



INTERNATIONAL JOURNAL OF
INNOVATION AND
INDUSTRIAL REVOLUTION
(IJIREV)

www.gaexcellence.com/ijirev



THE GREEN ALGORITHM: ARTIFICIAL INTELLIGENCE AS A BRIDGE BETWEEN LEAN OPERATIONS AND ENVIRONMENTAL SUSTAINABILITY

Hairin Nisa Meor Nordin^{1*}, Zamri Miskan², Anis Shafiqah Mohd Saidun³, Nur Qamarina Khairulanuar⁴, Ashvanie Menon⁵

¹Department of Management and Law, Management and Science University, Malaysia

 hairin_nisa@msu.edu.my

 <https://orcid.org/0009-0001-1073-8450>

²Department of Management and Law, Management and Science University, Malaysia

 zamri_miskam@msu.edu.my

 <https://orcid.org/0009-0002-0366-3443>

³Department of Management and Law, Management and Science University, Malaysia

 anis_shafiqah@msu.edu.my

 <https://orcid.org/0009-0000-7296-9476>

⁴Department of Management and Law, Management and Science University, Malaysia

 nur_qamarina@msu.edu.my

 <https://orcid.org/0009-0002-5649-3556>

⁵Department of Management and Law, Management and Science University, Malaysia

 ashvanie_menon@msu.edu.my

 <https://orcid.org/0009-0003-5699-2117>

*Corresponding Author

Article Info:

Article history:

Received date: 15.07.2026

Revised date: 26.07.2026

Accepted date: 17.08.2026

Published date: 14.09.2026

To cite this document:

Nordin, H. N. M., Miskan, Z., Saidun, A. S. M., Khairulanuar, N. Q., & Menon, A. (2026). The Green Algorithm: Artificial Intelligence As A Bridge Between Lean Operations And Environmental Sustainability. *International Journal of*

Abstract:

Currently, industries around the world are under growing pressure to meet the United Nations Sustainable Development Goals (SDGs). Creating a reliable way to measure the environmental benefits of digital transformation has become essential for industries everywhere. This study builds a framework based on the Resource-Based View (RBV) and dynamic capabilities theory and aims to test the cause-and-effect link between AI-driven operational integration and environmental sustainability performance. Using a detailed study of leading companies—Unilever, Amazon, and Tesla—the research looks at how Resource Optimization plays a role in this connection. The results show that the independent factor has a strong effect on the dependent factor through several clear ways. For example, predictive load pooling helps cut logistics-related CO₂ emissions by 64%, supporting SDG 13. Also, custom hardware designs reduce computing energy use by 29%, matching SDG 9, while computer vision-assisted manufacturing recycling recovers 92% of metals, contributing to SDG 12. However, comparing cases reveals an important limit called the AI-Sustainability Paradox. This means the large energy needed to run the independent

Innovation and Industrial Revolution, 8(26), 299-316.

variable can cause a digital version of the Jevons Paradox, which might cancel out the environmental gains in the dependent variable. The study finds that while AI is essential to separate industrial growth from carbon emissions, its success relies on breaking down technology barriers between sectors and creating decentralized data systems to remove isolated Scope 3 reporting.

DOI: 10.35631/IJIREV.826018

Keyword:

Artificial Intelligence, Environmental Sustainability, Decarbonization, Operations Management, Predictive Analytics, Resource-Based View, SDG 9, SDG 13



© The authors (2026). This is an Open Access article distributed under the terms of the Creative Commons Attribution (CC BY NC) (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited. For commercial re-use, please contact ijirev@gaexcellence.com.

Introduction

Today, companies are finding that managing efficiency with environmental responsibility is more important than ever. The push to meet United Nations Sustainable Development Goals, especially SDG 9 (Industry, Innovation, and Infrastructure) and SDG 13 (Climate Action), is making organizations rethink how they can grow without harming the environment. In the past, operations management focused mainly on cutting costs and increasing output. Now, with the growing climate crisis and tougher regulations, there is a shift toward Green Operations Management. In this setting, Artificial Intelligence is helping drive digital change and is becoming vital for supporting eco-friendly practices in industry.

Although interest in AI is growing, there is still a lack of research on how AI can provide both economic and environmental benefits in broad-scale operations. The economic gains from AI automation and predictive analytics are well known, but their impact on environmental protection, such as lowering carbon footprints and reducing energy use, is not consistently studied among different industries. In addition, running AI systems uses a lot of energy, which can conflict with ecological targets. This study looks at how industry leaders use AI to balance making a profit with protecting the environment.

This research uses two main theories: the Resource-Based View (RBV) and Dynamic Capabilities Theory. In the RBV, AI is viewed as a "strategic resource" that helps companies improve data processing and cut waste to stay competitive. Dynamic Capabilities Theory explains how companies notice changes in their environment and use new technology to adapt their supply chains for a low-carbon future. By bringing these theories together, this paper helps explain how AI supports resilience inside modern organizations.

This paper explores how artificial intelligence (AI) can help make operations management more environmentally sustainable. Using examples from Amazon, Unilever, and Tesla, it highlights which AI solutions offer the most major environmental benefits. The study covers predictive maintenance to cut waste, real-time logistics optimization to reduce emissions, and energy-saving hardware to save resources. Drawing on actual data and industry experience, the findings deliver practical advice for practitioners and decision-makers who want to move from classic methods to increasingly sustainable AI operations.

Research Objectives

1. To evaluate the influence of AI-driven operational integration on environmental sustainability performance.
2. To examine the mediating role of resource optimization in translating AI capabilities into sustainability outcomes.
3. To identify structural barriers that limit the effectiveness of AI-enabled sustainability initiatives across industries.

