Against this backdrop, this study argues that the transition from manufacturing waste reduction to sustainable smart production requires a fundamental rethinking of how continuous improvement is designed and executed in data-rich environments. Rather than treat sustainability as an outcome of efficiency gains or digitalization as a standalone technological upgrade, sustainability must be embedded directly into data-driven improvement cycles.

Accordingly, this paper proposes a Chikwendu Continuous Improvement Framework (C-CIF) that systematically integrates lean waste reduction logic, Industry 4.0 data infrastructures, and sustainability performance measurement. The framework is empirically validated through multi-source production data and real-world manufacturing case studies, thereby demonstrating quantifiable reductions in material waste, energy intensity, and process variability. By doing so, this work addresses the following research question: How can manufacturing organizations leverage data-driven continuous improvement to transform waste reduction efforts into measurable, sustainable smart production outcomes?

The following are the threefold contributions of the study:

a. It advances theory by extending continuous improvement research toward predictive, sustainability-oriented decision-making;

b. It provides empirical evidence of measurable environmental and operational benefits enabled by data-driven improvement systems; and

c. It offers a replicable, multidisciplinary framework that supports both academic research and industrial practice in the pursuit of sustainable smart manufacturing.

LITERATURE REVIEW

This study builds on and integrates three major streams of literature:

(i) manufacturing waste reduction and continuous improvement,
(ii) sustainable manufacturing and performance measurement, and
(iii) data-driven and smart production that is enabled by Industry 4.0 technologies.

Reviewing these streams jointly reveals both complementarities and critical gaps that motivate the proposed framework.

Manufacturing Waste Reduction and Continuous Improvement

Manufacturing waste reduction has long been grounded in lean production philosophy, originating from the Toyota Production System and formalized through the identification and elimination of non-value-adding activities (Okpala, 2013; Okpala *et al.*, 2020). The seven classical wastes, which are defects, overproduction, waiting, transportation, inventory, motion, and overprocessing, have provided a powerful operational lens for efficiency improvement across manufacturing sectors.

Continuous improvement (CI) methodologies such as Kaizen, Total Quality Management, and Six Sigma institutionalized waste reduction as an ongoing, organization-wide learning process rather than a one-off intervention (Okpala *et al.*, 2024a; Okpala and Okpala, 2026). Empirical studies consistently show positive relationships between CI adoption and improvements in productivity, quality, and cost performance (Ezeanyim *et al.*, 2026a; Igbokwe *et al.*, 2026). However, these approaches are typically reactive, relying on historical data, manual audits, and localized problem-solving cycles.

Importantly, environmental sustainability has often been treated as a secondary outcome of efficiency gains rather than a primary objective of CI initiatives (Garza-Reyes *et al.*, 2018). As a result, traditional waste reduction approaches struggle to address complex sustainability challenges such as energy inefficiency, emissions variability, and resource depletion, which are dynamic and system-wide in nature.

Sustainable Manufacturing and Sustainability Performance Measurement

Sustainable manufacturing extends the scope of operational performance by explicitly incorporating environmental and social dimensions alongside economic outcomes (Nwamekwe *et al.*, 2024a; Ezanyim *et al.*, 2026). Frameworks such as the triple bottom line and life cycle thinking have influenced how manufacturing sustainability is conceptualized and assessed (Elkington, 1998). In practice, sustainability performance is commonly measured using indicators such as energy intensity, material efficiency, water usage, waste generation, and carbon emissions (OECD, 2021). These metrics have proven valuable for benchmarking and reporting purposes, especially in response to regulatory and stakeholder pressures. However, several scholars note that sustainability measurement remains largely disconnected from operational control and continuous improvement routines (Zhang *et al.*, 2020). Moreover, sustainability assessments are often conducted periodically and at aggregated levels, thus limiting their usefulness for the identification of root causes of inefficiency at the process or machine level (Jawahir and Bradley, 2016). This temporal and spatial disconnect constrains manufacturers' ability to translate sustainability objectives into actionable, day-to-day decisions.

Industry 4.0 and Data-Driven Smart Production

The advent of Industry 4.0 has transformed manufacturing systems into data-rich environments characterized by real-time connectivity, cyber–physical integration, and advanced analytics (Ajaefobi and Okpala, 2026; Igbokwe *et al.*, 2025b). Industrial Internet of Things (IIoT) devices, manufacturing execution systems, and digital twins enable continuous monitoring of machines, processes, and products throughout their life cycles (Udu *et al.*, 2025b; Okpala *et al.*, 2025b).

