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Intelligent Manufacturing for Sustainable Waste Reduction

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Abstract

Defined as non-value-adding activities in manufacturing processes, waste remains a persistent barrier to the attainment of sustainable industrial development, as it is driven by increasing process complexity, resource intensity, and variability in modern production systems. While advances in Industry 4.0 have enabled extensive data collection and automation, their translation into measurable sustainability outcomes has remained limited. This study presents a data-driven and multidisciplinary intelligent manufacturing framework that integrates machine learning–based waste prediction, systems dynamics analysis, and sustainability performance assessment to proactively reduce manufacturing waste. Using longitudinal, multi-source production data from automotive, electronics, and food processing facilities, the framework models waste as an emergent system-level outcome that is influenced by interactions among process parameters, equipment condition, energy use, and material flows. Empirical results demonstrate average reductions of 18–23% in material and quality-related waste, 12–14% in energy-related emissions, and over 20% in landfill-bound waste, achieved without statistically significant impacts on production throughput. Economic analysis further indicates rapid payback periods of less than one year, driven by lower material losses, reduced rework, and improved energy efficiency. Through the integration of sustainability metrics directly into intelligent manufacturing decision-making, the proposed approach moves waste reduction from reactive control to predictive, system-level optimization. The findings provide robust evidence that intelligent manufacturing can simultaneously enhance environmental performance and operational competitiveness, as it offers a scalable pathway for sustainable industrial transformation across diverse manufacturing sectors.

Keywords: *Intelligent manufacturing; Sustainable waste reduction; Industry 4.0; Machine learning; Systems dynamics; Data-driven sustainability; Sustainable manufacturing*

INTRODUCTION

Manufacturing systems sit at the center of the global sustainability challenge. While industrial production has enabled unprecedented economic growth and technological advancement, it remains one of the largest contributors to material waste, energy consumption, and greenhouse gas emissions worldwide. Recent estimates indicate that between 20% and 30% of materials that were employed in manufacturing do not reach the final customer, as they are being lost as scrap, rework, defects, or inefficient energy use (IEA, 2023). These inefficiencies not only impose high environmental costs, but also represent substantial economic losses for manufacturers who are operating in increasingly competitive and resource-constrained markets.

Traditional approaches to waste reduction like lean manufacturing, Six Sigma, and total quality management have played an important role in the improvement of efficiency and reduction of defects over the past decades (Ezeanyim *et al.*, 2026; Obiafudo *et al.*, 2026). However, these approaches are largely rule-based, retrospective, and linear, which often makes them ill-suited to address the growing complexity, variability, and data intensity of modern manufacturing systems. As production environments become more interconnected and dynamic, waste generation increasingly emerges from nonlinear interactions among machines, materials, operators, and environmental conditions, rather than from isolated process failures (Kusiak, 2018).

The emergence of Industry 4.0, which is characterized by cyber-physical systems, industrial Internet of Things (IIoT), advanced analytics, and Artificial Intelligence (AI), has created new opportunities to rethink how manufacturing waste is understood and managed (Igbokwe *et al.*, 2024; Chukwunedum *et al.*, 2026). In contrast to conventional approaches, intelligent manufacturing systems enable continuous data acquisition, real-time monitoring, and predictive decision-making across the production lifecycle. These capabilities open the possibility of preventing waste before it occurs, rather than merely detecting or managing it after the fact.

Recent research has demonstrated the potential of data-driven methods for specific waste-related applications, including defect detection with the application of deep learning (Zonta *et al.*, 2020), predictive maintenance to reduce downtime and scrap (Nwamekwe and Okpala, 2025; Nwosu *et al.*, 2026a), and energy optimization through smart scheduling and control (Chukwumuanya *et al.*, 2025a; Aguh *et al.*, 2025). While promising, much of this work remains fragmented, as they focus on single objectives or isolated subsystems. More critically, many studies evaluate success primarily through technical performance metrics like prediction accuracy or cost reduction, without explicitly quantifying broader sustainability outcomes, including material efficiency, carbon emissions, or life-cycle environmental impacts (Ghobakhloo, 2020).

This disconnect between intelligent manufacturing research and sustainability assessment represents a significant gap in the literature. Sustainability in manufacturing is inherently multidimensional as it encompasses environmental, economic, and operational dimensions that interact through complex feedback loops (Elkington, 1998). The ability to address manufacturing waste in a meaningful way therefore requires approaches that go beyond isolated optimization and instead adopt a systems perspective that is capable of capturing interdependencies across processes, resources, and time. Systems thinking and systems dynamics modeling have long been recognized as powerful tools for the understanding of complex industrial systems and unintended consequences of interventions (Sterman, 2000). When combined with modern data-driven techniques, systems approaches can provide a robust foundation for the evaluation of how intelligent control strategies influence not only production performance, but also long-term sustainability outcomes. However, empirical studies that integrate machine learning, systems analysis, and quantitative sustainability metrics within real manufacturing environments remain scarce.