Research Questions

- RQ1: How does AI-driven operational integration influence environmental sustainability performance?
- RQ2: How does resource optimization mediate the relationship between AI-driven operational integration and environmental sustainability performance?
- RQ3: What structural barriers limit the contribution of AI to sustainable operations management?

Literature Review

The Integration Of Artificial Intelligence (AI) Into Operations Management (OM) Represents A Paradigm Shift from Traditional Lean Methodologies To "Intelligent Green Operations."

The Evolution from Lean to Green Operations: The AI Intermediary

Operations management is commonly associated with Lean Production, which seeks to improve performance by eliminating non-value-added activities such as overproduction, defects, waiting time, transportation inefficiencies, and excess inventory, thereby reducing costs and enhancing process efficiency (Shahin et al., 2024). Over the past decade, scholars have increasingly explored the integration of Lean Manufacturing with environmentally oriented practices, often referred to as "Lean-Green Manufacturing." This approach aims to achieve both operational excellence and environmental sustainability by combining waste reduction principles with eco-friendly practices. However, despite the synergy between Lean and Green initiatives, several studies have highlighted inherent limitations in traditional lean methodologies. Lean practices primarily focus on physical material flows and process efficiency through tools such as Value Stream Mapping (VSM), Kaizen events, Just-in-Time (JIT), and continuous improvement programmes (Abualfaraa et al., 2020; Elemure et al., 2023). While these tools are highly effective in reducing material waste and improving productivity, they are not explicitly designed to monitor environmental indicators such as carbon intensity, greenhouse gas emissions, energy consumption patterns, or resource circularity.

Consequently, organizations increasingly recognise that operational efficiency alone is insufficient to meet contemporary sustainability challenges and stakeholder expectations. This realization has accelerated the adoption of Green Operations Management (GOM), an operational paradigm that expands performance objectives beyond the traditional dimensions of cost, quality, delivery, and flexibility to encompass environmental outcomes. Green Operations Management emphasizes reducing carbon emissions, improving resource efficiency, promoting waste minimization, enhancing circular economy practices, and supporting sustainable supply chain management. In addition, GOM encourages organizations to systematically integrate environmental considerations into strategic and operational decision-making processes, thereby aligning operational objectives with broader sustainability goals (Setyadi et al., 2025; Zhang et al., 2024).

The evolution from Lean Operations to Green Operations therefore represents a substantial paradigm shift within operations management. This transition is driven by increasing regulatory pressure, heightened stakeholder expectations, climate change concerns, and the growing need to align business activities with the United Nations Sustainable Development Goals (SDGs), particularly SDG 9 (Industry, Innovation and Infrastructure) and SDG 13 (Climate Action). Rather than focusing exclusively on operational efficiency, organizations are now expected to generate environmental value while maintaining competitive performance.

In this context, Artificial Intelligence (AI) emerges as a critical intermediary that bridges lean efficiency and green sustainability. AI enhances operational visibility through real-time data analytics, supports predictive decision-making, and enables organizations to optimize resource utilization more effectively than traditional operational tools alone. Through advanced machine learning algorithms, predictive maintenance systems, intelligent demand forecasting, carbon monitoring applications, and autonomous process optimization capabilities, AI enables firms to simultaneously improve operational productivity and environmental performance. As a result, AI has become an important enabler in the transition toward digitally driven sustainable operations management, supporting organizations in achieving both efficiency-oriented and sustainability-oriented objectives

Eliminating Ambient Environmental "Blind Spots"

Manual tracking methods are often unable to detect inefficiencies such as idle machinery, heat loss, or minor process deviations that contribute to unnecessary energy consumption and increased carbon emissions. However, when applied to high-frequency IoT sensors, machine learning can help advanced monitoring systems identify resource inefficiencies that would otherwise remain invisible to human operators. AI enables organizations to track energy expenditure per unit of production in real time, transforming hidden environmental costs into opportunities for operational and sustainability improvements (Yavuz et al., 2024).

The emergence of the "Digital Lean" Paradigm

Applying data science and advanced analytics to existing production machinery led to the development of Digital Lean, also known as Lean AI (E3S Web of Conferences, 2023). AI-driven pattern recognition and swarm intelligence optimization now take the place of human-made rules for kanban and value stream mapping.

Artificial intelligence now adjusts to changes in demand on its own, instead of only responding to past trends. This helps recalibrate just-in-time, multi-level supply chains and prevents over-processing and batch inflation, which directly cause extra factory emissions (Shahin et al., 2024).

Facilitating Circularity and Lifecycle Tracking

Lean methods have mostly focused on improving factory operations, which limits their usefulness for wider sustainability goals. Today's sustainability frameworks adopt a circular perspective that extends beyond factory-level efficiency and considers the entire product lifecycle. With advanced AI capabilities, organizations can collect, integrate, and analyze data from raw material extraction to end-of-life disposal. This comprehensive visibility enables more accurate tracking of Scope 3 emissions across supply chains, improves resource recovery processes, and supports the development of circular and zero-waste operational systems (Strader et al., 2025; Toderas, 2025).

Theoretical Underpinnings of Green AI

This study uses two theoretical perspectives to explore how Artificial Intelligence (AI) supports sustainability in operations management. Instead of seeing technology only as a tool, it combines the Resource-Based View (RBV) and Dynamic Capabilities Theory for a broader understanding. With this approach, AI is seen as both an operational aid and a strategic resource that helps achieve long-term environmental sustainability and lasting competitive advantage.