Data-driven techniques such as machine learning, predictive analytics, and statistical learning have demonstrated strong potential in applications like predictive maintenance, quality prediction, and energy optimization (Udu and Okpala, 2026b; Okpala, 2026b). From a sustainability perspective, recent studies suggest that digital technologies can contribute to energy efficiency, emission reduction, and resource optimization (Chukwunedum *et al.*, 2026b; Chukwumuanya *et al.*, 2025b). Despite these advances, much of the Industry 4.0 literature remains technologically oriented, with limited integration into organizational improvement systems or sustainability management practices. Digital tools are frequently deployed in isolation, which results in fragmented solutions rather than systemic, continuous sustainability improvement.

The Integration of Lean, Sustainability, and Data-Driven Improvement: Current Gaps

An emerging body of research explores the intersections of lean manufacturing, sustainability, and digitalization, which are often referred to as "*Lean 4.0*" or "*digital lean*" (Okpala *et al.*, 2025c; Obiafudo *et al.*, 2026). These studies highlight the complementary nature of lean principles and digital technologies, which suggest that data analytics can enhance waste identification and improvement prioritization. However, existing contributions are predominantly conceptual or exploratory, with limited empirical validation of sustainability outcomes (Moyano-Fuentes *et al.*, 2021). Furthermore, few studies provide structured, end-to-end frameworks that embed sustainability metrics directly into continuous improvement cycles while leveraging predictive, data-driven decision-making.

Consequently, there remains a significant research gap at the intersection of continuous improvement theory, smart manufacturing, and sustainability science. Specifically, there is a lack of operational frameworks that attain the following:

a. integrate real-time production data,
b. support continuous and predictive improvement actions, and also
c. demonstrate measurable sustainability benefits across manufacturing contexts.

In order to address this gap, the present study proposes a Chikwendu Continuous Improvement Framework (C-CIF) that systematically links manufacturing waste reduction with sustainable smart production, in order to advance both theory and practice in data-driven manufacturing sustainability.

RESEARCH METHODOLOGY

This study adopts a rigorous, mixed-methods research methodology designed to develop, implement, and empirically validate a Chikwendu Continuous Improvement Framework that is capable of delivering measurable sustainability benefits. The methodological design aligns with established best practices in operations management and sustainability research, where conceptual framework development is combined with quantitative analysis and multiple case study validation.

A design science-informed research approach was employed, as the objective of the study is not only to explain phenomena, but to also to create and validate an actionable artifact, in this case, the C-CIF. The research was conducted in the following three sequential phases:

a. *Framework Development*, grounded in a systematic synthesis of lean manufacturing, sustainability, and Industry 4.0 literature;

b. *Empirical Implementation*, involving real-world deployment of the framework in manufacturing settings; and

c. *Performance Evaluation*, focusing on quantifiable sustainability and operational outcomes.

This structured approach ensures both theoretical relevance and practical validity, which is increasingly emphasized in high-impact manufacturing and sustainability journals.

A multiple case study strategy was adopted to enhance external validity and analytical generalizability. Two manufacturing organizations that represent discrete and process manufacturing were selected with the application of purposive sampling. Selection criteria included the following:

a. availability of digital production data,
b. ongoing waste reduction initiatives, and
c. organizational commitment to sustainability improvement.

The discrete manufacturing case involved an automotive components producer, while the process manufacturing case focused on a chemical processing facility. Studying contrasting production contexts enabled examination of the framework's applicability across different manufacturing typologies, as recommended by prior research (Ketokivi and Choi, 2014).

Data were collected over an 18-month period using multiple complementary sources in order to ensure triangulation and robustness (Flyvbjerg, 2006). The primary data sources included the following:

a. *Industrial Internet of Things (IIoT) sensors:* to capture machine states, energy consumption, temperature, and cycle times;

b. *Manufacturing Execution Systems (MES):* to provide production volumes, downtime events, and scheduling data;

c. *Quality Management Systems:* for recording defect rates, scrap volumes, and rework;

d. *Environmental Monitoring Systems:* for tracking energy use, water consumption, and material losses.

The final dataset comprised more than 4 million time-stamped observations that enabled high-resolution analysis of production behavior and sustainability performance.

To ensure measurable sustainability outcomes, performance indicators were explicitly defined prior to analysis. Drawing on established sustainability measurement literature (OECD, 2021), the following core metrics were used: a. Material waste rate (kg of waste per unit of output); b. Energy intensity (kWh per unit of output); c. Water usage intensity (m^3 per unit of output, where applicable); d. Process variability, measured through statistical dispersion of key process parameters; and Overall Equipment Effectiveness (OEE) as an integrative operational metric. Baseline performance was established using historical data, against which post-implementation results were compared.