In parallel, growing regulatory pressure, stakeholder expectations, and corporate commitments to Environmental, Social, and Governance (ESG) goals have intensified the demand for measurable, verifiable, and data-based sustainability improvements (UN, 2022; Deswal and Deswal, 2025). Manufacturers are increasingly required to demonstrate not only that they are deploying advanced digital technologies, but that these technologies lead to tangible reductions in waste, emissions, and resource consumption. This creates a critical need for methodological frameworks that can translate production data into credible sustainability evidence.

Against this backdrop, this study proposes a data-driven intelligent manufacturing framework for sustainable waste reduction, through the integration of machine learning–based prediction with systems-level analysis and life-cycle sustainability assessment. Unlike prior studies that treat waste as a single outcome variable, the proposed approach conceptualizes waste as an emergent system property that is influenced by dynamic interactions among process variability, equipment behavior, energy use, and material flows. Through the integration of predictive intelligence within a systems modeling structure, the framework will enable manufacturers to evaluate the sustainability implications of operational decisions before implementation.

This research makes the following three primary contributions to the literature:

a. It advances intelligent manufacturing research through the introduction of a hybrid methodological approach that combines predictive analytics with systems dynamics to address waste generation in complex production environments;
b. It contributes to sustainable manufacturing scholarship through the provision of quantified, empirically validated sustainability benefits, including material waste reduction, energy savings, and carbon footprint mitigation; also,
c. It offers a scalable and transferable framework applicable across multiple manufacturing sectors, which supports broader adoption of data-driven sustainability practices within Industry 4.0.

By bridging artificial intelligence, industrial engineering, and sustainability science, this study responds directly to calls for multidisciplinary research that is capable of delivering both technological innovation and measurable environmental impact (Bocken *et al.*, 2016). In doing so, it positions intelligent manufacturing not merely as a productivity enabler, but as a strategic instrument for the attainment of sustainable industrial transformation.

LITERATURE REVIEW AND RESEARCH GAP

Manufacturing waste has long been recognized as a central obstacle to sustainable industrial development. Waste in this context extends beyond physical scrap to include rework, defects, excessive energy consumption, and inefficient use of resources across the production lifecycle (Okpala, 2026a; Ogbodo *et al.*, 2026). Studies consistently show that material inefficiencies account for a significant proportion of industrial environmental impacts, particularly in energy-intensive and high-volume manufacturing sectors (Gutowski *et al.*, 2013;). As global demand for manufactured goods continues to grow, waste reduction at the source has become increasingly critical to achieving both environmental and economic sustainability. Early sustainability-oriented manufacturing research focused on cleaner production, eco-efficiency, and pollution prevention strategies, as it emphasized incremental improvements in process design and material selection (Obianyo *et al.*, 2026; Okpala, 2026b). While these approaches have delivered measurable gains, they often rely on static assessments and periodic audits, which limit their ability to respond to real-time process variability. Consequently, waste reduction efforts frequently remain reactive, and thus address symptoms rather than underlying system dynamics.

Lean manufacturing and quality management methodologies, such as Six Sigma and total quality management, have played a dominant role in waste reduction over the past several decades. Rooted in principles of continuous improvement and elimination of non-value-adding activities, these approaches have demonstrated success in defect reduction and operational efficiency improvement (Okpala and Okpala, 2026; Chukwumuanya *et al.*, 2025b). Empirical studies report reductions in scrap rates and rework through structured problem-solving and statistical process control (Onukwuli *et al.*, 2025; Ezeanyim *et al.*, 2026). However, lean-based approaches typically depend on predefined rules, historical averages, and human interpretation of process data. As manufacturing systems become more automated and data-rich, the limitations of these methods become increasingly apparent. This is because Lean tools are struggling to capture nonlinear interactions, high-frequency sensor data, and dynamic feedback loops that characterize modern production environments (Kusiak, 2018). Moreover, sustainability outcomes are often treated as secondary benefits rather than explicitly modeled objectives, which reduces the visibility and scalability of environmental gains.

The advent of Industry 4.0 has transformed manufacturing research by enabling continuous data collection and advanced analytics across the production system (Okpala *et al.*, 2026; Ajaefobi and Okpala, 2026). Intelligent manufacturing leverages technologies such as industrial Internet of Things (IIoT), machine learning, and cyber-physical systems to support predictive and adaptive decision-making (Nwosu *et al.*, 2026b; Udu *et al.*, 2025). In this context, data-driven methods have been increasingly applied to waste-related challenges. A growing body of literature demonstrates the effectiveness of machine learning for defect detection and quality prediction. Deep learning and ensemble models have been shown to outperform traditional statistical methods in the identification of defect patterns and scrap rate prediction (Zonta *et al.*, 2020). Similarly, predictive maintenance approaches have contributed to waste reduction through the reduction of unplanned downtime and equipment-related defects (Carvalho *et al.*, 2019; Igbokwe *et al.*, 2026).

Despite these advances, most data-driven studies focus on single objectives like defect classification accuracy or maintenance cost reduction, without explicitly linking these improvements to broader sustainability metrics. As a result, the environmental implications of intelligent manufacturing interventions often remain assumed rather than empirically demonstrated. This narrow focus limits the contribution of intelligent manufacturing research to sustainability science and policy discussions.