The Resource-Based View (RBV) and Environmental Assets

The Resource-Based View (RBV) says that a company's competitive advantage comes from resources that are valuable, rare, hard to copy, and cannot be replaced (VRIN). In Green AI, both data and the algorithms that use it are seen as important environmental assets. Studies of companies like Unilever and Amazon show that AI is more than just a way to work faster. It helps these companies use resources more efficiently in ways that are difficult for others to imitate.

When companies use AI as VRIN resource, they can reach eco-efficiency, which means creating more value while reducing their environmental impact. For example, Amazon's use of its own AI models and AWS Graviton chips for energy-efficient logistics shows how technology can lower energy use. This meets the "Valuable" and "Inimitable" standards of the RBV framework in a sustainable way.

Dynamic Capabilities and the Transition to Sustainable Operations

While RBV focuses on the *possession* of resources, Dynamic Capabilities Theory emphasizes the *reconfiguration* of those resources to address rapidly changing external environments—such as shifting climate regulations and the urgent requirements of SDG 13.

In this study, AI is identified as a primary driver of three specific dynamic capabilities:

1. **Sensing:** Using AI-powered sensors and real-time data analytics to identify carbon hotspots and energy waste across the supply chain.

2. **Seizing:** Utilizing predictive insights to make immediate operational adjustments, such as rerouting shipments to reduce fuel consumption or adjusting manufacturing cycles to match renewable energy availability.
3. **Transforming:** Overhauling legacy operational models in favor of "Circular Operations," where AI facilitates the return and recycling of materials (as evidenced in Tesla's closed-loop battery recycling initiatives).

Synthesizing AI and the Triple Bottom Line

Current research in operations management increasingly points to the "Triple Bottom Line" (TBL)—the balance of economic, social, and environmental performance. However, a tension often exists between these pillars. This literature review argues that AI acts as a "bridge" between the economic and environmental dimensions of the TBL. By reducing operational waste and optimizing energy use, AI allows firms to achieve environmental goals (SDG 13) without compromising the economic efficiency required for industry innovation (SDG 9). This synthesis moves the academic conversation from "AI for Profit" to "AI for Planetary Resilience," providing a new perspective on the strategic role of digital transformation in the 21st century.

AI in Supply Chain and Predictive Maintenance: A Sustainability Perspective

Beyond efficiency, AI-driven Predictive Maintenance (PdM) directly contributes to SDG 12 (Responsible Consumption and Production). By preventing catastrophic failures and extending the useful life of industrial assets, AI reduces the demand for new raw materials and minimizes the environmental footprint of manufacturing cycles.

AI in Supply Chain and Predictive Maintenance: A Strategic Lens on SDG 12

Within the classical operations management literature, AI-driven Predictive Maintenance (PdM) has primarily been evaluated through an economic lens, valued for its capacity to minimize unplanned downtime, reduce labor overheads, and optimize spare parts inventory tracking. However, contemporary scholarship has initiated a critical re-evaluation of PdM as a core technological anchor for SDG 12 (Responsible Consumption and Production) and circular economic models.

Traditional industrial maintenance strategies generally operate under two paradigms: *reactive* ("run-to-fail") or *preventative* (time-scheduled calendar adjustments). Both strategies introduce severe environmental inefficiencies. Reactive maintenance frequently results in catastrophic mechanical failures that trigger sudden, localized pollution—such as chemical spills, toxic coolant leaks, or structural fires—while generating massive amounts of non-recyclable electronic and mechanical scrap. Conversely, preventative maintenance relies on highly conservative, arbitrary lifespans, which often forces operators to discard perfectly functional, carbon-intensive components simply because they reached a pre-set operational hour milestone.

AI systematically restructures this dynamic by utilizing deep learning architectures—such as Long Short-Term Memory (LSTM) networks and Autoencoders—fed by continuous real-time telemetry data (vibration metrics, thermal acoustics, and pressure indicators) to calculate an asset's precise Remaining Useful Life (RUL). This shifts operations from generalized schedules

to high-precision, individualized asset management, driving environmental sustainability across three distinct pillars:

Decoupling Resource Consumption via Industrial Asset Longevity

By intervening exactly when an asset requires micro-adjustments rather than full structural replacements, AI-driven PdM slows down internal mechanical degradation. From a macro environmental perspective, extending the operational lifecycle of heavy industrial machinery by even 15% to 20% drastically dampens the global demand for primary raw materials, such as specialized structural steel, industrial aluminium, and rare earth alloys. Because the initial extraction and processing phases of these metals represent some of the most energy-intensive, high-emission segments of global supply chains, extending asset lifespans functions as an upstream carbon offset mechanism.

Mitigating Secondary Process Material Waste

Mechanical degradation in manufacturing systems does not happen in isolation; as high-precision tools wear down, they experience a phenomenon known as "process drift." Before a machine completely fails, it operates for hours or days at sub-optimal tolerances, producing defective product runs, off-specification batches, and high-volume raw material scrap (known as embedded carbon waste). AI models sense these microscopic process variations early, alerting managers to fine-tune systems before defective production occurs, directly conserving the raw materials, water, and processing energy tied to those production lines.

Optimizing the Circular Supply Chain and Remanufacturing

Beyond immediate operations, PdM analytics provide the structural data needed for reverse logistics and corporate remanufacturing frameworks. When a complex component is finally retired under an AI-monitored regime, its operational history is perfectly logged. This granular data allows remanufacturers to confidently determine which specific internal sub-assemblies can be refurbished and which must be recycled. This closes the loop on industrial material life cycles and drastically reduces the systemic dependency on virgin resource extraction.