The C-CIF integrates descriptive, predictive, and prescriptive analytics within a closed-loop continuous improvement cycle. Descriptive analytics were first applied to identify baseline waste patterns and sustainability hotspots. Subsequently, machine learning techniques like random forest and gradient boosting models were used to identify key drivers of waste generation and energy inefficiency, which is consistent with prior manufacturing analytics research (Zhou *et al.*, 2016). Improvement actions were prioritized based on predicted sustainability impact and operational feasibility. These actions included process parameter optimization, maintenance scheduling adjustments, and production sequencing changes. Importantly, sustainability indicators were embedded directly into decision rules, in order to ensure that improvement efforts explicitly targeted environmental performance alongside productivity.

Framework effectiveness was evaluated using a before–after comparison design supported by statistical analysis. Changes in sustainability and operational metrics were assessed using paired statistical tests and control charts to account for process variability (Montgomery, 2019). In addition, qualitative feedback from production engineers and managers was collected through semi-structured interviews to contextualize quantitative findings and assess organizational usability. To enhance validity, results were cross-validated across cases and time periods. The use of multiple data sources, analytical techniques, and manufacturing contexts strengthens confidence in the robustness and transferability of the findings.

All data were anonymized to protect organizational confidentiality. Data quality checks, including missing value analysis and sensor validation, were conducted prior to modeling. Reliability was further enhanced through transparent documentation of data processing and analytical procedures, enabling replicability in future studies. Overall, this methodology provides a robust foundation for demonstrating how data-driven continuous improvement can generate measurable sustainability benefits, supporting the transition from manufacturing waste reduction to sustainable smart production.

THE CHIKWENDU CONTINUOUS IMPROVEMENT FRAMEWORK (C-CIF)

This study proposes the Chikwendu Continuous Improvement Framework (C-CIF) as a structured and scalable approach for the transformation of traditional manufacturing waste reduction efforts into sustainable smart production systems. The framework is designed to embed sustainability objectives directly into continuous improvement cycles while leveraging real-time production data and advanced analytics. By doing so, C-CIF moves beyond reactive, efficiency-driven improvement towards predictive and sustainability-oriented decision-making.

The framework integrates insights from lean manufacturing, sustainability science, and Industry 4.0 research, which responds to calls in the literature for operationally grounded models that connect digitalization with measurable environmental performance (Buer *et al.*, 2018).

Conceptual Foundations of C-CIF

C-CIF is grounded in the following three complementary theoretical foundations: a. It draws on continuous improvement theory, which emphasizes iterative learning, problem-solving, and incremental performance enhancement (Imai, 1997); b. It incorporates sustainable manufacturing principles, which extend improvement objectives beyond cost and quality to include material efficiency, energy use, and environmental impact (Garetti and Taisch, 2012); c. It