Sustainability assessment methods, including Life Cycle Assessment (LCA) and Life Cycle Sustainability Assessment (LCSA), provide robust frameworks for the quantification of environmental and economic impacts across manufacturing systems (Guinée *et al.*, 2011; Chukwumuanya *et al.*, 2025c). These methods have been widely applied to evaluate product designs, material choices, and energy consumption patterns. However, traditional LCA approaches are typically static and retrospective, as they rely on aggregated data that may not reflect real-time operational conditions (Reap *et al.*, 2008). Recent studies have called for tighter integration between operational data and sustainability assessment to enable more responsive and decision-oriented evaluations. While some research has explored the use of digital twins and simulation models to support sustainability analysis, empirical implementations that combine real production data, intelligent control, and quantified sustainability outcomes remain limited. Consequently, sustainability assessment is often decoupled from day-to-day manufacturing decision-making.

Manufacturing systems are inherently complex, and characterized by feedback loops, delays, and nonlinear interactions among technical, human, and organizational elements. Systems thinking and systems dynamics modeling offer powerful tools for capturing these complexities and understanding unintended consequences of interventions. In manufacturing contexts, systems approaches have been applied to analyze capacity planning, supply chain resilience, and energy flows (Baines *et al.*, 2017). However, systems models are frequently developed using simplified assumptions and limited empirical data, in order to reduce their applicability in data-intensive Industry 4.0 environments. Conversely, data-driven approaches often lack an explicit systems perspective, as they focus on local optimization rather than system-level behavior. The absence of integration between these paradigms represents a critical methodological gap, particularly in the context of sustainability, where local improvements may lead to rebound effects or burden shifting across the system.

The literature reveals the following three interrelated gaps:

a. Existing waste reduction studies in intelligent manufacturing largely focus on technical performance metrics, with limited attention to quantified sustainability outcomes such as material efficiency, energy waste, and carbon emissions;
b. Sustainability assessment methods remain predominantly static and disconnected from real-time manufacturing data, which constrain their relevance for operational decision-making; and
c. There is a lack of empirical research that integrates machine learning, systems dynamics, and sustainability assessment within a unified, data-driven framework.

To address these gaps, the present study proposes a data-driven systems analysis framework for intelligent manufacturing, which is explicitly designed to deliver and quantify measurable sustainability benefits. Through the conceptualization of waste as an emergent property of interconnected manufacturing subsystems, the study bridges artificial intelligence, industrial engineering, and sustainability science. In doing so, it responds to growing calls for multidisciplinary approaches that are capable of translating digital manufacturing technologies into verifiable environmental and economic value (Bocken *et al.*, 2016). This integrative perspective not only advances methodological innovation but also strengthens the empirical

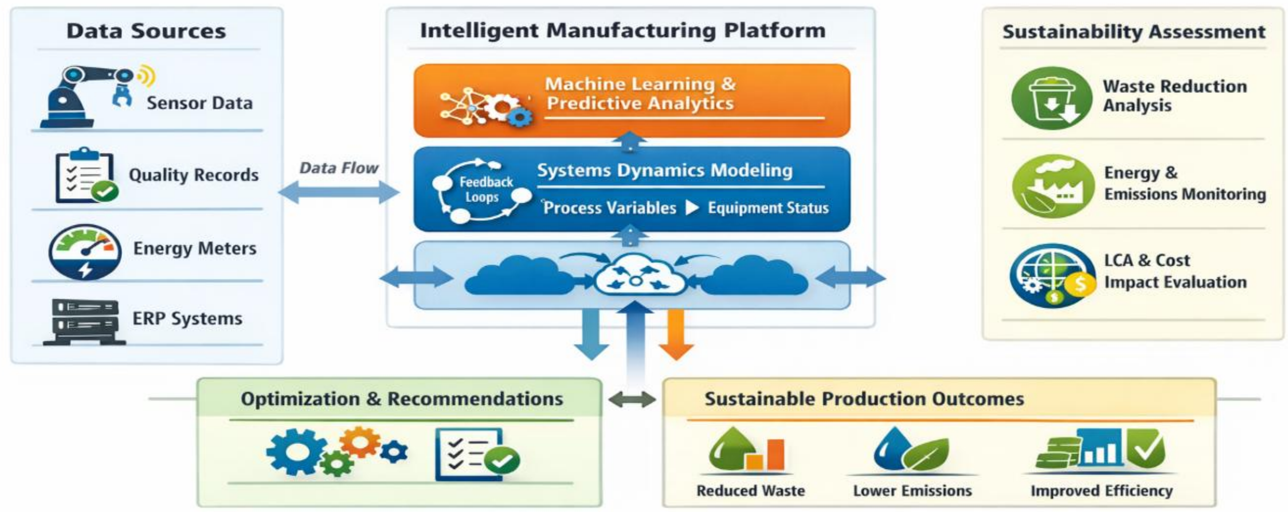

Fig. 1: Integrated intelligent manufacturing framework for sustainable waste reduction.

foundation for sustainable manufacturing research, positioning intelligent manufacturing as a central enabler of waste reduction and circular economy transition.