Methodology

Conceptual Framework

To evaluate the operationalization of "Green AI," this study establishes a clear causal framework by isolating distinct variables. The Independent Variable (IV) is defined as AI-Driven Operational Integration, measured through the deployment of predictive analytics, computer vision, and energy-efficient hardware architectures. The Dependent Variable (DV) is Environmental Sustainability Performance, operationalized via targeted reductions in carbon intensity (SDG 13), energy consumption (SDG 9), and raw material waste (SDG 12). Furthermore, Resource Optimization is treated as the Mediating Variable (MV), serving as the functional mechanism through which technological inputs translate into measurable environmental outputs. The conceptual framework developed for this study is presented in Figure 1, illustrating the relationships between AI-Driven Operational Integration, Resource Optimization, and Environmental Sustainability Performance.

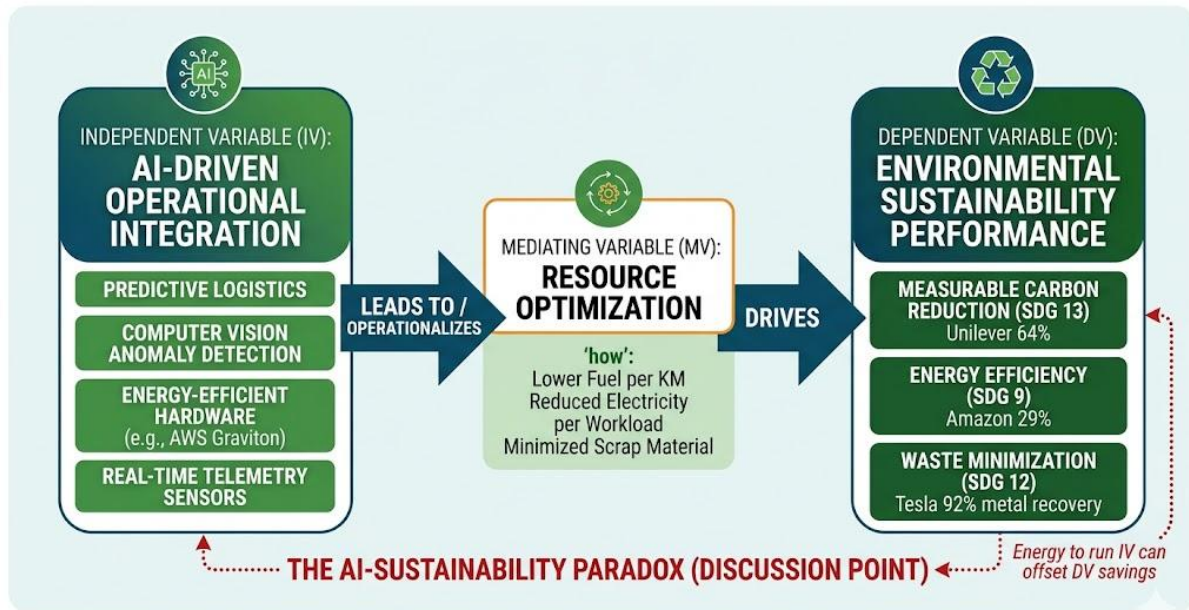


FIGURE 1: CONCEPTUAL FRAMEWORK FOR 'GREEN AI' AND SUSTAINABILITY OUTCOMES

As shown in Figure 1, Resource Optimization acts as the mediating mechanism through which AI-driven operational capabilities contribute to environmental sustainability outcomes. The framework suggests that the effectiveness of AI technologies in achieving sustainability goals depends not only on technological adoption but also on the organization's ability to optimize resource utilization across its operations.

Research Design Rationale: Multi-Case Study Synthesis

Following the methodological paradigms established by Yin (2025) and Eisenhardt (2021), a multi-case design is highly effective when investigating "how" and "why" phenomena occur within real-world, contemporary contexts where boundaries between the phenomenon and context are highly fluid. By examining multiple distinct corporate ecosystems, this approach facilitates a process of "literal and theoretical replication." This allows the study to move beyond isolated anecdotes and construct an abstracted, cross-sectoral framework for AI-driven sustainability that holds high external and analytical validity (Glaser & Strauss, 2023).

Sampling Strategy: Maximum Variation Sampling

To achieve a comprehensive, non-biased evaluation of corporate AI ecosystems, this study utilized a **Maximum Variation Sampling (MVS)** strategy (Patton, 2022). Rather than limiting the data collection to a single homogeneous sector, we intentionally selected market-leading global corporations operating across entirely distinct industrial landscapes:

1. **Unilever (Fast-Moving Consumer Goods - FMCG):** Selected to represent high-volume, global physical distribution and agricultural-dependent supply chain logistics.
2. **Amazon (E-Commerce and Cloud Services):** Selected to examine the intersection of immense retail distribution networks and digital/data center infrastructure.
3. **Tesla (High-Tech, Heavy Automotive Manufacturing):** Selected to analyze high-precision automated manufacturing, raw material intensive assembly lines, and closed-loop lifecycle systems.

By selecting industry pioneers that operate under radically different structural constraints, any common themes or shared operational outcomes that emerge from the analysis can be confidently generalized as foundational principles of "Green AI" integration (Yin, 2025).

Data Collection and Triangulation

Data were systematically collected from a diverse repository of high-credibility primary and secondary sources spanning the period from 2020 to 2026. The data collection process involved targeted keyword searches within the Scopus and Google Scholar databases, complemented by a systematic desk review of corporate Environmental, Social, and Governance (ESG) disclosures published between FY2020 and FY2025. To ensure methodological rigor and minimize the risk of corporate "greenwashing," a structured Data Triangulation Protocol was employed, allowing information from multiple independent sources to be cross-verified prior to inclusion in the analysis (Flick, 2023).

