Towards Industry 5.0 Circular Manufacturing: AI-Based Frameworks for Zero-Waste, Net-Zero, and Resource-Optimized Production

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Abstract

Manufacturing industries are increasingly challenged to achieve sustainability targets amid rising resource scarcity, waste accumulation, and global net-zero commitments. The transition from Industry 4.0 to Industry 5.0 introduces a paradigm shift in which manufacturing systems must become not only intelligent and connected, but also human-centric, resilient, and environmentally regenerative. In this study, an AI-based circular manufacturing framework is proposed to operationalize Industry 5.0 principles through the integration of real-time industrial sensing, digital twin simulation, machine learning prediction, reinforcement learning optimization, and lifecycle sustainability analytics. The framework is designed to enable measurable progress towards zero-waste production, net-zero carbon pathways, and resource-optimized industrial ecosystems. A simulation-based case study of a mid-scale discrete manufacturing facility demonstrates that the proposed Industry 5.0 circular AI model can reduce total waste generation by up to 38%, lower energy consumption by 27%, and decrease lifecycle-equivalent CO_2 emissions by 31% when compared to conventional linear production systems. Additionally, resource circularity performance improved from 0.22 in baseline operations to 0.68 under AI-enabled closed-loop optimization. These findings highlight the transformative role of AI-driven circular intelligence in supporting sustainable manufacturing transitions beyond traditional Industry 4.0 approaches. The study contributes a scalable methodological foundation for future industrial deployment, sustainability policy alignment, and interdisciplinary research advancement towards regenerative and climate-neutral manufacturing systems.

Keywords: *Industry 5.0; Circular manufacturing; Artificial intelligence; Net-zero production; Zero-waste systems; Digital twins; Sustainability*

INTRODUCTION

Manufacturing systems are undergoing a profound transformation as global industries confront the intertwined challenges of climate change, resource scarcity, and escalating waste generation. Industrial production remains one of the most resource-intensive sectors, as they account for substantial shares of global energy use, carbon emissions, and material consumption (Obiafudo *et al.*, 2026; Igbokwe *et al.*, 2026). Despite decades of technological progress, conventional manufacturing continues to operate largely within a linear economic paradigm that is characterized by "*take–make–dispose*" models, which are increasingly incompatible with sustainability imperatives and planetary boundaries (Udu *et al.*, 2025a). As governments and manufacturing companies commit to net-zero targets and circular economy roadmaps, there is a growing urgency to redesign production ecosystems towards zero-waste and climate-neutral industrial pathways.

In this context, the evolution from Industry 4.0 to Industry 5.0 represents a critical turning point. While Industry 4.0 has been widely associated with automation, cyber-physical systems, and smart factories, its primary focus has often remained on productivity, efficiency, and digital connectivity (Okpala *et al.*, 2026a; Chukwunedum *et al.*, 2026). Industry 5.0 expands this vision by explicitly emphasizing human-centricity, resilience, and sustainability as core industrial values (Udu *et al.*, 2025b; Okpala and Chukwumuanya, 2026). This emerging paradigm calls for manufacturing systems that not only optimize operational performance, but also regenerate resources, minimize environmental burdens, and enhance societal well-being.

Circular manufacturing has therefore emerged as a foundational pillar for Industry 5.0 sustainability transitions. Circular production systems aim to maintain materials and products at their highest utility through strategies such as remanufacturing, recycling, reuse, and closed-loop supply chain integration (Egwuagu and Okpala, 2026; Udu and Okpala, 2025). Unlike traditional end-of-pipe waste management, circular manufacturing promotes restorative and regenerative industrial ecosystems, which aligns closely with the United Nations Sustainable Development Goals (SDGs) and decarbonization agendas (Nwamekwe and Okpala, 2025; Udu *et al.*, 2025c). However, the implementation of circularity at scale remains complex due to multi-objective trade-offs across material flows, energy efficiency, economic constraints, and lifecycle environmental impacts.

Artificial Intelligence (AI) is increasingly recognized as a transformative enabler for overcoming these challenges. AI-driven manufacturing systems can enhance sustainability through predictive maintenance, intelligent resource scheduling, adaptive process control, and real-time optimization of energy and material usage (Oladapo *et al.*, 2026; Okpala and Okpala, 2026). Machine learning models can detect inefficiencies, forecast waste streams, and support decision-making across production and supply networks (Udu and Okpala, 2026; Okpala, 2026). More recently, digital twin technologies have enabled dynamic virtual representations of manufacturing environments, allowing simulation-based optimization of emissions, waste reduction, and circular resource loops (Nwosu *et al.*, 2026; Ogboh *et al.*, 2026). These developments indicate that AI has the potential to serve not merely as an automation tool, but as an intelligence engine for sustainable industrial transformation.

Nevertheless, existing research remains fragmented. Many current approaches address sustainability dimensions in isolation, for example, solely focus on energy efficiency, carbon accounting, or recycling logistics without the provision of integrated frameworks that are capable of simultaneously achieving zero-waste, net-zero, and resource-optimized production (de Sousa Jabbour *et al.*, 2018). Moreover, methodological limitations persist in the translation of AI advancements into measurable sustainability benefits through standardized indicators such as circularity rates, lifecycle carbon intensity, and waste minimization indices. However, the lack of holistic and operationalizable AI-based circular manufacturing architectures represents a major barrier to scaling Industry 5.0 sustainability solutions (Nobre and Tavares, 2021).

To address these gaps, this study proposes an AI-based multidisciplinary framework for Industry 5.0 circular manufacturing that integrates machine learning optimization, digital twin simulation, lifecycle sustainability analytics, and human-in-the-loop governance mechanisms. The framework is designed to enable measurable progress towards zero-waste systems, net-zero carbon manufacturing, and resource-optimized industrial production. Through the combination of circular economy principles with real-time AI intelligence, the proposed approach advances beyond traditional Industry 4.0 smart factory models towards regenerative and climate-resilient industrial ecosystems.

THEORETICAL FOUNDATIONS

The transition towards Industry 5.0 circular manufacturing is grounded in an interdisciplinary convergence of sustainability science, advanced manufacturing theory, circular economy principles, and artificial intelligence-driven optimization. The ability to understand these theoretical foundations is essential for the development of integrated frameworks that are capable of achieving measurable progress towards zero-waste systems, net-zero carbon production, and resource-optimized industrial ecosystems. The concept of Industry 5.0 has emerged as a response to the limitations of Industry 4.0, which has largely emphasized automation, connectivity, and productivity improvements through cyber-physical systems, industrial IoT, and smart factories (Okpala *et al.*, 2026b). While Industry 4.0 has transformed manufacturing operations through digitalization, critics argue that its dominant efficiency-driven orientation has not sufficiently addressed the escalating environmental and societal challenges facing industrial systems (Ajaefobi and Okpala, 2026; Igbokwe *et al.*, 2024).

Industry 5.0 extends beyond technological advancement as it positioned sustainability, resilience, and human well-being as central objectives of industrial transformation (EC, 2021). Rather than replace human agency with automation, Industry 5.0 promotes human–machine collaboration, ethical industrial governance, and regenerative value creation. This shift aligns manufacturing with broader global priorities such as climate neutrality, circular economy transitions, and inclusive industrial development (Nahavandi, 2019). Importantly, Industry 5.0 introduces a sustainability-by-design perspective; it emphasized that industrial intelligence must be evaluated not only through productivity gains but also through measurable reductions in carbon emissions, waste generation, and resource depletion (Mourtzis *et al.*, 2022). Thus, Industry 5.0 provides the conceptual foundation for the integration of AI-enabled circular manufacturing strategies into future industrial ecosystems.