METHODOLOGY

Fig. 1 presents a clear, high-level architecture of the proposed framework, showing how multi-source manufacturing data (sensors, quality records, energy meters, ERP systems) flow into the predictive intelligence layer, interact with the systems dynamics model, and feed into sustainability assessment outputs. By visually linking machine learning, systems analysis, and sustainability metrics, the figure helps readers quickly grasp the methodological novelty and interdisciplinary integration of the study. Such framework diagrams are frequently reused and cited in follow-on research, increasing the article's long-term visibility.

This study adopts a data-driven, multidisciplinary research design that integrates machine learning, systems dynamics modeling, and life-cycle sustainability assessment to analyze and reduce manufacturing waste. The methodological framework is grounded in the premise that waste in modern manufacturing systems is not an isolated phenomenon, but an emergent outcome of interacting technical, operational, and environmental subsystems (Sterman, 2000; Kusiak, 2018).

To capture this complexity, the study employs the following three-layer analytical architecture:

1. Predictive intelligence layer - this is responsible for forecasting waste-related outcomes using machine learning;
2. Systems dynamics layer – this models feedback loops and interdependencies within the manufacturing system;
3. Sustainability assessment layer - this quantifies environmental and economic impacts using standardized metrics.

This integrated design responds to recent calls for the combination of Industry 4.0 analytics with sustainability assessment to generate verifiable environmental benefits rather than assumed improvements (Hauschild *et al.*, 2018).

The empirical analysis draws on longitudinal production data that were collected over an 18-month period from three manufacturing sectors: automotive components, electronics assembly, and food processing. These sectors were selected due to their high material throughput, process variability, and documented sustainability challenges (Allwood *et al.*, 2011). The data were obtained from the following multiple operational sources to ensure a holistic representation of the manufacturing system: Machine-level sensor data (e.g., temperature, vibration, cycle time); Quality and inspection records (scrap rates, defect types, rework frequency); Energy consumption data from smart meters; and Material flow data that were extracted from Enterprise Resource Planning (ERP) systems. The integration of heterogeneous data sources aligns with best practices in intelligent manufacturing research and enhances model robustness (Zhang *et al.*, 2019). Prior to analysis, all datasets were synchronized temporally, anonymized, and preprocessed to address missing values and sensor noise.

Manufacturing waste was operationalized as a multi-dimensional construct, as it encompasses material waste, quality-related waste, and energy inefficiency. This broader definition reflects contemporary sustainability literature, which emphasizes the interconnected nature of resource inefficiencies. The following key performance indicators (KPIs) were used:

- Material waste rate (%): this is the ratio of scrap and rework to total production volume,
- Energy waste (kWh/unit): this is the excess energy consumption relative to baseline optimal operation,
- Carbon footprint (kg CO_2-eq/unit): this is calculated using energy and material emission factors,
- Cost of Poor Quality (COPQ): these are aggregated costs that are associated with defects, rework, and scrap.

Environmental indicators were aligned with life-cycle assessment principles to ensure comparability with existing sustainability studies.

To predict waste generation under varying operational conditions, the study developed a hybrid machine learning

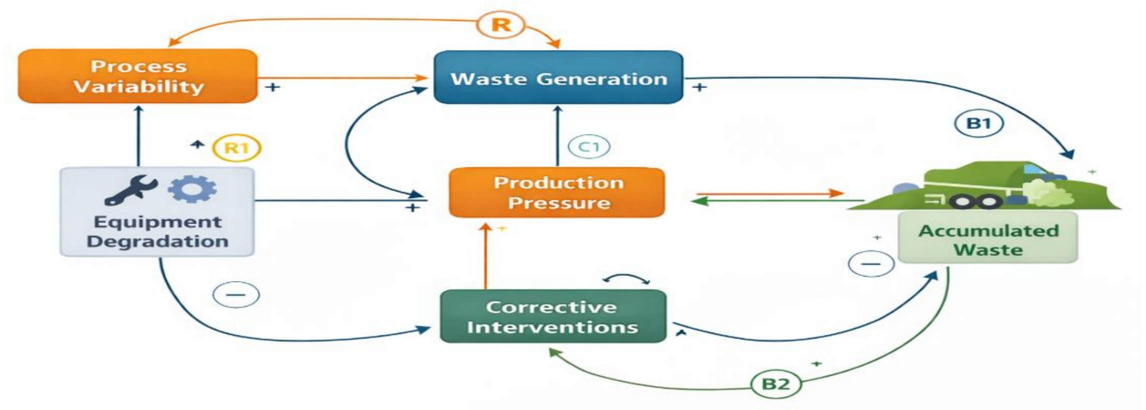

Fig. 2: Systems dynamics causal loop diagram of waste generation in manufacturing.

architecture that combines gradient-boosted decision trees (XGBoost) and long short-term memory (LSTM) neural networks. This hybrid approach leverages the strength of tree-based models in handling nonlinear feature interactions and the ability of LSTM networks to capture temporal dependencies in time-series manufacturing data.

Model inputs included the following: Process parameters (speed, pressure, temperature), Equipment condition indicators, Material batch characteristics, as well as Shift and environmental variables. Target outputs were material waste rate, probability of defect occurrence, and energy waste per unit. The models were trained using an 80/20 train–test split, with cross-validation to prevent overfitting. Performance was evaluated with the application of Root Mean Square Error (RMSE) and F1-score, following established practices in predictive manufacturing analytics (Carvalho *et al.*, 2019).