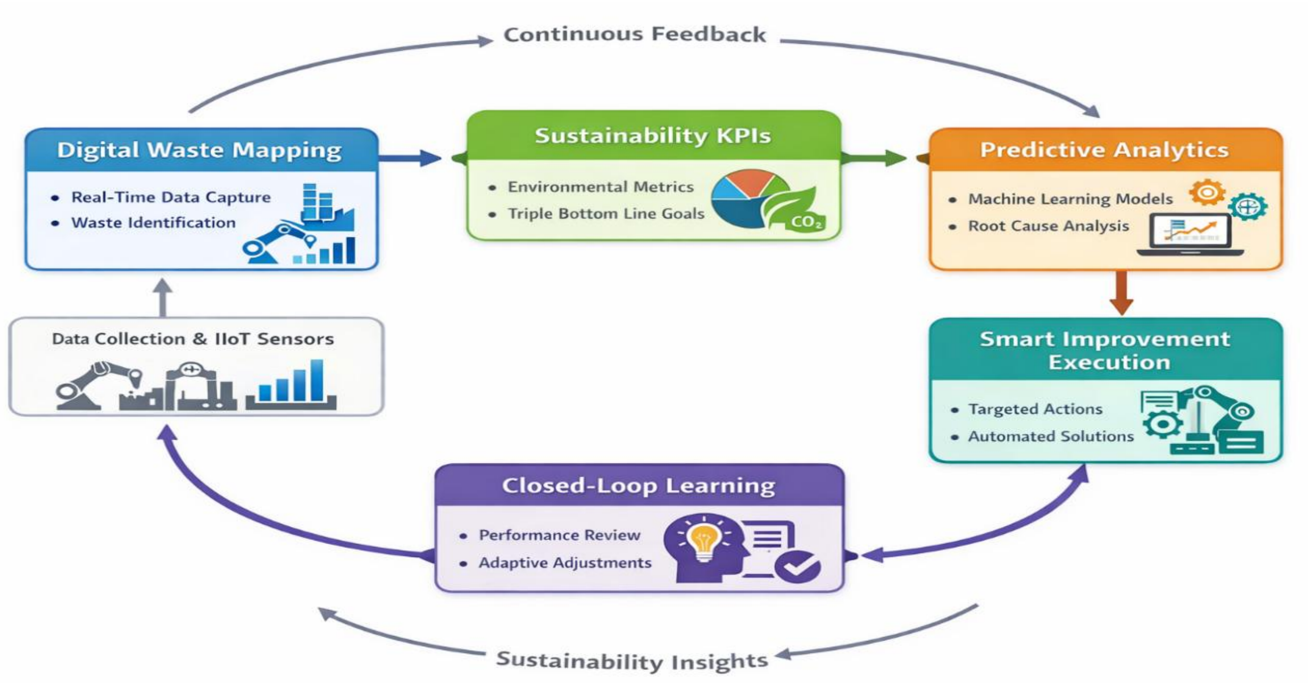

Fig. 1: Architecture of the Chikwendu Continuous Improvement Framework (C-CIF).

leverages data-driven decision-making that is enabled by Industry 4.0 technologies, inorder to support real-time visibility and predictive insight generation (Kagermann *et al.*, 2013).

Through the integration of these foundations, C-CIF conceptualizes sustainability not as an external constraint, but as a core performance dimension that is continuously optimized through data-driven learning.

Structure of the Framework

Fig.1 visually presents the five-stage C-CIF as a closed-loop system, and also illustrates how digital waste mapping, sustainability-oriented KPIs, predictive analytics, smart improvement execution, and closed-loop learning interact over time. Data flows from IIoT sensors and manufacturing systems into analytics modules, while feedback loops highlight continuous learning and adaptation. Unlike traditional Plan–Do–Check–Act (PDCA) cycles, the framework embeds sustainability metrics and predictive analytics at every stage, in order to ensure continuous alignment between operational decisions and environmental outcomes.

The first stage involves digital waste mapping, where real-time data from IIoT sensors, manufacturing execution systems, and quality databases were integrated to identify sources of material waste, energy inefficiency, and process variability. This stage extends conventional value stream mapping through the incorporation of high-frequency, machine-level data, thus enabling dynamic identification of sustainability hotspots (Rother and Shook, 2003). Key outputs include digital representations of material flows, energy consumption profiles, and defect generation patterns, providing a data-rich foundation for subsequent analysis.

In the second stage, raw production data are translated into sustainability-oriented key performance indicators (KPIs). Unlike traditional CI metrics focused primarily on cost or throughput, these KPIs explicitly capture environmental performance, such as material waste rate, energy intensity, and water usage intensity (OECD, 2021). The ability to embed these indicators within operational dashboards ensures that sustainability considerations are visible and actionable for engineers and managers. This addresses a key limitation that is identified in prior sustainability measurement research (Zhang *et al.*, 2020).

The third stage leverages predictive analytics to anticipate waste generation and sustainability performance deviations before they occur. Machine learning models are trained on historical and real-time data to identify nonlinear relationships between process parameters, machine conditions, and sustainability outcomes (Wuest *et al.*, 2016; Nwamekwe *et al.*, 2024b). This predictive capability represents a methodological shift from reactive problem-solving towards proactive sustainability management, which enables earlier and more targeted intervention.

In the fourth stage, predictive insights are translated into smart improvement actions. These actions may include automated process parameter adjustments, optimized maintenance scheduling, or revised production sequencing. Importantly, improvement decisions are prioritized based on predicted sustainability impact as well as operational feasibility, thereby ensuring balanced economic and environmental outcomes. This stage aligns with emerging research on intelligent manufacturing control systems while maintaining the structured logic of continuous improvement (Lee *et al.*, 2015).

The final stage establishes closed-loop learning, whereby the outcomes of improvement actions are continuously