Circular manufacturing is theoretically rooted in the broader circular economy paradigm, which aims to decouple economic growth from finite resource extraction and environmental degradation (Geissdoerfer *et al.*, 2017). Unlike the traditional linear economy, circular systems emphasize restorative and regenerative industrial loops, where products, components, and materials remain in continuous cycles of value retention (Egwuagu *et al.*, 2026). Circular economy theory is often structured around the "R-strategies," including reduce, reuse, recycle, remanufacture, and redesign, which collectively aim to extend product lifecycles and minimize waste outputs (Bocken *et al.*, 2016). In manufacturing contexts, circularity requires systemic transformation across product design, process engineering, and supply chain integration.

Circular manufacturing systems operationalize these principles through closed-loop production models that integrate reverse logistics, remanufacturing pathways, industrial symbiosis, and waste-to-resource conversion. Such systems enable industries to transition from waste management towards waste prevention and resource regeneration, which support the achievement of zero-waste production targets (Genovese *et al.*, 2017). However, the implementation of circularity at industrial scale remains highly complex due to multi-objective trade-offs that involve cost, quality, energy efficiency, and lifecycle environmental impacts. These challenges highlight the need for intelligent decision-support systems that are capable of optimizing circular resource flows dynamically.

Net-zero manufacturing represents a critical sustainability target for industrial decarbonization, as it requires that greenhouse gas emissions across production systems be reduced as close to zero as possible, with remaining emissions offset through verified removal pathways (Chukwumuanya *et al.*, 2025; Deswal, 2025a). The attainment of net-zero manufacturing is particularly challenging because emissions arise not only from direct energy use, but also from upstream material extraction, logistics, and end-of-life disposal processes (Deswal, 2025b). Therefore, lifecycle-based measurement frameworks are essential. Life Cycle Assessment (LCA) has become one of the most widely adopted methodologies for the quantification of environmental impacts across cradle-to-grave industrial value chains (ISO, 2006). LCA provides standardized metrics for the evaluation of carbon intensity, energy footprints, and material circularity outcomes, thus supporting evidence-based sustainability decision-making.

In circular manufacturing contexts, lifecycle sustainability analytics enable industries to quantify measurable benefits such as emissions reduction, waste diversion, and resource efficiency improvements. Consequently, the integration of AI optimization with lifecycle-based sustainability metrics is fundamental for the operationalization of net-zero and circular production objectives within Industry 5.0 frameworks.

Artificial intelligence has rapidly emerged as a transformative enabler of sustainable manufacturing transitions, particularly through its ability to analyze complex industrial datasets, optimize resource flows, and support real-time decision-making (Okpala and Nwamekwe, 2025a, b; Chukwumuanya and Okpala, 2025). AI techniques such as machine learning, reinforcement learning, and predictive analytics can significantly enhance sustainability performance through waste reduction, energy consumption minimization, and material utilization efficiency improvement (Aguh and Okpala, 2025; Okpala and Nwankwo, 2025). For example, predictive maintenance models reduce equipment failure and scrap generation, while intelligent scheduling algorithms enable carbon-aware production planning, AI also supports adaptive process optimization, where manufacturing parameters are continuously adjusted to reduce emissions and resource inefficiencies. Within circular economy systems, AI plays an especially critical role in enabling closed-loop intelligence, where waste streams are identified as valuable secondary resources, and production networks are dynamically optimized for reuse and recycling pathways. However, scholars emphasize that AI must be governed ethically and transparently to align industrial intelligence with Industry 5.0's human-centric sustainability goals (Xu *et al.*, 2021).

Digital twin theory represents one of the most promising methodological innovations for Industry 5.0 circular manufacturing. Digital twins are dynamic virtual replicas of physical manufacturing systems that integrate real-time sensor data, simulation models, and AI analytics to optimize industrial performance (Okpala and Okpala, 2025; Udu *et al.*, 2025d). In sustainability contexts, digital twins enable manufacturers to simulate emissions pathways, forecast waste generation, and test circular process interventions without disrupting physical operations. This capability is essential for multi-objective optimization, where production decisions must simultaneously balance economic performance with environmental constraints. Furthermore, digital twin architectures support resource-optimized manufacturing ecosystems by enabling the following: Circular material flow modeling; Carbon footprint forecasting; Zero-waste process redesign; and Net-zero energy scheduling. As Industry 5.0 increasingly emphasizes resilience and sustainability, digital twins provide a critical bridge between AI intelligence and measurable environmental performance improvements.

Collectively, Industry 5.0 theory, circular economy principles, net-zero sustainability measurement, AI-driven optimization, and digital twin architectures form the multidisciplinary theoretical foundation for next-generation circular manufacturing systems. The convergence of these domains enables a paradigm shift from efficiency-centered smart factories towards regenerative, climate-neutral, and resource-optimized production ecosystems. The proposed framework builds upon these foundations through the integration of AI intelligence, lifecycle sustainability metrics, and human-centric governance mechanisms to operationalize measurable progress towards zero-waste and net-zero Industry 5.0 manufacturing.

AI-BASED FRAMEWORK FOR INDUSTRY 5.0 CIRCULAR MANUFACTURING

The transition towards Industry 5.0 circular manufacturing requires more than incremental improvements in automation or digital connectivity. Instead, it demands an integrated intelligence-driven architecture that will concurrently address waste elimination, net-zero decarbonization, and optimal resource circulation across industrial ecosystems. While Industry 4.0 technologies have enabled smart factories through IoT connectivity and cyber-physical production systems, sustainability outcomes have often remained secondary or fragmented (Xu *et al.*, 2021; de Sousa Jabbour *et al.*, 2018). Industry 5.0 expands this landscape through the integration of sustainability, resilience, and human-centric value creation as core manufacturing objectives (EC, 2021). To operationalize these principles, this study proposes a multidisciplinary AI-based framework for circular Industry 5.0 manufacturing that embeds real-time data intelligence, digital twins, machine learning optimization, lifecycle sustainability analytics, and human-in-the-loop governance. The framework is designed to enable measurable progress towards zero-waste and net-zero production systems while also enhancing resource efficiency and industrial resilience.

The proposed framework positions AI as the central decision-making engine that will enable circular manufacturing loops. Rather than treat waste, emissions, and resource efficiency as separate sustainability challenges, the framework adopts a systems-level optimization approach that integrates the following: Closed-loop material flow intelligence; Carbon-aware production scheduling; Digital twin-enabled simulation of circular pathways; and Lifecycle-based sustainability performance evaluation. Such integration is essential because circular manufacturing involves complex multi-objective trade-offs across economic performance, energy intensity, waste minimization, and environmental compliance. AI technologies, particularly machine learning and reinforcement learning, offer the computational capacity to manage these trade-offs dynamically by continuously learning from industrial data streams and optimizing production decisions in real time (Nwamekwe *et al.*, 2025; Aguh *et al.*, 2025).

Fig. 1 visually presents the full five-layer architecture of the proposed framework; it reveals how real-time IoT sensing feeds into a digital twin environment, which then connects to the AI optimization engine, lifecycle sustainability analytics, and finally the human-centric governance layer.

The framework is structured into five interconnected layers, each contributing to measurable sustainability benefits and Industry 5.0 alignment.

Layer 1: Smart Sensing and Industrial Data Acquisition

The foundation of circular Industry 5.0 manufacturing lies in real-time visibility of industrial resource flows. This layer integrates IoT-enabled sensing systems and cyber-physical infrastructure to capture continuous data on the following: Material consumption rates; Energy demand profiles; Waste generation streams; Machine performance and process inefficiencies; and Emission-relevant operational parameters. Smart sensing is essential for enabling data-driven sustainability interventions and has been widely recognized as a core enabler of cleaner manufacturing systems. Without high-resolution data, circularity optimization and net-zero monitoring will remain mere theoretical.