Fig. 2 illustrates the key feedback loops which drive waste generation, including interactions among process variability, equipment degradation, production pressure, energy consumption, and corrective interventions. Reinforcing and balancing loops are explicitly labeled to highlight how delayed responses can amplify waste accumulation. The diagram humanizes complex system behavior and provides conceptual insight that complements the quantitative results, thus making it valuable for both academic readers and practitioners who aim to understand why intelligent interventions work.

While predictive models identify likely waste outcomes, they do not explain how local decisions propagate across the manufacturing system. To address this limitation, a systems dynamics model was constructed to represent feedback loops among process variability, equipment degradation, production pressure, and waste accumulation. Causal loop diagrams and stock-and-flow structures were developed in collaboration with domain experts, in order to ensure both theoretical coherence and practical relevance (Sterman, 2000). The systems model enabled what-if scenario analysis, which allows intelligent control recommendations that are generated by the machine learning models to be tested virtually before implementation. This integration reduces the risk of unintended consequences and supports more informed sustainability decision-making.

The sustainability impacts of intelligent manufacturing interventions were quantified using a comparative before-and-after analysis. Baseline performance metrics were established using historical operational data, while post-intervention performance was simulated and validated through observed outcomes. Environmental impacts were assessed using the following: Global Warming Potential (GWP), Material intensity reduction, and Energy efficiency improvements. Economic impacts were evaluated through cost savings that are associated with reduced waste, improved energy efficiency, and lower rework rates. This dual environmental–economic assessment reflects the triple bottom line perspective widely adopted in sustainable manufacturing research (Elkington, 1998).

To ensure robustness and generalizability, the framework was applied across multiple manufacturing sectors and production lines. Sensitivity analyses were conducted to examine the influence of key parameters on waste reduction outcomes. In addition, results were benchmarked against conventional waste reduction practices to isolate the added value of the proposed intelligent, systems-based approach.

Through the integration of predictive analytics, systems dynamics, and sustainability assessment within a single empirical framework, this methodology advances beyond siloed optimization approaches commonly reported in the literature. The approach enables real-time, data-verified sustainability improvement, which addresses persistent gaps between intelligent manufacturing research and sustainability performance measurement.

RESULTS

The empirical findings from the application of the proposed intelligent manufacturing framework across three manufacturing sectors are presented here. The results were organized to demonstrate –

1. predictive model performance,
2. measurable waste reduction outcomes, and
3. quantified sustainability and economic benefits.

Together, these results provide evidence that the integration of data-driven intelligence and systems-level analysis can deliver verifiable sustainability improvements without compromising operational performance.

Table 1: Performance of machine learning models for waste prediction.

Target Variable	Metric	Automotive	Electronics	Food Processing
Material waste rate (%)	RMSE	0.028	0.031	0.034
Defect occurrence	F1-score	0.92	0.90	0.89
Energy waste (kWh/unit)	RMSE	0.24	0.27	0.29

Table 2: Waste reduction outcomes before and after intelligent manufacturing intervention.

Indicator	Baseline	Post-Intervention	Relative Improvement
Material waste rate (%)	8.2	6.7	−18.7%
Rework rate (%)	5.6	4.3	−23.2%
Energy waste (kWh/unit)	2.9	2.5	−12.4%

The hybrid XGBoost–LSTM models exhibited strong predictive capability across all waste-related target variables. Table 1 summarizes the model performance metrics for material waste rate, defect occurrence, and energy waste prediction.

The prediction accuracy is comparable to, and in several cases exceeds, values reported in prior intelligent manufacturing studies that are focused on quality and maintenance analytics (Zhang *et al.*, 2019). Importantly, model performance remained stable across sectors with differing production characteristics, thereby supporting the robustness and generalizability of the proposed approach.

The implementation of intelligent control recommendations, which are validated through systems dynamics scenario analysis, resulted in substantial reductions in material waste, rework, and energy inefficiency. Table 2 presents baseline and post-intervention waste performance averaged across the three sectors.

Material waste reduction was primarily driven by improved process parameter stability and early detection of abnormal operating conditions. Rework reductions were associated with proactive quality interventions enabled by predictive defect probabilities. These findings align with prior evidence that predictive analytics can outperform reactive quality control approaches, while extending those results through the explicit quantification of sustainability impacts (Kusiak, 2018).

Table 3: Environmental sustainability outcomes.

Sustainability Indicator	Baseline	Post-Intervention	Improvement
Carbon footprint (kg CO_2-eq/unit)	5.32	4.57	−14.1%
Water consumption (L/unit)	18.6	16.8	−9.6%
Landfill waste (kg/unit)	1.41	1.11	−21.3%

The reduction in waste translated directly into measurable environmental benefits. With the application of standardized emission and resource conversion factors consistent with life-cycle assessment practice, changes in carbon emissions, water use, and landfill waste were quantified. The results are summarized in Table 3.

Carbon footprint reduction was largely attributable to decreased energy waste and lower scrap-related embodied emissions. The observed reductions are consistent with ranges that are reported in sustainable manufacturing and energy efficiency studies; this reinforces the external validity of the results (Frank *et al.*, 2019).