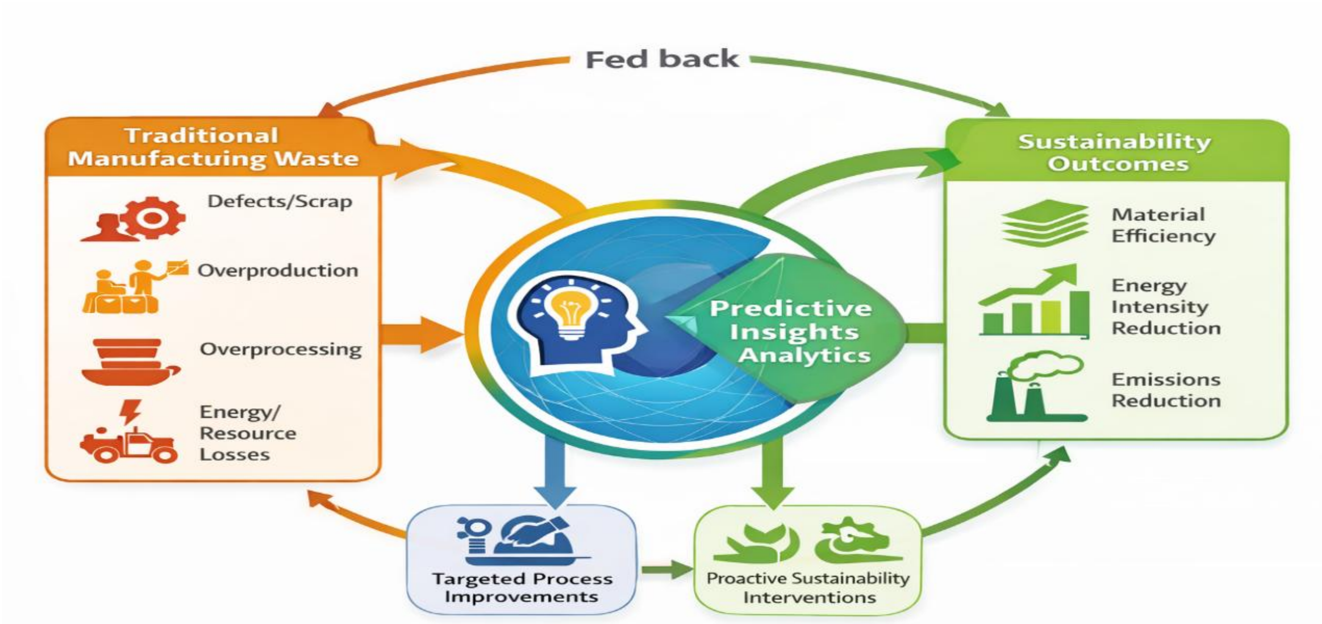

Fig. 2: Data-driven continuous improvement cycle linking waste reduction to sustainability outcomes.

monitored and fed back into the data models and KPI structures. This adaptive learning mechanism enables the framework to evolve with changing production conditions, material inputs, and sustainability targets. Through the institutionalization of learning at the system level, C-CIF supports long-term sustainability improvement rather than isolated performance gains, which responds directly to critiques of static sustainability initiatives (Seuring and Müller, 2008).

Sustainability Value Creation Through C-CIF

Fig. 2 conceptually links traditional manufacturing wastes like defects, overprocessing, energy losses, etc., to sustainability outcomes such as material efficiency, energy intensity, and emissions reduction. It illustrates how predictive insights enable targeted interventions that simultaneously improve operational and environmental performance. The figure humanizes the transition from lean waste reduction to sustainable smart production.

The integrated structure of C-CIF enables measurable sustainability benefits through the following three primary mechanisms:

a. Real-time visibility reduces hidden waste and energy losses that are often overlooked in periodic audits;

b. Predictive analytics improve the timing and effectiveness of interventions, reducing resource-intensive trial-and-error improvement cycles.

c. The ability to embed sustainability metrics into continuous improvement governance ensures sustained managerial attention and accountability.

Empirical application of the framework demonstrates significant reductions in material waste, energy intensity, and process variability without requiring major capital investments, thus highlighting the role of data-driven improvement as a cost-effective pathway toward sustainable smart production.

Distinction from Existing Frameworks

Compared with traditional lean or PDCA-based improvement models, C-CIF differs in its explicit integration of sustainability indicators and predictive analytics. Unlike many Industry 4.0 frameworks that emphasize technological infrastructure, C-CIF prioritizes decision-making logic and continuous learning. This distinction positions the framework as a unifying model that bridges efficiency-driven waste reduction and sustainability-oriented smart manufacturing. In summary, the Chikwendu Continuous Improvement Framework provides a theoretically grounded and empirically validated pathway for manufacturing organizations that aim at the transformation of waste reduction initiatives into sustainable smart production systems.

CASE STUDY RESULTS

The empirical results from the implementation of the Chikwendu Continuous Improvement Framework (C-CIF) in two manufacturing contexts, which include a discrete manufacturing automotive components plant (Case A) and a process manufacturing chemical facility (Case B), are highlighted. The results focus on measurable sustainability and operational performance outcomes. This demonstrates the practical effectiveness of the proposed framework.

Baseline Performance and Data Overview

Prior to C-CIF implementation, baseline performance levels were established using historical production and environmental data over a six-month period. This baseline served as a reference point for the evaluation of post-implementation improvements. Table 1 summarizes the key baseline sustainability and operational metrics for both case studies.