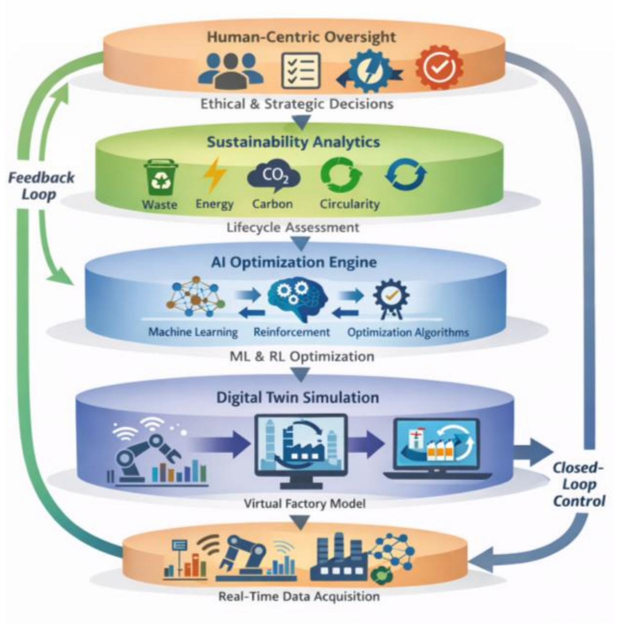

Fig. 1: AI-based Industry 5.0 circular manufacturing framework architecture.

Layer 2: Digital Twin-Based Circular Simulation Environment

Digital twins represent one of the most significant methodological innovations in sustainable Industry 5.0 manufacturing. Within circular manufacturing contexts, digital twins support the following: Waste flow mapping and reduction scenario testing; Predictive emissions forecasting; Resource loop redesign through virtual experimentation; and Evaluation of remanufacturing and recycling interventions. Digital twins enable manufacturers to shift from reactive sustainability measures towards predictive and proactive circular process redesign. Through the integration of circular economy parameters into the twin model, industries can quantify measurable sustainability improvements before the implementation of physical changes.

Layer 3: AI Optimization and Circular Decision Intelligence Engine

At the core of the proposed framework lies the AI-driven optimization engine, which transforms industrial data into actionable circular manufacturing decisions. This engine integrates the following three complementary AI mechanisms:

a. *Machine Learning for Predictive Circularity Analytics:* Supervised learning models forecast the following: Waste generation hotspots; Material loss probabilities; Resource demand fluctuations; and Equipment degradation and scrap risks. Predictive AI reduces unnecessary resource extraction and minimizes production waste through anticipatory interventions.

b. *Reinforcement Learning for Multi-Objective Sustainability Optimization:* Reinforcement learning is particularly suitable for circular manufacturing because it can optimize sequential decision-making under complex constraints, such as balancing the following: Productivity targets; Energy efficiency; Waste minimization; and Carbon emission reduction. RL-based scheduling enables carbon-aware and resource-efficient production planning, a critical requirement for net-zero manufacturing pathways.

c. *Closed-Loop Resource Routing Algorithms:* AI-driven circular routing enables waste streams to be reclassified as secondary resources, dynamically allocating materials into the following: Reuse loops; Recycling pathways; Remanufacturing processes; and Industrial symbiosis networks. Such intelligence supports the transition from waste management towards waste prevention and value regeneration.

Layer 4: Lifecycle Sustainability and Net-Zero Performance Analytics

To ensure measurable sustainability benefits, the framework incorporates lifecycle-based evaluation metrics that are aligned with internationally recognized LCA standards. This layer quantifies key indicators like: Lifecycle carbon intensity ($kg.CO_2eq/unit$); Waste Reduction Index (WRI); Resource Circularity Rate (RCR); and Energy Optimization Efficiency (EOE). Lifecycle analytics are quite essential because manufacturing emissions are not limited to factory operations, but extend across supply chains, material extraction, and end-of-life recovery. By embedding lifecycle sustainability measurement directly into AI decision loops, the framework enables verifiable progress toward net-zero and zero-waste production.

Layer 5: Human-Centric Governance and Industry 5.0 Sustainability Control

A defining feature of Industry 5.0 is the reintegration of human agency into industrial intelligence systems. Rather than fully autonomous optimization, Industry 5.0 requires human-in-the-loop governance in order to ensure that AI-driven circular decisions remain transparent and explainable, ethically aligned, socially accountable, and resilient under uncertainty. Industry 5.0 manufacturing must prioritize human-centered value creation, thereby positioning AI as a collaborative sustainability partner rather than a purely efficiency-maximizing tool. This governance layer therefore integrates the following: Explainable AI dashboards; Decision-support systems for sustainability managers; as well as Ethical compliance mechanisms for circular operations.

The proposed AI-based Industry 5.0 circular manufacturing architecture enables quantifiable sustainability benefits, including: significant waste reduction through predictive circular interventions, carbon emission minimization via net-zero scheduling optimization, resource efficiency improvements through closed-loop material circulation, and lifecycle sustainability transparency supporting ESG compliance. Through the integration of AI optimization with circular economy theory and Industry 5.0 governance principles, the framework provides a scalable methodological foundation for regenerative manufacturing ecosystems. The framework advances the literature in three key ways: It bridges Industry 5.0 sustainability principles with operational AI architectures; it integrates digital twins, machine learning, and lifecycle analytics into a unified circular manufacturing model; and also it provides measurable, KPI-driven pathways toward zero-waste and net-zero production. As such, the proposed approach contributes to the emerging global agenda of circular Industry 5.0 manufacturing by offering a highly transferable structure for future industrial deployments, policy frameworks, and interdisciplinary research.

SUSTAINABILITY METRICS AND MEASURABLE INDICATORS

A central challenge for the advancement of Industry 5.0 circular manufacturing lies not only in the development of intelligent frameworks, but also in the establishment of standardized, measurable sustainability indicators that can quantify progress towards zero-waste, net-zero, and resource-optimized production. While sustainability has become a defining priority of Industry 5.0, the absence of harmonized metrics often limits the operationalization, benchmarking, and scalability of circular manufacturing solutions (Sala *et al.*, 2021). Sustainability performance in manufacturing is inherently multidimensional, as it encompasses material efficiency, waste minimization, carbon neutrality, energy optimization, and lifecycle environmental impacts. Therefore, the proposed AI-based Industry 5.0 circular manufacturing framework integrates a suite of quantitative indicators that are designed to enable data-driven monitoring, AI optimization, and cross-industry comparability.

Importantly, these metrics are aligned with established sustainability methodologies such as LCA, circular economy performance indicators, and international environmental management standards. By embedding measurable indicators into the AI decision-making loop, the framework ensures that circular intelligence translates into verifiable sustainability outcomes.

Waste elimination is a defining target of circular manufacturing systems. Unlike traditional waste management approaches, Industry 5.0 circular production aims to prevent waste generation at the source by redesigning processes, improving material utilization, and closing industrial loops. To quantify progress towards zero-waste manufacturing, the framework adopts the Waste Reduction Index (WRI):

$$1 - \frac{W_{circular}}{W_{linear}} \tag{1}$$

where:
$W_{circular}$ represents waste generated under AI-enabled circular operations; and
W_{linear} represents waste generated under conventional linear production

A WRI approaching 1 indicates strong movement towards zero-waste production.