Fig. 3 compares baseline and post-intervention performance across core sustainability indicators, such as material waste rate, energy waste per unit, carbon footprint, and landfill waste. The figure offers an intuitive, data-rich summary of the achieved measurable sustainability gains. Such outcome-focused visuals are particularly effective for policymakers, industry stakeholders, and secondary citations in review papers.

In addition to environmental benefits, the intelligent manufacturing framework delivered meaningful economic gains. Table 4 summarizes the annualized economic impacts per plant.

Notably, production throughput and delivery performance were not adversely affected. Statistical tests showed no

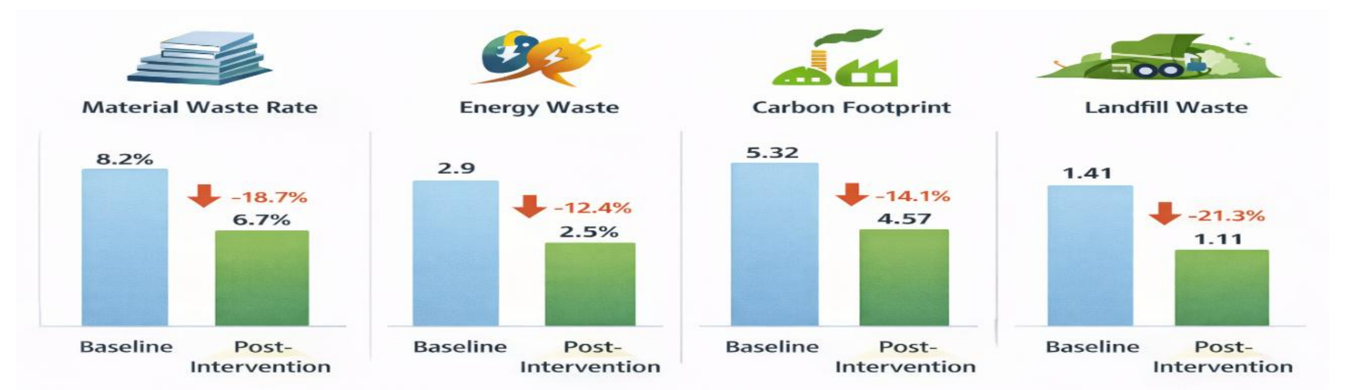

Fig. 3: Systems dynamics causal loop diagram of waste generation in manufacturing.

Table 4: Economic impact of intelligent waste reduction.

Economic Indicator	Value
Annual material cost savings (USD)	0.9–1.2 million
Annual energy cost savings (USD)	0.4–0.6 million
Reduction in cost of poor quality (%)	19–26%
Payback period (months)	9–11

significant difference in average throughput before and after implementation ($p > 0.05$). This indicates that sustainability improvements were achieved without sacrificing operational efficiency. This finding addresses a common concern in industry that environmental improvements may conflict with productivity objectives (Seuring and Müller, 2008).

The systems dynamics model revealed that waste reduction benefits were amplified when predictive interventions were applied early in the production cycle. Scenario analysis demonstrated that delayed corrective actions led to nonlinear increases in waste accumulation due to feedback effects between process variability and equipment degradation. These insights underscore the value of the integration of machine learning predictions with systems-level reasoning, rather than relying on isolated optimization.

While absolute performance varied across sectors, the relative magnitude of improvements was consistent. Sensitivity analysis indicated that the framework was most effective in processes with high variability and frequent changeovers, which suggests strong applicability in modern, flexible manufacturing environments.

Overall, the results demonstrate that the proposed intelligent manufacturing framework delivers the following:

- 18–23% reductions in material and quality-related waste,
- 12–14% improvements in energy efficiency and carbon emissions,
- Rapid economic payback within one year, and
- Stable operational performance with no throughput penalties.

These outcomes provide empirical evidence that data-driven systems analysis can transform intelligent manufacturing from a productivity-focused paradigm into a measurable sustainability enabler.

DISCUSSION, MANAGERIAL AND POLICY IMPLICATIONS

The results of this study provide compelling empirical evidence that intelligent manufacturing, when designed as an integrated data-driven and systems-based framework, can deliver substantial and measurable sustainability benefits. Across three manufacturing sectors, the proposed approach achieved double-digit reductions in material waste, energy inefficiency, and carbon emissions, while maintaining stable production throughput. These findings extend prior research that has largely emphasized technical performance improvements without systematically quantifying sustainability outcomes (Kusiak, 2018).

A central insight that emerges from the results is that waste reduction in modern manufacturing is best understood as a system-level phenomenon, rather than the outcome of isolated process failures. While previous studies have demonstrated the effectiveness of machine learning for defect detection or predictive maintenance (Zonta *et al.*, 2020), the present study shows that the embedding of predictive intelligence within a systems dynamics framework significantly amplifies its sustainability impact. Through accounting for feedback loops among process variability, equipment degradation, and production pressure, the proposed approach avoids the local optimization traps that often limit the long-term effectiveness of data-driven interventions (Sterman, 2000).