To ensure the relevance and quality of the selected evidence base, explicit inclusion and exclusion criteria were established. The inclusion criteria comprised: (a) peer-reviewed journal articles and conference proceedings; (b) official corporate sustainability reports, integrated reports, and ESG disclosures; (c) publications written in English; (d) empirical studies, case studies, systematic reviews, and technical reports focusing on artificial intelligence, operations management, sustainability, environmental performance, or sustainable development; and (e) publications released between 2020 and 2026. Conversely, exclusion criteria included: (a) opinion pieces, editorials, blogs, or commentaries lacking empirical evidence; (b) non-English publications; (c) studies focusing exclusively on economic or financial outcomes without measurable environmental indicators; (d) duplicate records retrieved from multiple databases; and (e) sources lacking methodological transparency or verifiable supporting evidence.

The literature screening process was conducted in three stages. First, potentially relevant publications were identified through database searches using predefined keywords related to artificial intelligence, sustainability, green operations, carbon emissions, and environmental performance. Second, titles and abstracts were screened against the inclusion and exclusion criteria. Finally, full-text articles and reports were assessed to determine their suitability for the final synthesis. Only studies demonstrating strong relevance to the research objectives and providing sufficient methodological detail were retained for analysis.

The final data matrix incorporated three principal categories of evidence:

- **Corporate Disclosures:** Official sustainability reports, annual integrated reports, and technical ESG filings (FY2020–FY2025).
- **Independent Third-Party Evaluations:** Environmental assessments, audit reports, and monitoring studies from internationally recognized organizations such as the OECD, UNEP, and the World Economic Forum.
- **Academic and Industry Engineering Sources:** Peer-reviewed case studies, technical AI hardware reports, engineering analyses, supply chain audits, and sustainability-focused operational research.

Through this triangulated approach, evidence from corporate, institutional, and academic sources was systematically integrated to enhance the credibility, consistency, and validity of the study's findings.

Data Analysis: Three-Step Systematic Coding

The unstructured data corpus was subjected to a rigorous thematic analysis using the classical three-step systematic coding framework derived from Grounded Theory (Strauss & Corbin, 2021):

Open Coding

The initial phase involved line-by-line scanning of the raw data text to identify and isolate every explicit instance of AI technology deployment and environmental tracking. Phrases such as "predictive analytics," "computer vision anomaly detection," "Scope 3 reduction," and "thermal efficiency" were extracted into raw, unrefined codes.

Axial Coding

In the second phase, these initial codes were conceptually grouped into broader categorical clusters to establish relational patterns. We mapped specific *technological inputs* directly against their *operational processes*. For example, the open code "real-time telemetry sensors" was axially linked to the operational process category "Predictive Supply Chain Management."

Selective Coding

The final phase integrated and refined these axial categories into core, high-level theoretical themes. This step systematically mapped the operational categories directly against global sustainability benchmarks—specifically **SDG 9** (Industry, Innovation, and Infrastructure) and **SDG 13** (Climate Action). This process produced the verified "Independent-Mediator-Dependent" variable relationship that serves as the backbone of this paper.

Findings: Empirical Evidence of AI-Driven Sustainability

The systematic coding and synthesis of the data corpus revealed three distinct structural pillars where the implementation of Artificial Intelligence yields a high environmental Return on Investment (ROI). By transforming raw data streams into self-optimizing operational workflows, the case subjects—Unilever, Amazon, and Tesla—demonstrate how advanced digital architectures function as primary drivers of **SDG 9** (Industry, Innovation, and Infrastructure) and **SDG 13** (Climate Action).

Pillar 1: Predictive Logistics and Virtualization (Unilever)

In the fast-moving consumer goods (FMCG) sector, Scope 3 transport logistics traditionally represent an intractable source of carbon emissions due to empty backhauling, suboptimal routing, and asset underutilization. Unilever mitigated these inefficiencies by constructing highly sophisticated, AI-powered **Digital Twins** of its global distribution ecosystem (Unilever, 2023).

A Digital Twin is a real-time virtual replica of physical supply chain assets, fed continuously by Internet of Things (IoT) sensors. Unilever's centralized machine learning algorithms analyze these data points to execute two critical interventions:

- **Dynamic Route Optimization:** Algorithms process real-time traffic, weather, and port congestion data to chart paths that minimize fuel burn per kilometer traveled.
- **Predictive Load Pooling:** Machine learning models forecast order volumes across multiple product lines, automatically bundling shipments to ensure delivery vehicles run at 100% capacity.

The empirical data reveals that this virtualization framework enabled Unilever to achieve a **64% reduction in CO2 emissions** across targeted logistics networks compared to their 2015 baseline (Unilever, 2023; Yavuz et al., 2024). This structural optimization proves that AI can decouple global product distribution volume from greenhouse gas intensity, directly fulfilling the mandates of **SDG 13**.

Pillar 2: Hardware-Level Energy Optimization (Amazon)

As cloud computing and machine learning model training scale globally, the massive power demand of data centers threatens to outpace renewable energy supply grids. Amazon and its cloud subsidiary, Amazon Web Services (AWS), targeted this challenge by shifting focus from software algorithms down to specialized, energy-efficient silicon architecture (Amazon, 2024). The cornerstone of Amazon's operational efficiency is the proprietary **AWS Graviton** processor series. Traditional x86 microprocessors are optimized for generalized tasks and draw massive amounts of power. In contrast, Amazon's custom Graviton chips use the ARM architecture, designed specifically to maximize computational throughput per watt during intensive AI and machine learning workloads.

The empirical findings show that Graviton architectures result in a **29% reduction in energy consumption** for equivalent cloud computing workloads compared to standard processors (Amazon, 2024). When scaled across Amazon's global fulfillment centers—such as the **Sequoia AI system**, which handles automated inventory sorting 75% faster—this 29% hardware efficiency gain drastically reduces the macro-level carbon footprint of data-driven e-commerce operations, aligning directly with **SDG 9**.