In addition, the Waste Diversion Rate (WDR) measures the proportion of waste redirected into reuse, recycling, or remanufacturing loops:

$$WDR = \frac{W_{reused}+W_{recycled}}{W_{total}} \tag{2}$$

These indicators provide measurable evidence of circularity effectiveness and are frequently emphasized in circular economy implementation studies.

Net-zero manufacturing requires systematic decarbonization across industrial operations and value chains. Since manufacturing emissions arise from both direct energy use and upstream material processes, carbon neutrality assessment must extend beyond factory-level monitoring toward lifecycle-based emissions accounting (IEA, 2021).

The framework evaluates net-zero progress using the Carbon Neutrality Progress metric (CNP):

$$CNP = \frac{CO_{2,baseline} - CO_{2,AI}}{CO_{2,baseline}} \tag{3}$$

where:

$CO_{2,baseline}$ represents emissions under conventional production; and
$CO_{2,AI}$ represents emissions after AI-based optimization

This indicator enables manufacturers to quantify decarbonization gains from carbon-aware scheduling, energy optimization, and circular material substitution.

Furthermore, the Carbon Intensity of Production (CIP) is defined as:

$$CIP = \frac{CO_{2,total}}{Q_{output}} \tag{4}$$

where Q_{output} denotes production output volume. Lower CIP values indicate more climate-efficient manufacturing systems. These indicators are consistent with industrial decarbonization frameworks which emphasize measurable pathways towards net-zero targets (Sala *et al.*, 2021). Resource optimization is central to Industry 5.0 circular manufacturing, as the goal is not only to reduce waste, but also to maximize the retention of material value within closed-loop systems. The Resource Circularity Rate (RCR) measures the share of input materials that remain within circular loops:

$$RCR = \frac{M_{reused}+M_{recycled}+M_{remanufactured}}{M_{total}} \tag{5}$$

where:
M_{total}represents total material input

M_{reused}, $M_{recycled}$, $M_{remanufactured}$ represent recovered material flows

A higher RCR reflects stronger circular manufacturing performance. Additionally, Material Utilization Efficiency (MUE) quantifies how effectively raw materials are converted into valuable products:

$$MUE = \frac{M_{product}}{M_{input}} \tag{6}$$

Such indicators are essential for the evaluation of resource decoupling and regenerative production outcomes.

Energy efficiency remains a major driver of both cost reduction and emissions mitigation in manufacturing. Industry 5.0 sustainability requires that energy optimization be integrated with AI-driven production intelligence (Jamwal *et al.*, 2021).

The framework employs the Energy Optimization Efficiency (EOE):

$$EOE = 1 - \frac{E_{optimized}}{E_{baseline}} \tag{7}$$

where:
$E_{baseline}$ is energy use under traditional manufacturing; and
$E_{baseline}$ is energy use after AI-based scheduling and process optimization.

Also, Renewable Energy Utilization Share ($REUS$) is introduced to capture progress toward clean energy transitions:

$$REUS = \frac{E_{renewable}}{E_{total}} \tag{8}$$

These indicators support measurable pathways towards net-zero industrial energy systems.

Because circular manufacturing sustainability extends beyond production boundaries, lifecycle-based indicators are essential for the evaluation of cradle-to-grave impacts (ISO, 2006).

The framework integrates Life Cycle Impact Reduction ($LCIR$):

$$LCIR = 1 - \frac{LCA_{circular}}{LCA_{linear}} \tag{9}$$

where:
LCA_{linear} represents lifecycle impacts under conventional systems; and
$LCA_{circular}$ represents lifecycle impacts under circular AI-optimized systems.

This ensures alignment with international LCA standards and sustainability policy evaluation frameworks. In addition, Industry 5.0 sustainability assessment must include resilience and human-centric value creation. Thus, future extensions of the framework may incorporate socio-technical indicators such as worker well-being, safety improvements, and ethical AI transparency. Fig. 2 illustrates how sustainability

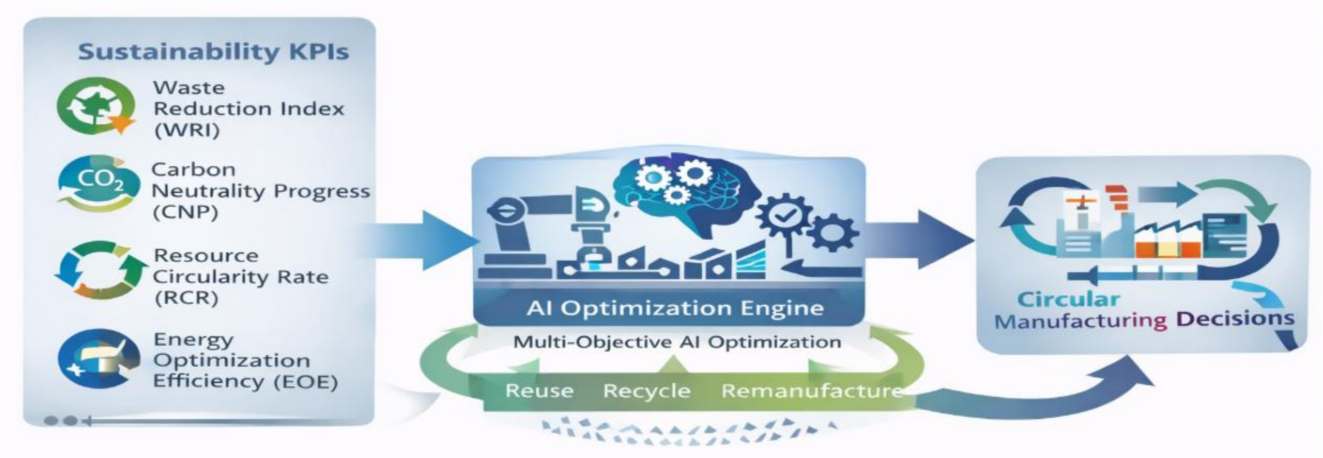

Fig. 2: Sustainability metrics integration into AI optimization (KPI-driven circular decision loop).

indicators such as waste reduction, carbon neutrality progress, energy efficiency, and resource circularity are not only evaluated after production, but are embedded directly into the AI optimization objectives. It clearly demonstrates the measurable, data-driven nature of the framework and strengthens the methodological contribution.

A major methodological contribution of this study is the integration of sustainability indicators directly into the AI optimization engine. Rather than treat metrics as post-hoc evaluation tools, they are embedded as objective functions in multi-criteria decision-making algorithms. This enables AI systems to optimize simultaneously for the following: Waste minimization; Carbon neutrality progress; Resource circularity maximization; and Energy efficiency improvement. Such KPI-driven AI sustainability architectures represent a critical advancement beyond fragmented Industry 4.0 approaches and provide measurable pathways for the operationalization of Industry 5.0 circular manufacturing.

CASE SIMULATION RESULTS

To demonstrate the operational feasibility and measurable sustainability benefits of the proposed AI-based Industry 5.0 circular manufacturing framework, a simulation-based case study was conducted. Simulation remains a widely adopted methodological approach for the evaluation of sustainability interventions in manufacturing, particularly when real-world industrial deployment is costly, disruptive, or constrained by data access limitations. Through the leveraging of digital twin environments, manufacturers can assess circular strategies, waste reduction pathways, and net-zero optimization scenarios before physical implementation. The case simulation presented in this study evaluates the extent to which AI-enabled circular intelligence can outperform conventional linear manufacturing and Industry 4.0 smart production systems in achieving zero-waste, net-zero, and resource-optimized outcomes.