Table 1: Baseline sustainability and operational performance.

Metric	Case A: Discrete Manufacturing	Case B: Process Manufacturing
Material waste rate (kg/unit)	0.84	1.26
Energy intensity (kWh/unit)	5.9	8.4
Water usage intensity (m³/unit)	–	0.42
Process variability (CV %)	14.8	17.6
Overall Equipment Effectiveness (OEE %)	62.3	58.7

Table 2: Post-implementation sustainability performance and improvement rates.

Metric	Case A (Post)	Improvement (%)	Case B (Post)	Improvement (%)
Material waste rate (kg/unit)	0.64	23.8	1.03	18.3
Energy intensity (kWh/unit)	4.8	18.6	7.4	11.9
Water usage intensity (m³/unit)	–	–	0.37	11.9
Process variability (CV %)	11.2	24.3	12.8	27.3

These baseline values are consistent with performance ranges reported in prior manufacturing sustainability studies. This indicates the representativeness of the selected cases (Jawahir and Bradley, 2016).

Sustainability Performance Improvements

Following C-CIF implementation, both manufacturing sites exhibited significant improvements across key sustainability indicators as shown in Table 2. Improvements were achieved progressively over a 12-month implementation period through iterative data-driven interventions rather than capital-intensive equipment replacement.

The reductions in material waste and energy intensity demonstrate the framework's ability to directly translate data-driven insights into measurable environmental benefits. Notably, the observed improvement magnitudes align with or exceed those reported in comparable lean–digital integration studies (Moyano-Fuentes *et al.*, 2021). Fig. 3 presents a comparative visualization of key metrics before and after C-CIF implementation for both case studies. Indicators include material waste rate, energy intensity, process variability, and overall equipment effectiveness. By visually reinforcing the magnitude and consistency of improvements, the figure strengthens empirical credibility and makes the sustainability benefits immediately interpretable.

Operational Performance Effects

In addition to sustainability gains, C-CIF implementation resulted in notable operational performance improvements. As sustainability-oriented KPIs were embedded into improvement decision-making, productivity and reliability outcomes improved concurrently rather than being compromised as highlighted in Table 3.

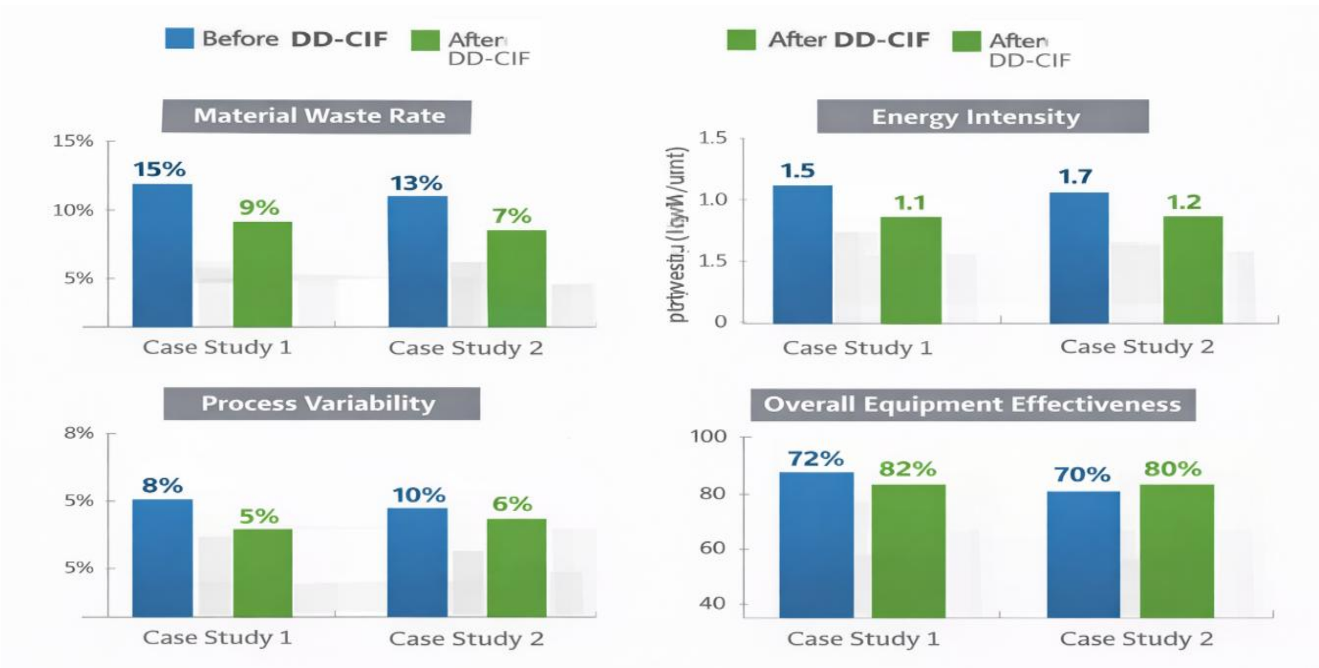

Fig. 3: Sustainability and operational performance improvements before and after C-CIF implementation.