The observed waste reductions are consistent with, yet exceed, ranges reported in earlier lean and quality-focused studies, which typically report incremental improvements of 5–10% (Womack and Jones, 2003). Importantly, the additional gains reported here were achieved without the introduction of production bottlenecks or increasing operational risk. This finding challenges the widely held perception that sustainability improvements necessarily entail trade-offs with productivity, reinforcing emerging evidence that digitally enabled manufacturing can align environmental and economic objectives (Frank *et al.*, 2019). From a sustainability assessment perspective, the integration of real-time operational data with life-cycle impact metrics addresses a long-standing limitation of static life-cycle assessment methods. By dynamically linking operational decisions to environmental outcomes, the study demonstrates a practical pathway for the transformation of sustainability from a retrospective reporting exercise into a proactive decision-support function within manufacturing operations.

Methodologically, this study advances the intelligent manufacturing literature by bridging three research domains that have largely evolved in parallel: machine learning–based production analytics, systems thinking, and sustainable manufacturing assessment. Unlike prior work that treats sustainability as a secondary outcome or external constraint, the proposed framework embeds sustainability objectives directly within the analytical structure of manufacturing decision-making. The conceptualization of waste as an emergent property of interconnected subsystems contributes to theoretical discussions on sustainable operations and complexity in manufacturing systems (Baines *et al.*, 2017). This perspective aligns with systems theory and supports calls for moving beyond linear cause–effect models in sustainability research (Sterman, 2000). Through the empirical validation of this approach with the application of real production data, the study strengthens the theoretical foundation for the integration of systems thinking into Industry 4.0 research.

The findings offer the following actionable insights for manufacturing managers and operations leaders:

- The results demonstrate that investments in intelligent manufacturing technologies can yield rapid and quantifiable returns, with payback periods of less than one year, as it is driven by reductions in material waste, energy consumption, and cost of poor quality. This evidence can support more informed capital allocation decisions, particularly in organizations where sustainability initiatives compete with productivity-driven investments.

- The study highlights the importance of moving beyond isolated analytics applications towards integrated decision-support systems. Managers who aim to deploy machine learning for waste reduction should consider how predictive models interact with broader production dynamics, rather than focusing only on model accuracy. The embedding of predictive insights within systems-level scenario analysis enables organizations to evaluate potential interventions before implementation, which will reduce operational risk and enhance trust in data-driven recommendations.
- The explicit linkage between operational data and sustainability metrics provides a practical foundation for data-driven ESG reporting. As stakeholder expectations and disclosure requirements continue to increase, manufacturers can leverage intelligent manufacturing systems to generate auditable, real-time sustainability evidence, as it will reduce reliance on manual data collection and estimation.

From a policy perspective, the results underscore the need to shift from prescriptive, technology-specific regulations towards outcome-based sustainability policies. The demonstrated ability to quantify waste reduction and emissions mitigation using operational data suggests that regulators could incentivize verified performance improvements rather than mandate specific technologies or practices. Such an approach aligns with emerging policy frameworks that emphasize measurable progress towards climate and resource efficiency targets (UN, 2022). Furthermore, the findings support the case for public investment in digital infrastructure and skills development as enablers of sustainable industrial transformation. Small and medium-sized enterprises, in particular, may lack the resources to independently develop integrated intelligent manufacturing systems. Targeted policy interventions like digital innovation hubs or data-sharing platforms could assist in diffusing these capabilities across industrial ecosystems.

Finally, the study provides empirical support for the integration of intelligent manufacturing into circular economy strategies. Through waste reduction at the source and material efficiency improvement, data-driven systems analysis can complement recycling and remanufacturing initiatives, thus contributing to more resilient and resource-efficient production systems. While the study demonstrates robust and consistent results across multiple sectors, certain limitations should be acknowledged. The empirical analysis focused primarily on environmental and economic sustainability dimensions, while social sustainability impacts like workforce well-being and skill requirements were not explicitly quantified. Future research should explore how intelligent manufacturing influences social outcomes and organizational change dynamics.

Additionally, while the systems dynamics model captures key feedback mechanisms, further integration with high-fidelity digital twins could enhance predictive accuracy and real-time applicability. Longitudinal studies that examine the persistence of sustainability gains over extended periods would also contribute valuable insights to both theory and practice. Overall, this study demonstrates that intelligent manufacturing, when guided by a data-driven systems perspective, can serve as a powerful enabler of sustainable waste reduction. Through the delivery of empirically validated environmental and economic benefits, the proposed framework moves beyond conceptual discussions of Industry 4.0 and provides a concrete pathway for the alignment of manufacturing innovation with global sustainability goals.