The simulation represents a mid-scale discrete manufacturing facility producing industrial mechanical components, a sector commonly associated with high material scrap rates and energy-intensive machining processes (Zhang *et al.*, 2020). The production system includes the following: Raw material input (steel and aluminum alloys); CNC machining and assembly lines; Industrial energy demand from electrical equipment; and Waste streams including metal scrap, defective parts, and packaging waste.

The following three scenarios were modeled for comparative evaluation:

- *Scenario A:* Conventional Linear Manufacturing (Baseline)
- *Scenario B:* Industry 4.0 Smart Factory Benchmark (IoT monitoring without closed-loop circular AI optimization)
- *Scenario C:* Proposed Industry 5.0 AI-Based Circular Manufacturing Framework

The simulation integrates real-time sensing, digital twin forecasting, reinforcement learning scheduling, and circular routing of waste streams into secondary production loops.

Performance was evaluated using the measurable indicators introduced earlier, including: Waste Reduction Index (WRI); Carbon Neutrality Progress (CNP); Resource Circularity Rate (RCR); Energy Optimization Efficiency (EOE); as well as Carbon Intensity of Production (CIP). These metrics are consistent with circular economy measurement approaches and lifecycle-based sustainability evaluation standards.

Table 1 summarizes the baseline operational characteristics of the simulated production system.

Table 1: Baseline manufacturing inputs and environmental outputs (Scenario A).

Parameter	Baseline Value (Monthly)	Unit
Production output	10,000	units
Raw material consumption	520	tons (t)
Energy consumption	1,200	MWh
Total waste generated	95	tons (t)
Recycled/reused waste	18	tons (t)
CO_2 emissions (Scope 1–2 equivalent)	610	$t.CO_2eq$
Carbon intensity of production (CIP)	0.061	$t.CO_2/unit$

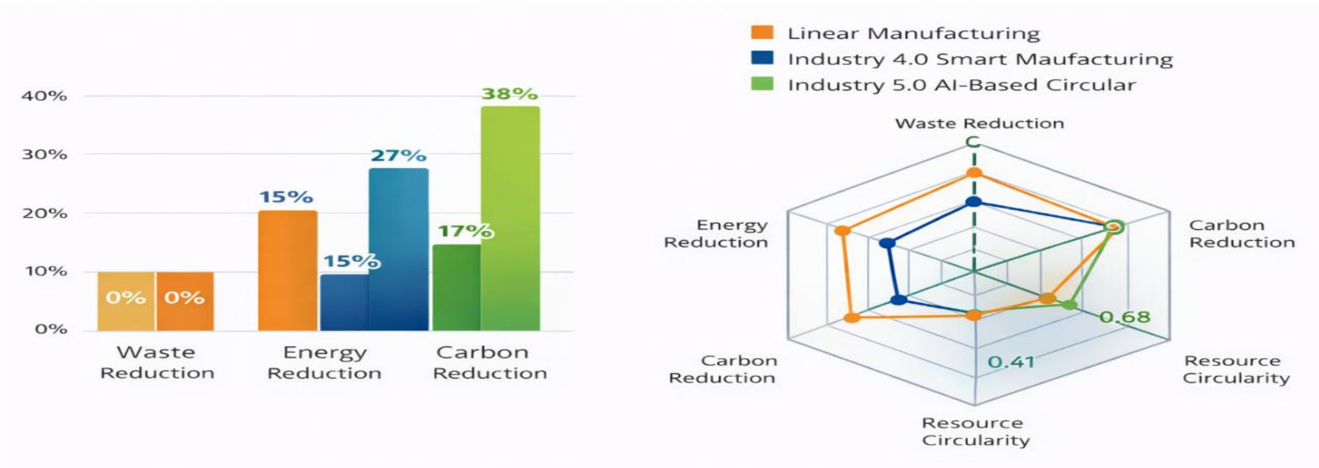

Fig. 3: Comparative sustainability performance results across scenarios.

Table 2: Sustainability KPI outcomes across scenarios.

Sustainability Indicator	Scenario A: Linear	Scenario B: Industry 4.0	Scenario C: Proposed Industry 5.0 AI Circular
Waste Reduction Index (WRI)	–	0.19	**0.38**
Waste Diversion Rate (WDR)	0.19	0.34	**0.62**
Resource Circularity Rate (RCR)	0.22	0.41	**0.68**
Energy Optimization Efficiency (EOE)	–	0.15	**0.27**
Carbon Neutrality Progress (CNP)	–	0.17	**0.31**
Carbon intensity (CIP) ($t.CO_2/unit$)	0.061	0.051	**0.042**

Table 3: Waste stream optimization results.

Waste Category	Baseline Waste (tons)	Industry 4.0 Waste (tons)	Industry 5.0 AI Circular Waste (tons)
Metal scrap	52	44	31
Defective parts	28	22	15
Packaging waste	15	11	8
Total Waste	95	77	59

Table 4: Energy and carbon emissions reduction results.

Indicator	Baseline	Industry 4.0	Industry 5.0 AI Circular
Energy consumption ($MWh/month$)	1,200	1,020	876
Energy reduction (%)	–	15%	27%
CO_2 emissions ($t.CO_2eq/month$)	610	506	421
Carbon reduction (%)	–	17%	31%

These baseline values reflect typical manufacturing sustainability profiles that are reported in cleaner production studies (Ghisellini *et al.*, 2016). Fig. 3 provides a clear visual comparison of sustainability outcomes between conventional linear manufacturing, Industry 4.0 smart factories, and the proposed Industry 5.0 AI circular model.

The results, as highlighted in Table 2, demonstrate that while Industry 4.0 smart monitoring provides moderate sustainability improvements, the proposed Industry 5.0 circular AI framework delivers substantially higher reductions in waste, emissions, and resource inefficiency.

Waste minimization represents one of the most significant measurable benefits of the proposed framework. Under the Industry 5.0 AI-based circular scenario, total waste generation declined from 95 tons/month to 59 tons/month, which represents a 38% reduction relative to the linear baseline.

These reductions, as highlighted in Table 3, were primarily enabled by AI-driven predictive maintenance and closed-loop scrap recovery, consistent with findings that AI can significantly reduce industrial waste generation.

Energy consumption was also substantially reduced under the proposed framework, as shown in Table 4. Reinforcement learning-based production scheduling shifted energy-intensive operations away from peak demand periods and improved machine utilization efficiency. The emissions reduction achieved reflects the dual impact of energy efficiency improvements and material circularity substitution, which aligns with net-zero manufacturing decarbonization strategies that were emphasized by the IEA (2021).

The simulation further demonstrates strong progress towards resource-optimized manufacturing. The Resource Circularity Rate increased from 0.22 in the baseline to 0.68 under the proposed Industry 5.0 AI circular model. This improvement reflects the system's ability to redirect waste streams into reuse and remanufacturing loops, thus supporting circular economy theory that waste should be treated as an industrial input rather than an output (Geissdoerfer *et al.*, 2017). Overall, the simulation confirms that Industry 5.0 circular manufacturing frameworks must extend beyond digital monitoring toward AI-enabled closed-loop optimization. While Industry 4.0 provides foundational connectivity, Industry 5.0 enables measurable sustainability transformation through the following: Intelligent waste prevention, Carbon-aware production scheduling, Digital twin-driven circular scenario testing, and Lifecycle-based sustainability KPI integration. These results support emerging scholarship that emphasizes that Industry 5.0 is not simply a technological upgrade, but a sustainability-driven industrial paradigm shift (EC, 2021).