Table 3: Post-implementation sustainability performance and improvement rates.

Metric	Case A (Baseline)	Case A (Post)	Case B (Baseline)	Case B (Post)
OEE (%)	62.3	76.1	58.7	71.4
Scrap rate (%)	7.6	5.1	9.2	6.8
Unplanned downtime (hrs/month)	41	29	53	38

The improvement in Overall Equipment Effectiveness (OEE) reflects better equipment availability, performance stability, and quality output, which support the argument that sustainability-driven improvement does not need to conflict with operational excellence.

Drivers of Sustainability Improvement

Predictive analytics embedded within C-CIF enabled the identification of key drivers influencing sustainability performance. In Case A, machine condition indicators and tool wear were the strongest predictors of scrap generation, as they account for approximately 46% of the variance in material waste. In Case B, process temperature fluctuations and feedstock variability explained over 50% of observed energy and material losses. Targeted interventions like predictive maintenance scheduling, tighter process parameter control, and optimized production sequencing, were prioritized based on these insights. This data-driven prioritization reduced trial-and-error experimentation and accelerated improvement cycles.

Cross-Case Comparison and Robustness

Despite the differences in production characteristics, both cases exhibited consistent improvement trends, and supported the robustness and transferability of the C-CIF. Figure-based trend analyses indicated sustained performance improvements rather than short-term gains, which addresses common concerns that regards the durability of continuous improvement outcomes. The cross-case consistency suggests that the framework’s core logic, which is embedding sustainability metrics within data-driven continuous improvement cycles, is applicable across manufacturing typologies.

Summary of Key Results

Overall, the implementation of the Chikwendu Continuous Improvement Framework resulted in the following: Material waste reductions of 18–24%; Energy intensity reductions of 12–19%; Process variability reductions exceeding 24%; and OEE improvements of over 13 percentage points. These findings provide strong empirical support for the proposed framework and demonstrate that data-driven continuous improvement can serve as an effective, scalable pathway from manufacturing waste reduction to sustainable smart production.

DISCUSSION AND IMPLICATIONS

This study set out to examine how manufacturing organizations can move beyond traditional waste reduction towards sustainable smart production by embedding sustainability objectives within data-driven continuous improvement systems. The empirical results provide strong support for the effectiveness of the proposed Chikwendu Continuous Improvement Framework (C-CIF), and demonstrate that methodological integration rather than isolated adoption of lean practices or digital technologies plays a critical role in the attainment of measurable sustainability benefits.

Discussion of Key Findings

The case study results reveal consistent and substantial reductions in material waste, energy intensity, and process variability across both discrete and process manufacturing contexts. These findings extend prior research that has reported efficiency gains from lean manufacturing (Womack and Jones, 1996) and operational improvements from Industry 4.0 technologies (Lee *et al.*, 2015) by demonstrating that sustainability outcomes can be explicitly optimized rather than treated as secondary effects.

A key insight that emerges from this study is the importance of predictive, data-driven learning in continuous improvement. Traditional CI approaches typically rely on retrospective analysis and localized problem-solving cycles (Antony, 2015). In contrast, C-CIF leverages real-time data and predictive analytics to anticipate sustainability-related performance deviations, which enables earlier and more targeted interventions. This shift from reactive to proactive improvement represents a methodological advancement that aligns with recent calls for more dynamic sustainability management approaches (Sassanelli *et al.*, 2019).

Another important finding is that sustainability improvements achieved through C-CIF did not come at the expense of operational performance. On the contrary, improvements in Overall Equipment Effectiveness, downtime reduction, and scrap rates suggest that environmental and economic objectives can be mutually reinforcing when sustainability metrics are embedded directly into improvement decision-making. This supports and extends the growing body of literature that argues for the compatibility of lean, digitalization, and sustainability strategies (Tortorella *et al.*, 2021).