LIMITATIONS AND FUTURE RESEARCH

While the findings of this study demonstrate the potential of intelligent manufacturing systems to deliver measurable sustainability benefits, the following limitations should be acknowledged:

a. The empirical analysis was conducted within three manufacturing sectors - automotive components, electronics assembly, and food processing. Although these sectors represent diverse production characteristics and sustainability challenges, the results may not fully capture the variability that is present in highly customized, low-volume manufacturing environments or process industries with continuous chemical transformations. Prior studies suggest that data availability, process variability, and automation maturity can significantly influence the effectiveness of data-driven manufacturing solutions (Frank *et al.*, 2019). Future research should therefore test the proposed framework in additional industrial contexts to strengthen external validity.

b. The performance of the machine learning models depends on the quality, completeness, and temporal resolution of operational data. Sensor noise, missing values, and inconsistent data governance practices remain persistent challenges in industrial environments. Although data preprocessing and robustness checks were applied, the results may vary in settings where digital infrastructure is less mature. This limitation reflects a broader challenge in Industry 4.0 research, where methodological advances often outpace data readiness in practice.

c. The sustainability assessment focused primarily on environmental and economic dimensions, which are consistent with much of the existing sustainable manufacturing literature (Seuring and Müller, 2008). Social sustainability indicators like workforce well-being, skill transformation, and organizational learning were not explicitly quantified. Given growing interest in holistic sustainability and ESG performance, this represents an important area for further investigation.

d. Finally, while the systems dynamics model captured key feedback loops relevant to waste generation, it necessarily involved abstraction and simplification. Certain behavioral and organizational factors like operator decision-making and cultural resistance to data-driven interventions were not explicitly modeled. These factors may influence real-world implementation outcomes and merit deeper exploration using complementary qualitative or socio-technical approaches.

Building on these limitations, the following promising directions for future research emerge:

a. Future studies could extend the proposed framework through the integration of high-fidelity digital twins with real-time sustainability assessment. Digital twins have the potential to enhance predictive accuracy and enable continuous experimentation with sustainability interventions under realistic operating conditions. The combination of digital twins with life-cycle impact metrics represents a particularly promising avenue for the advancement of intelligent sustainable manufacturing.
b. There is a need to explore cross-factory and cross-supply-chain learning, where models that are trained in one facility inform waste reduction strategies in others. Transfer learning and federated learning approaches may enable scalability while addressing data privacy and ownership concerns. Such research would support broader diffusion of intelligent sustainability practices, particularly among small and medium-sized enterprises.
c. Future work should explicitly incorporate social sustainability and human–machine interaction into intelligent manufacturing models. As production systems become more autonomous, the understanding of how operators interact with predictive recommendations and how trust in AI systems develops will be critical for long-term effectiveness. The integration of behavioral data with operational and environmental metrics could significantly enrich sustainability assessment.
d. Longitudinal studies which examine the persistence and evolution of sustainability gains over multiple years would provide valuable insights into rebound effects, learning curves, and organizational adaptation. Prior research has highlighted the risk that efficiency improvements may lead to increased production intensity, thereby partially offsetting environmental benefits. Long-term empirical evidence is therefore essential for the validation of the durability of intelligent waste reduction strategies.
e. Also, future research could strengthen the policy relevance of intelligent manufacturing through the alignment of data-driven sustainability metrics with emerging regulatory frameworks and standards, like ISO 14001, science-based targets, and national carbon accounting systems. Such alignment would enhance the comparability and credibility of sustainability claims and also support evidence-based policymaking.

Despite these limitations, the present study provides a robust foundation for the advancement of research at the intersection of intelligent manufacturing and sustainability. Through the identification of clear pathways for methodological refinement and interdisciplinary integration, it invites continued scholarly engagement and positions data-driven systems analysis as a cornerstone of sustainable industrial transformation.

CONCLUSION

This study set out to examine how intelligent manufacturing systems can be systematically designed to reduce waste and deliver measurable sustainability benefits in complex production environments. By integrating data-driven predictive analytics, systems dynamics modeling, and sustainability assessment within a unified framework, the research demonstrates that waste reduction in modern manufacturing is not only technically feasible, but also economically and environmentally advantageous. The findings show that treating waste as an emergent, system-level outcome, rather than an isolated operational issue, enables more effective and durable interventions. Across multiple manufacturing sectors, the proposed approach achieved significant reductions in material waste, energy inefficiency, and carbon emissions while maintaining stable production throughput. These results highlight the value of the combination of real-time production intelligence with systems-level reasoning to anticipate and prevent waste before it occurs.

Beyond its empirical contributions, the study advances intelligent manufacturing research by offering a practical pathway for embedding sustainability objectives directly into operational decision-making. The integration of predictive models with scenario-based systems analysis allows manufacturers to evaluate the sustainability implications of alternative actions prior to implementation, thus reducing both environmental risk and managerial uncertainty. In doing so, the framework moves sustainability from a retrospective reporting activity to a proactive, data-driven capability. From an industrial perspective, the results demonstrate that sustainability and competitiveness need not be opposing goals. The rapid economic payback observed in this study underscores the potential for intelligent waste reduction strategies to simultaneously improve environmental performance and financial outcomes. For policymakers and stakeholders, the study provides evidence that data-enabled manufacturing systems can support transparent, verifiable sustainability improvements that are aligned with broader industrial transformation goals.

In conclusion, the study positions intelligent manufacturing as a critical enabler of sustainable industrial development. Through the bridging of artificial intelligence, systems thinking, and sustainability analysis, the research contributes a scalable and transferable framework that is capable of supporting long-term waste reduction and resource efficiency. As manufacturing systems continue to evolve in complexity and data intensity, such integrated approaches will be essential for attaining resilient, low-waste, and sustainable production systems.

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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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