DISCUSSION, POLICY, AND FUTURE RESEARCH DIRECTIONS

The transition towards Industry 5.0 represents a fundamental shift in manufacturing priorities, as it moves beyond efficiency-centered automation towards sustainability-driven, human-centric, and resilient industrial ecosystems. The simulation results highlight substantial sustainability gains, including significant reductions in waste generation, energy consumption, and carbon emissions, alongside major improvements in resource circularity performance. These outcomes provide evidence that Industry 5.0 circular manufacturing is not merely a conceptual aspiration but a quantitatively measurable pathway towards regenerative industrial transformation.

The results of the case simulation confirm the following three critical insights:

a. While Industry 4.0 technologies provide foundational connectivity and monitoring, they often remain insufficient for the attainment of deep sustainability transitions because they lack integrated circular optimization architectures. In the simulation, Industry 4.0 improvements were moderate, whereas the proposed Industry 5.0 AI-based circular model achieved substantially higher reductions in waste and emissions. This reinforces the argument that Industry 5.0 represents not simply an incremental technological upgrade, but a paradigm shift towards sustainability-by-design manufacturing systems (Nahavandi, 2019).

b. The findings demonstrate that AI-driven circular intelligence enables measurable sustainability outcomes by dynamically optimizing complex trade-offs across waste prevention, energy efficiency, and carbon neutrality. Machine learning forecasting, reinforcement learning scheduling, and digital twin simulation collectively enhanced industrial decision-making in ways that traditional linear production models cannot support. This aligns with emerging scholarship emphasizing that AI is a central enabler of sustainable manufacturing transitions when linked to lifecycle performance metrics (Sala *et al.*, 2021).

c. The framework underscores the importance of standardized sustainability indicators. Metrics such as the Waste Reduction Index, Resource Circularity Rate, and Carbon Neutrality Progress provide quantifiable benchmarks that enable both academic comparability and industrial implementation. Without measurable indicators, circular manufacturing remains difficult to operationalize across sectors.

This study contributes to the theoretical development of Industry 5.0 circular manufacturing in the following ways:

a. *Bridging Industry 5.0 and Circular Economy Theory*: While circular economy research has expanded rapidly, much of the literature remains focused on macro-level conceptual frameworks rather than operational AI-driven architectures for industrial deployment (Ghisellini *et al.*, 2016). This study advances theory through the demonstration of how Industry 5.0 sustainability objectives can be operationalized through integrated AI systems that close resource loops and enable regenerative production ecosystems.

b. *Embedding AI within Lifecycle Sustainability Governance*: The framework extends beyond automation by embedding AI optimization directly into lifecycle-based sustainability analytics. This contributes to the emerging discourse on “Industrial AI” as a tool not only for productivity, but also for decarbonization, circularity, and net-zero transformation (Lee *et al.*, 2021).

c. *Human-Centric Sustainability Intelligence*: A defining feature of Industry 5.0 is the reintegration of human agency into industrial decision-making. The inclusion of human-in-the-loop governance mechanisms contributes to theory through the alignment of AI optimization with ethical, transparent, and socially accountable sustainability outcomes (Nahavandi, 2019).

d. *Policy Implications for Zero-Waste and Net-Zero Industrial Transitions*: The findings of this study offer important policy insights for governments, regulators, and industrial sustainability strategists.

e. *Standardization of Circular Manufacturing Sustainability KPIs*: Policymakers should prioritize the development of standardized circular manufacturing metrics that are aligned with ISO-based lifecycle frameworks. Without harmonized KPIs, industries face challenges in benchmarking sustainability progress and also in complying with emerging ESG reporting requirements.

f. *Incentivizing AI-Enabled Circular Innovation*: Industrial decarbonization policies should move beyond renewable energy adoption alone and explicitly support AI-driven circular manufacturing investments. Subsidies, tax incentives, and innovation funding can accelerate the deployment of digital twins, predictive circular analytics, and reinforcement learning scheduling systems that deliver measurable sustainability gains (IEA, 2021).

g. *Supporting Circular Supply Chain Ecosystems*: Circular manufacturing cannot be achieved solely within factory boundaries. Policies should enable closed-loop supply chain infrastructure, reverse logistics systems, and industrial symbiosis networks that allow waste streams from one sector to become resource inputs for another (Kirchherr *et al.*, 2017).

h. *Ethical and Human-Centric AI Governance Frameworks:* As AI becomes central to Industry 5.0 sustainability decision-making, regulatory frameworks must ensure transparency, explainability, and accountability in industrial AI systems. Human-centered governance will be essential for the alignment of AI optimization with societal well-being rather than purely economic efficiency.

Although this study provides a foundational AI-based framework for Industry 5.0 circular manufacturing, the following research directions remain critical for the advancement of the field:

a. *Real-World Industrial Validation and Pilot Deployments*: Future work should test the proposed framework through large-scale industrial pilots across different sectors like automotive manufacturing, electronics, and heavy industry. Empirical validation will strengthen the generalizability of simulation-based findings (Negri *et al.*, 2017).

b. *Integration of Scope 3 Emissions and Full Supply Chain Circularity*: While this study emphasizes factory-level circular optimization, future research should incorporate Scope 3 emissions, upstream extraction impacts, and downstream end-of-life recovery pathways in order to achieve full lifecycle net-zero manufacturing systems.

c. *Advanced Multi-Objective Optimization and Explainable AI*: Further methodological innovation is required in multi-objective AI optimization that balances sustainability goals with economic constraints, while remaining explainable and interpretable for human decision-makers.

d. *Socio-Technical and Workforce Dimensions of Industry 5.0 Circularity*: Industry 5.0 requires sustainability transitions that enhance worker well-being, inclusivity, and social resilience. Future research should expand circular manufacturing metrics to incorporate socio-technical indicators such as job quality, safety improvements, and equitable industrial development outcomes.

e. *Policy-Driven Circular Manufacturing Roadmaps*: Finally, interdisciplinary research is needed to connect AI-based circular frameworks with national and regional policy roadmaps, in order to enable scalable net-zero industrial transformation aligned with SDG agendas and climate commitments.

The proposed AI-based Industry 5.0 circular manufacturing framework demonstrates that measurable sustainability benefits like waste reduction, emissions minimization, energy efficiency, and resource circularity can be achieved through intelligent closed-loop optimization architectures. The findings reinforce Industry 5.0 as a sustainability-driven paradigm shift and provide a scalable foundation for future industrial deployment, regulatory alignment, and multidisciplinary research advancement.

CONCLUSION

This study set out to advance the emerging vision of Industry 5.0 by proposing an AI-based circular manufacturing framework capable of supporting zero-waste, net-zero, and resource-optimized production systems. As manufacturing industries face increasing pressure to decarbonize operations, reduce waste generation, and transition away from linear production models, the integration of circular economy principles with intelligent digital technologies has become both timely and essential. The proposed framework contributes a multidisciplinary architecture that combines real-time industrial data acquisition, digital twin-enabled simulation, machine learning prediction, reinforcement learning optimization, lifecycle sustainability analytics, and human-centric governance mechanisms. Through the embedding of measurable sustainability indicators directly into AI-driven decision-making processes, the framework moves beyond conventional Industry 4.0 smart factory approaches towards a more regenerative and sustainability-oriented Industry 5.0 paradigm.

The case simulation results demonstrate that AI-enabled circular manufacturing can deliver substantial and quantifiable environmental benefits. When compared with traditional linear production systems, the proposed Industry 5.0 circular model achieved significant reductions in industrial waste generation, energy consumption, and carbon emissions, while simultaneously improving resource circularity performance. These outcomes highlight the transformative potential of closed-loop AI intelligence in enabling manufacturing systems that are not only efficient but also environmentally restorative and climate-aligned. Beyond technical performance, this study emphasizes that Industry 5.0 circular manufacturing must remain human-centered, transparent, and ethically governed. Sustainability transformation in manufacturing is not solely a technological challenge, but also a socio-industrial transition that requires responsible innovation, collaborative decision-making, and supportive policy ecosystems. Overall, the work provides a scalable methodological foundation for future research and industrial deployment of AI-based circular manufacturing systems. Through the linking of Industry 5.0 principles with measurable sustainability outcomes, the study offers a pathway towards next-generation production ecosystems that can meet the environmental demands of the 21st century, while also supporting resilient, resource-efficient, and net-zero industrial development.