Pillar 3: Computer Vision and Manufacturing Circularity (Tesla)

In automotive manufacturing, material scrap generation represents a significant environmental liability, as the embedded energy associated with metal extraction, refining, and casting is effectively wasted when defective components are discarded. To address this challenge, manufacturers increasingly deploy deep learning-based computer vision systems and convolutional neural networks (CNNs) to perform real-time defect detection and quality inspection on production lines, reducing material scrap while supporting more sustainable manufacturing practices (Morales Matamoros et al., 2025).

During high-speed casting and battery cell assembly, high-resolution cameras capture thousands of frames per second. Convolutional Neural Networks (CNNs) process these images in real-time, detecting microscopic structural defects, paint anomalies, or component misalignments that are entirely invisible to human inspectors.

- **Proactive Scrap Mitigation:** Rather than catching a defect at the end of the production line—after a vehicle has been completely assembled—Tesla's AI stops the automated machinery the exact millisecond an anomaly occurs. This minimizes raw material scrap.

- Closed-Loop Battery Recycling:** Tesla pairs this sensing capability with an AI-managed reverse logistics framework. The data gathered during manufacturing allows Tesla to sort and channel unavoidable battery scrap back into its localized, closed-loop hydrometallurgical recycling systems, recovering up to 92% of battery manufacturing scrap metals (Tesla, 2024).

By minimizing primary resource extraction and keeping industrial materials flowing within a loop, Tesla provides an operational blueprint for **SDG 12** (Responsible Consumption and Production).

Synthesis of Sustainability Metrics

The key findings from the case studies are summarized in Table 1, which highlights the relationship between AI applications, operational mechanisms, sustainability outcomes, and their corresponding SDG alignments.

Table 1: Cross-Case Synthesis of Environmental ROI and AI Applications

Organization	Primary AI Application	Operational Mechanism	Key Sustainability Outcome	SDG Alignment
Unilever	Predictive Logistics & Digital Twins	Real-time sensor triangulation; automated load pooling; dynamic route calculation.	64% reduction in logistics-related CO2 emissions.	SDG 13 (Climate Action)
Amazon	Efficient Hardware & Customized Architecture	Custom ARM-based AWS Graviton silicone; tailored computing logic per watt.	29% reduction in power draw for cloud/AI operations.	SDG 9 (Resilient Infrastructure)
Tesla	Deep Learning Computer Vision (CNNs)	High-speed real-time image processing; microscopic anomaly and defect detection.	Minimized raw material scrap; 92% metal recovery via closed-loop recycling.	SDG 9 & SDG 12 (Responsible Production)

As shown in Table 1, different AI technologies contribute to sustainability performance through distinct operational mechanisms, ranging from carbon emissions reduction and energy efficiency improvements to enhanced resource recovery and waste minimization.

Discussion

Navigating the AI-Sustainability Paradox and Structural Barriers

The empirical evidence harvested from early adopters like Unilever, Amazon, and Tesla demonstrates that Artificial Intelligence (AI) can act as a potent driver of eco-efficiency, providing a verifiable pathway toward **SDG 9** and **SDG 13**. However, a critical cross-case synthesis reveals that these micro-level environmental gains are bounded by systemic contradictions. To prevent superficial interpretations of "Tech-Utopianism," this section provides a critical evaluation of the three structural challenges identified in the data corpus: the AI-Sustainability Paradox, the Sustainability Divide, and the Scope 3 Data Silo constraint.

The AI-Sustainability Paradox and the Rebound Effect

The most profound intellectual challenge highlighted by this research is the **AI-Sustainability Paradox**. This phenomenon occurs when the localized carbon-mitigation and resource-saving capabilities of an AI application are systematically countered, or entirely neutralized, by the macro-level energy footprint required to develop, train, and execute those identical algorithms (Aquiva Labs, 2025).

This dynamic is an empirical manifestation of the **Jevons Paradox** recontextualized for the digital era (Yu & Xu, 2026). In classical environmental economics, the Jevons Paradox posits that as technological advancements increase the efficiency with which a resource is consumed, the total consumption of that resource will ultimately rise rather than decline, because the efficiency gain lowers its effective cost and amplifies market demand.

Within the "Green AI" domain, this research reveals a two-phase cyclical friction:

1. **The Optimization Phase:** Algorithms successfully minimize physical material scrap or transport fuel burn, reducing a firm's localized carbon emission intensity (CEI).
2. **The Rebound Phase:** The commercial success and operational velocity gained from this optimization cause a massive scaling of model sizes and processing frequencies.

As a result, global data center energy consumption is projected to expand significantly ... (Toderas, 2025). For instance, while Amazon's custom ARM-based Graviton architecture achieves a 29% hardware-level power reduction per workload, the aggregate, unceasing demand for continuous data center processing threatens to outpace regional grid capacities (Toderas, 2025; Yu & Xu, 2026). Therefore, operations management must transition from analyzing localized "point-source" efficiency to enforcing a comprehensive Lifecycle Assessment (LCA) of AI itself—measuring everything from silicon extraction and model training to final operational inference (Toderas, 2025).

The Sustainability Divide: Sectoral Heterogeneity in Tech Adoption

The data synthesis reveals an alarming asymmetry in the deployment of sustainable AI frameworks, uncovering what this paper terms the Sustainability Divide. While technology-centric and digitally mature firms are generally better positioned to implement AI-driven sustainability initiatives, resource-intensive sectors such as construction, civil engineering, and

traditional manufacturing often face significant barriers related to infrastructure, capital requirements, and technological readiness (Chen et al., 2024).