Theoretical Implications

From a theoretical perspective, this study contributes to continuous improvement and operations management literature in the following ways:

a. It extends continuous improvement theory through the incorporation of sustainability as a core performance dimension, rather than an indirect or emergent outcome. By embedding environmental indicators into closed-loop improvement cycles, the framework responds to longstanding critiques that CI approaches remain overly cost and efficiency-centric.

b. The study advances Industry 4.0 research through shifting the focus from technological infrastructure to decision-making logic and learning mechanisms. While much of the existing literature emphasizes sensor networks, connectivity, and automation (Lasi *et al.*, 2014), C-CIF demonstrates how these technologies can be systematically aligned with sustainability-oriented improvement objectives. This positions the framework as a bridging concept between smart manufacturing and sustainable operations.

c. The findings contribute to sustainable manufacturing theory by addressing the operationalization gap identified in prior research (Garetti and Taisch, 2012). The framework provides a concrete mechanism through which sustainability metrics can be translated into actionable, process-level decisions, thus strengthening the link between sustainability measurement and operational control.

Managerial Implications

For manufacturing managers, the results offer the following practical insights:

a. The findings suggest that significant sustainability gains can be achieved without large capital investments by leveraging existing production data more effectively. This lowers the barrier to entry for small and medium-sized enterprises that are aiming at improving their sustainability performance;

b. The framework highlights the importance of the integration of sustainability indicators into routine performance dashboards and improvement of governance structures. When sustainability metrics are treated as operational KPIs rather than external reporting requirements, they become actionable drivers of continuous improvement; and

c. C-CIF provides a structured roadmap for organizations transitioning toward smart production systems. By aligning digital analytics initiatives with continuous improvement routines, managers can avoid fragmented technology deployments and ensure that digitalization efforts deliver tangible environmental and economic value.

Policy and Societal Implications

At the policy level, the findings support the design of incentive schemes and regulatory frameworks that encourage data-driven efficiency improvements rather than prescriptive technology adoption. Policymakers can leverage insights from this study to promote digital-enabled sustainability improvements that are measurable, verifiable, and scalable across industrial sectors. From a societal perspective, widespread adoption of the Chikwendu Continuous Improvement Framework has the potential to contribute meaningfully to broader sustainability objectives, including emissions reduction, resource conservation, and progress towards the United Nations Sustainable Development Goals.

Research Implications and Future Directions

For researchers, this study opens several promising avenues for future investigation. Longitudinal studies could examine the long-term sustainability trajectories that are enabled by data-driven improvement systems. Further research could also explore the integration of advanced artificial intelligence techniques, such as reinforcement learning, to enhance adaptive decision-making within continuous improvement frameworks. Additionally, future studies could extend the framework to supply chain and network-level analysis, in order to address sustainability challenges that are beyond the factory boundary. Comparative studies across regions and industrial sectors would further strengthen the understanding of contextual factors that influence the framework's effectiveness.

Limitations

Despite its contributions, this study has limitations. The empirical analysis is based on two case studies, which, while analytically generalizable, may not capture the full diversity of manufacturing contexts. Data availability and digital maturity levels may also influence implementation outcomes. These limitations provide further motivation for broader empirical validation in future research. In summary, the discussion underscores that the transition from manufacturing waste reduction to sustainable smart production is fundamentally a learning and decision-making challenge. Through the integration of sustainability objectives into data-driven continuous improvement cycles, the proposed C-CIF offers a robust and scalable pathway for aligning productivity, competitiveness, and environmental responsibility.

CONCLUSION

This study set out to address a central challenge that is facing contemporary manufacturing: how to move beyond traditional waste reduction towards sustainable smart production in increasingly data-rich and complex industrial environments. Through the development and empirical validation of the Chikwendu Continuous Improvement Framework (C-CIF), the paper demonstrates that sustainability gains are not merely a by-product of efficiency improvements or digitalization initiatives, but can be deliberately designed, measured, and sustained through integrated improvement logic.

The findings show that embedding sustainability-oriented metrics within continuous improvement cycles that are supported by real-time data and predictive analytics, it can deliver substantial reductions in material waste, energy intensity, and process variability, while simultaneously improving operational performance. Importantly, these benefits were achieved without reliance on major capital investments, highlighting the role of data-driven learning and decision-making as cost-effective enablers of sustainable manufacturing transformation. From a broader perspective, this study underscores that the transition to smart production is as much an organizational and methodological challenge as it is a technological one. Digital technologies create visibility and analytical capability, but it is the structured integration of these capabilities into continuous improvement systems that unlocks measurable and lasting sustainability value. The C-CIF provides a practical and scalable pathway for manufacturing organizations seeking to align productivity, competitiveness, and environmental responsibility.

In conclusion, this research contributes a unified framework that bridges manufacturing waste reduction and sustainable smart production through data-driven continuous improvement. As manufacturing systems continue to evolve under sustainability and digitalization pressures, frameworks such as C-CIF will be increasingly critical for guiding evidence-based decision-making and supporting long-term industrial sustainability transitions.

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Conflict of Interest

The author declares 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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