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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.

REFERENCES

1) Aguh, P.S. and Okpala, C.C. (2025) 'Learning in the age of artificial intelligence tutors: Cognitive outcomes and equity in automated education systems', *International Journal of Engineering Research and Development*, 21(12), pp. 88-98. https://ijerd.com/paper/vol21-issue12/21128898.pdf
2) Aguh, P.S., Udu, C.E., Chukwumuanya, E.O., *et al.* (2025) 'Machine learning applications for production scheduling optimization', *Journal of Exploratory Dynamic Problems*, 2(4), pp. 63-79. https://edp.web.id/index.php/edp/article/view/137
3) Ajaefobi, J.O. and Okpala, C.C. (2026) 'Six Sigma in the era of Industry 4.0: A bibliometric and benchmarking review', *International Journal of Engineering Research and Development*, 22(3), pp. 71-84. https://www.ijerd.com/paper/vol22-issue3/22037184.pdf
4) Bocken, N.M.P., de Pauw, I., Bakker, C., *et al.* (2016) 'Product design and business model strategies for a circular economy', *Journal of Industrial and Production Engineering*, 33(5), pp. 308-320. https://doi.org/10.1080/21681015.2016.1172124
5) Chukwumuanya, E.O. and Okpala, C.C. (2025) 'Responsible artificial intelligence for global challenges: Frameworks for fairness, transparency, and policy impact', *International Journal of Engineering Research and Development*, 21(12), pp. 77-87. https://ijerd.com/paper/vol21-issue12/21127787.pdf
6) Chukwumuanya, E.O., Okpala, C.C. and Udu, C.E. (2025) 'Carbon accounting at the shop-floor: The integration of real-time energy monitoring, process modeling and LCA for net-zero targets', *Jurnal Teknik Indonesia*, 4(1), pp. 28-41. https://jurnal.seaninstitute.or.id/index.php/juti/article/view/728
7) Chukwunedum, O.C., Okpala, C.C. and Udu, C.E. (2026) 'A data-driven integration of total productive maintenance and Industry 4.0 technologies: A machine learning framework for predictive OEE optimization', *International Journal of Engineering Research and Development*, 22(3), pp. 85-95. https://www.ijerd.com/paper/vol22-issue3/22038595.pdf
8) de Sousa Jabbour, A.B.L., Jabbour, C.J.C., Foropon, C., *et al.* (2018) 'When titans meet: Industry 4.0 and the circular economy: A proposed