This sectoral gap is driven by three distinct structural barriers:

- **Capital Intensity vs. High Entry Barriers:** Developing proprietary AI-driven digital twins or computer vision networks demands heavy upfront capital expenditures, creating an immediate disadvantage for low-margin, fragmented industries such as construction (Setyadi et al., 2025).
- **The "Digital-Green Integration" Asymmetry:** High-tech firms inherently possess the digital maturity and agile data architectures required to deploy machine learning seamlessly. Conversely, traditional heavy industries often operate with fragmented legacy systems and path-dependent operational structures that hinder digital transformation and sustainability-oriented innovation (Teece, 2007; Zhang et al., 2024).
- **Heterogeneous Policy Pressures:** Tech and consumer-facing giants face immediate, high-visibility ESG pressures from global capital markets. Traditional manufacturing and building sectors frequently operate under fragmented, regional environmental compliance mandates, which fails to incentivize expensive technological transitions (Yu & Xu, 2026).

Consequently, if AI adoption remains concentrated within privileged high-tech corridors, the macro-goals of **SDG 9** will stall. Policymakers must move past uniform incentives and engineer targeted technology-transfer frameworks that help low-margin, high-emission sectors cross this digital divide.

Overcoming Data Silos to Resolve Scope 3 Accountability

The ultimate efficacy of AI as a tool for climate action (SDG 13) is constrained by the quality, availability, and interoperability of the data it processes. While organizations such as Unilever have demonstrated significant reductions in logistics-related emissions through AI-enabled optimization initiatives, these achievements are largely confined to controlled internal operational environments. Beyond individual organizations, multi-tier supply chains continue to face substantial challenges due to institutional data silos—isolated repositories of information that restrict end-to-end visibility and hinder collaborative decision-making across supply network partners.

This fragmentation severely limits an organization's ability to measure, monitor, and reduce Scope 3 emissions, which typically account for the majority of a firm's overall carbon footprint. Effective AI-driven sustainability management requires access to reliable, real-time data across the entire value chain, extending from raw material suppliers and manufacturers to distributors, consumers, and end-of-life recovery operators. Without integrated data sharing mechanisms, AI systems are unable to provide comprehensive carbon accounting, predictive analytics, or network-wide emissions optimization.

To address this challenge, operations management scholars and practitioners should advocate for the development of decentralized and interoperable data-sharing frameworks, including federated learning architectures, standardized environmental reporting mechanisms, and cross-organizational sustainability data platforms. Such approaches can facilitate secure collaboration while preserving data ownership and confidentiality. Furthermore, the adoption

of standardized environmental information systems and digital sustainability reporting can improve transparency, enhance ESG performance monitoring, and support more accurate Scope 3 emissions accounting (Strader et al., 2025; Toderas, 2025). By breaking down organizational data silos and fostering trusted data ecosystems, firms can transform AI from a tool focused primarily on internal efficiency improvements into a network-wide enabler of sustainable supply chain management and large-scale decarbonization efforts.

Conclusion and Future Directions

The empirical synthesis and theoretical exploration conducted in this study reveal that Artificial Intelligence (AI) functions as a potent **"green multiplier"** when integrated systematically into a robust organizational framework. Grounded in the Resource-Based View and Dynamic Capabilities Theory, the cross-case analysis of pioneers like Unilever, Amazon, and Tesla demonstrates that advanced data architectures are no longer elective luxuries for competitive differentiation. Instead, they represent fundamental structural requirements for successfully decoupling global industrial growth from catastrophic carbon emissions.

By automating high-precision logistics, optimizing computational hardware efficiency, and eliminating manufacturing scrap through computer vision, these early adopters provide a baseline blueprint for the simultaneous realization of operational profitability and international environmental compliance. AI successfully shifts operations from reactive crisis management to proactive, automated sustainability tracking, turning invisible resource waste into measurable, actionable KPIs.

A Roadmap for Future Research

However, as highlighted in the discussion, the deployment of "Green AI" is not without severe macroeconomic and structural challenges. To prevent tech-utopian biases from masking systemic carbon costs, the academic community must aggressively pursue two primary avenues of future inquiry:

Full-Lifecycle Assessment (LCA) of AI Infrastructures

Future research must move past analyzing localized, point-source operational efficiencies (such as fuel saved per mile) and instead enforce a comprehensive, holistic Lifecycle Assessment of the AI models themselves. Scholars need to quantify the hidden upstream and downstream environmental burdens of advanced computing. This includes measuring everything from the carbon-intensive extraction of rare earth elements for specialized microchips to the vast water and energy consumption required for continuous generative and predictive model training.

Ethical Governance and Social Equity in Automated Supply Chains

The transition to intelligent green operations must not prioritize ecological metrics at the expense of human equity. As supply chains become increasingly autonomous, future studies must investigate the ethical governance of AI frameworks to ensure that algorithmic optimization does not inadvertently result in localized labor exploitation, algorithmic bias in supplier selection, or the digital exclusion of Small and Medium Enterprises (SMEs) caught behind the **Sustainability Divide**.