research agenda and current challenges', *Technological Forecasting and Social Change*, 132, pp. 18-25. https://doi.org/10.1016/j.techfore.2018.01.017
9) Deswal, P. (2025a) *Carbon neutrality versus net-zero*. Drug and Device World. https://druganddeviceworld.com/2025/04/07/carbon-neutrality-versus-net-zero/
10) Deswal, P. (2025b) *What are GHG emissions*. Drug and Device World. https://druganddeviceworld.com/2025/04/06/what-are-ghg-emissions/
11) Egwuagu, O.M. and Okpala, C.C. (2026) 'Engineering of the factory of the future: Production systems for circularity and net-zero performance', *International Journal of Technology, Health and Sustainability*, 2(2), pp. 893-902. https://ijths.com/wp-content/uploads/IJTHS-0202070.pdf
12) Egwuagu, O.M., Okpala, C.C. and Udu, C.E. (2026) 'Circular economy and net-zero manufacturing: A data-driven multidisciplinary framework for sustainable industrial transformation', *International Journal of Technology, Health and Sustainability*, 2(2), pp. 540-550. https://ijths.com/wp-content/uploads/IJTHS-0202021.pdf
13) EC (2021) *Industry 5.0: Towards a sustainable, human-centric and resilient European industry*. Publications Office of the European Union, European Commission.
14) Genovese, A., Acquaye, A.A., Figueroa, A., *et al.* (2017) 'Sustainable supply chain management and the transition towards a circular economy: Evidence and some applications', *International Journal of Production Research*, 55(8), pp. 2403-2418. https://doi.org/10.1080/00207543.2016.1235712
15) Geissdoerfer, M., Savaget, P., Bocken, N.M.P., *et al.* (2017) 'The circular economy—A new sustainability paradigm?', *Journal of Cleaner Production*, 143, pp. 757-768. https://doi.org/10.1016/j.jclepro.2016.12.048
16) Ghisellini, P., Cialani, C. and Ulgiati, S. (2016) 'A review on circular economy: The expected transition to a balanced interplay of environmental and economic systems', *Journal of Cleaner Production*, 114, pp. 11-32. https://doi.org/10.1016/j.jclepro.2015.09.007
17) Igbokwe, N.C., Okpala, C.C. and Nwamekwe, C.O. (2026) 'Total productive maintenance impact quantification on sustainable manufacturing performance: A multi-plant longitudinal big data analysis', *International Journal of Technology, Health and Sustainability*, 2(3), pp. 968-979. https://ijths.com/wp-content/uploads/IJTHS-0203002.pdf
18) Igbokwe, N.C., Okpala, C.C. and Nwankwo, C.O. (2024) 'Industry 4.0 implementation: A paradigm shift in manufacturing', *Journal of Inventive Engineering and Technology*, 6(1), pp. 20-26. https://jiengtech.com/index.php/INDEX/article/view/113/135
19) IEA (2021) *World energy outlook 2021*. International Energy Agency Publications.
20) ISO (2006) *ISO 14040: Environmental management—Life cycle assessment—Principles and framework*. International Organization for Standardization.
21) Jamwal, A., Agrawal, R., Sharma, M., *et al.* (2021) 'Industry 4.0 technologies for manufacturing sustainability: A systematic review and future research directions', *Journal of Cleaner Production*, 286, 125140. https://doi.org/10.1016/j.jclepro.2020.125140
22) Kirchherr, J., Reike, D. and Hekkert, M. (2017) 'Conceptualizing the circular economy: An analysis of 114 definitions', *Resources, Conservation and Recycling*, 127, pp. 221-232. https://doi.org/10.1016/j.resconrec.2017.09.005
23) Lee, J., Davari, H., Singh, J., *et al.* (2021) 'Industrial AI for sustainable manufacturing: Applications and future directions', *Manufacturing Letters*, 28, pp. 1-6. https://doi.org/10.1016/j.mfglet.2021.02.001
24) Mourtzis, D., Angelopoulos, J. and Panopoulos, N. (2022) 'Industry 5.0: The era of human-centric and sustainable manufacturing', *Procedia CIRP*, 107, pp. 250-255. https://doi.org/10.1016/j.procir.2022.04.041
25) Nahavandi, S. (2019) 'Industry 5.0—A human-centric solution', *Sustainability*, 11(16), 4371. https://doi.org/10.3390/su11164371
26) Negri, E., Fumagalli, L. and Macchi, M. (2017) 'A review of the roles of digital twin in CPS-based production systems', *Computers in Industry*, 100, pp. 1-15. https://doi.org/10.1016/j.compind.2018.02.002
27) Nobre, G.C. and Tavares, E. (2021) 'The quest for a circular economy: An overview of circular economy practices in manufacturing', *Journal of Cleaner Production*, 281, 124489. https://doi.org/10.1016/j.jclepro.2020.124489
28) Nwamekwe, C.O. and Okpala, C.C. (2025) 'Circular economy strategies in industrial engineering: From theory to practice', *International Journal of Multidisciplinary Research and Growth Evaluation*, 6(1), pp. 1773-1782. https://www.allmultidisciplinaryjournal.com/uploads/archives/20250212103754_MGE-2025-1-288.1.pdf
29) Nwamekwe, C.O., Ewuzie, N.V., Okpala, C.C., *et al.* (2025) 'Optimizing machine learning models for soil fertility analysis: Insights from feature engineering and data localization', *Gazi University Journal of Science*, 12(1). https://dergipark.org.tr/en/pub/gujsa/issue/90827/1605587
30) Nwosu, O.C., Okpala, C.C. and Igbokwe, N.C. (2026) 'Digital twins for smart supply chain transformation: A multidisciplinary review', *International Journal of Technology, Health and Sustainability*, 2(3), pp. 1005-1015. https://ijths.com/wp-content/uploads/IJTHS-0203009.pdf
31) Obiafudo, O.J., Okpala, C.C. and Oladapo, B.F. (2026) 'The integration of lean manufacturing, big data analytics, and explainable AI in modern industries', *International Journal of Technology, Health and Sustainability*, 2(3), pp. 1066-1076. https://ijths.com/wp-content/uploads/IJTHS-0203015.pdf
32) Ogboh, V.C., Obianyo, R.U. and Okpala, C.C. (2026) 'A data-driven framework for smart manufacturing: IoT sensor electronics, digital twins, and predictive analytics for production optimization', *International Journal of Technology, Health and Sustainability*, 2(3), pp. 931-941. https://ijths.com/wp-content/uploads/IJTHS-0202072.pdf
33) Okpala, C.C. (2026) 'Machine learning-enabled design of composite materials: Scalable structure-processing-property relationships across applications', *International Journal of Technology, Health and Sustainability*, 2(1), pp. 154-161. https://ijths.com/wp-content/uploads/IJTHS-020166.pdf
34) Okpala, C.C. and Chukwumuanya, E.O. (2026) 'Industry 5.0-enabled strategies for energy-efficient and carbon-neutral manufacturing systems', *International Journal of Technology, Health and Sustainability*, 2(3), pp. 1092-1103. https://ijths.com/wp-content/uploads/IJTHS-0203021.pdf
35) Okpala, C.C. and Nwamekwe, C.O. (2025a) 'Artificial intelligence-augmented edge computing: Architectures, challenges, and future directions', *International Journal of Engineering Inventions*, 14(9), pp. 18-27. https://www.ijeijournal.com/papers/Vol14-Issue9/14091827.pdf
36) Okpala, C.C. and Nwankwo, C.O. (2025b) 'Blockchain and artificial intelligence integration in cybersecurity: Towards intelligent and decentralized defenses', *International Journal of Engineering Inventions*, 14(9), pp. 9-17. https://www.ijeijournal.com/papers/Vol14-Issue9/14090917.pdf
37) Okpala, C.C., Nwamekwe, C.O. and Onukwuli, S.K. (2026b) 'Ergonomics in the age of Industry 5.0: A multilevel data analytics approach linking human-robot collaboration, cognitive load, and productivity in smart manufacturing systems', *International Journal of Engineering Research and Development*, 22(3), pp. 59-70. https://www.ijerd.com/paper/vol22-issue3/22035970.pdf
38) Okpala, C.C., Okpala, P.C. and Udu, C.E. (2026a) 'Artificial intelligence-optimized predictive safety and sustainability in Industry 4.0 smart factories', *International Journal of Technology, Health and Sustainability*, 2(2), pp. 857-868. https://ijths.com/wp-content/uploads/IJTHS-0202061.pdf
39) Okpala, S.C. and Okpala, C.C. (2025) 'Human digital twins: A paradigm shift in personalized healthcare and predictive medicine', *International Journal of Medical Evaluation and Physical Report*, 9(6), pp. 12-26. https://doi.org/10.56201/ijmepr.v9.no6.2025.pg12.26
40) Okpala, S.C. and Okpala, C.C. (2026) 'Data-driven Lean Six Sigma for complex systems: The integration of artificial intelligence for quality, resilience, and sustainability', *International Journal of Technology, Health and Sustainability*, 2(2), pp. 612-623. https://ijths.com/wp-content/uploads/IJTHS-0202030.pdf
41) Oladapo, B.F., Okpala, C.C. and Obiafudo, O.J. (2026) 'Human factors, organizational culture, and artificial intelligence in total productive maintenance', *International Journal of Technology, Health and Sustainability*, 2(3), pp. 1053-1065. https://ijths.com/wp-content/uploads/IJTHS-0203014.pdf
42) Sala, S., Reale, F., Cristobal-Garcia, J., Marelli, L. and Pant, R. (2021) 'Life cycle assessment for the impact assessment of policies: A systematic approach', *Sustainability*, 13(3), 122. https://doi.org/10.3390/su13030122
43) Udu, C.E. and Okpala, C.C. (2025) 'Circular economy in wastewater management: Water reuse and resource recovery strategies', *International Journal of Latest Technology in Engineering, Management and Applied Science*, 14(3), pp. 128-136. https://doi.org/10.51583/IJLTEMAS.2025.140300016

44) Udu, C.E. and Okpala, C.C. (2026) 'Artificial intelligence-enabled resilient scheduling: A systematic review and research roadmap for digital twin and machine learning in disruption-aware operations', *International Journal of Technology, Health and Sustainability*, 2(2), pp. 486-497. https://ijths.com/wp-content/uploads/IJTHS-0202014.pdf
45) Udu, C.E., Okpala, C.C. and Edeh, M.O. (2025a) 'Global roadmap for circular economies: The integration of digital innovation, governance, and sustainable development goals', *International Journal of Industrial and Production Engineering*, 3(4), pp. 1-17. https://journals.unizik.edu.ng/ijipe/article/view/6764
46) Udu, C.E., Okpala, C.C. and Nwamekwe, C.O. (2025b) 'Human-centric design integration in Industry 5.0: A framework for resilient smart manufacturing', *International Journal of Industrial and Production Engineering*, 3(4), pp. 18-33. https://journals.unizik.edu.ng/ijipe/article/view/6772
47) Udu, C.E., Okpala, C.C. and Nwamekwe, C.O. (2025c) 'Circular economy principles' implementation in electronics manufacturing: Waste reduction strategies in chemical management', *International Journal of Industrial and Production Engineering*, 3(2), pp. 29-42. https://journals.unizik.edu.ng/ijipe/article/view/5593/5056
48) Udu, C.E., Uche, C.J. and Okpala, C.C. (2025) 'Digital twins in wastewater treatment plants: A real-time optimization framework', *International Journal of Engineering and Modern Technology*, 11(7), pp. 91-106. https://doi.org/10.56201/ijemt.vol.11.no7.2025.pg91.106
49) Xu, X., Lu, Y., Vogel-Heuser, B., *et al.* (2021) 'Industry 4.0 and Industry 5.0—Inception, conception and perception', *Journal of Manufacturing Systems*, 61, pp. 530-535. https://doi.org/10.1016/j.jmsy.2021.10.006
50) Zhang, Y., Ren, S., Liu, Y., *et al.* (2020) 'A big data analytics architecture for cleaner manufacturing and industrial sustainability', *Journal of Cleaner Production*, 248, 119128. https://doi.org/10.1016/j.jclepro.2019.119243