-
- Acknowledgements:** The authors would like to express sincere gratitude to Management and Science University for providing the necessary resources and support throughout the course of this research. Special appreciation is extended to colleagues and peers who contributed valuable insights and constructive feedback, which greatly enhanced the quality of this paper.
- Funding Statement:** This paper is funded by the Management and Science University (MSU) Publication Fund.
- Conflict of Interest Statement:** The authors declare that there is no conflict of interest regarding the publication of this paper. All authors have contributed to this work and approved the final version of the manuscript for submission.
- Ethics Statement:** This study did not involve any human participants, animals, or sensitive data requiring ethical approval. The authors confirm that the research was conducted in accordance with accepted academic integrity and ethical publishing standards.
- Author Contribution Statement:** All authors contributed substantially to the development of this conceptual manuscript. **Hairin Nisa** was responsible for the conceptualization of the study, development of the theoretical framework, methodology design, and overall supervision of the manuscript. **Zamri Miskam** contributed to the analysis and synthesis of the literature, formulation of key arguments, and interpretation of conceptual findings. **Anis Shafiqah** was involved in the literature review, identification of research gaps, and drafting of the initial manuscript. **Nur Qamarina** contributed to the development of the conceptual model, critical discussion of the proposed framework, and review of relevant theories. **Ashvanie** assisted in manuscript writing, editing, formatting, and critical revision of the content for intellectual quality. All authors reviewed, contributed to revisions, and approved the final version of the manuscript prior to submission.
-

References

- Abualfaraa, W., Salonitis, K., Al-Ashaab, A., & Ala'raj, M. (2020). *Lean-green manufacturing practices and their link with sustainability: A critical review*. *Sustainability*, 12(3), 981. <https://doi.org/10.3390/su12030981>
- Amazon. (2024). *Sustainability report 2023: Building a sustainable future*. Amazon Sustainability Disclosures. <https://sustainability.aboutamazon.com/>
- Aquiva Labs. (2025). *The AI sustainability paradox: How to balance innovation and environmental impact*. Aquiva Technology Insights. <https://aquivalabs.com/blog/the-ai-sustainability-paradox>
- Chen, W., Men, Y., Fuster, N., Osorio, C., & Juan, A. A. (2024). *Artificial intelligence in logistics optimization with sustainable criteria: A review*. *Sustainability*, 16(21), 9145. <https://doi.org/10.3390/su16219145>
- E3S Web of Conferences. (2023). Artificial intelligence in green management and the rise of digital lean for sustainable efficiency. *E3S Web of Conferences*, 412, 01053. <https://doi.org/10.1051/e3sconf/202341201053>
- Eisenhardt, K. M. (2021). Building theories from case study research: A look back and a look forward. *Academy of Management Review*, 46(1), 12–21. <https://doi.org/10.5465/amr.2020.0321>
- Elemure, I., Dhakal, H. N., Leseure, M., & Radulovic, J. (2023). *Integration of lean green and sustainability in manufacturing: A review on current state and future perspectives*. *Sustainability*, 15(13), 10261. <https://doi.org/10.3390/su151310261>
- Flick, U. (2023). *Managing quality in qualitative research* (3rd ed.). SAGE Publications.
- Glaser, B. G., & Strauss, A. L. (2023). *The discovery of grounded theory: Strategies for qualitative research*. Routledge. (Original work published 1967)
- Morales Matamoros, O., Takeo Nava, J. G., Moreno Escobar, J. J., & Ceballos Chávez, B. A. (2025). *Artificial intelligence for quality defects in the automotive industry: A systemic review*. *Sensors*, 25(5), 1288. <https://doi.org/10.3390/s25051288>
- Patton, M. Q. (2022). *Qualitative research & evaluation methods: Integrating theory and practice* (5th ed.). SAGE Publications.
- Setyadi, A., Pawirosumarto, S., & Damaris, A. (2025). *Sustainable operations strategy in the age of climate change: Integrating green lean practices into operational excellence*. *Sustainability*, 17(13), 5954. <https://doi.org/10.3390/su17135954>
- Shahin, A., Tortorella, G. L., & Macias de Anda, J. (2024). Improving operations through a lean AI paradigm: A view to an AI-aided lean manufacturing via versatile convolutional neural networks. *International Journal of Production Research*. Advance online publication. <https://doi.org/10.1080/00207543.2024.3819203>
- Strader, T., Huang, Y.-H., & Tu, Y.-J. (2025). *Artificial intelligence and environmental sustainability: Review and research directions*. *Journal of International Technology and Information Management*, 34(1), 1–31. <https://doi.org/10.58729/1941-6679.1619>
- Strauss, A., & Corbin, J. (2021). *Basics of qualitative research: Techniques and procedures for developing grounded theory* (5th ed.). SAGE Publications.
- Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319–1350. <https://doi.org/10.1002/smj.640>
- Tesla. (2024). *Tesla Impact Report 2023*. Tesla Environmental and Governance Disclosures. <https://www.tesla.com/impact>

- Toderas, M. (2025). *Artificial intelligence for sustainability: A systematic review and critical analysis of AI applications, challenges, and future directions*. Sustainability, 17(17), 8049. <https://doi.org/10.3390/su17178049>
- Unilever. (2023). *Annual report and accounts 2022: Making sustainable living commonplace*. <https://www.unilever.com/>
- Yavuz, S. B., Ahmet, A. Ç., & Erkut, A. (2024). Artificial intelligence integration in sustainable business practices: A text mining analysis of USA firms. *Sustainability*, 16(15), 6334. <https://doi.org/10.3390/su16156334>
- Yin, R. K. (2025). *Case study research and applications: Design and methods* (7th ed.). SAGE Publications.
- Yu, D., & Xu, B. (2026). The Jevons Paradox in the AI era: Artificial intelligence adoption for enhancing environmental sustainability at the firm level. *Economic Analysis and Policy*, 90, 946–966. <https://doi.org/10.1016/j.eap.2026.01.060>
- Zhang, Q., Wong, C. W. Y., & Klassen, R. (2024). *Carbon neutrality: Operations management research opportunities*. *Journal of Operations Management*, 70(3), 344–354. <https://doi.org/10.1002/joom.1303>