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A Comprehensive Review of Green AI Applications for Sustainable Manufacturing and Supply Chain Management

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Abstract: *This paper presents a comprehensive review of Green AI applications in sustainable manufacturing and supply chain management. As environmental concerns and resource scarcity intensify, manufacturing industries are increasingly adopting innovative approaches to reduce their ecological footprint while maintaining competitiveness. The evolution of sustainability in manufacturing has progressed from basic compliance to integrated sustainable practices, with artificial intelligence emerging as a powerful enabler of this transformation. This review systematically examines how Green AI contributes to various aspects of sustainable manufacturing, including supply chain optimisation, energy efficiency, waste reduction, predictive maintenance, carbon emission management, and resource optimisation. For each domain, conventional practices and their environmental impacts are analysed, followed by an examination of how AI-based solutions are implemented and the resulting sustainability improvements. Empirical evidence from various studies indicates that Green AI applications can achieve significant environmental benefits, including 15-20% reductions in resource wastage, 10-15% decreases in energy consumption, up to 20% lower carbon emissions, and 15-25% improvements in material recovery rates. Additionally, the implementation of AI in specialised areas, such as sustainable cutting tool manufacturing, green packaging, and reverse manufacturing, is explored. This review identifies promising research directions and highlights challenges in the widespread adoption of Green AI for manufacturing sustainability. The findings suggest that integrating artificial intelligence with sustainable manufacturing practices represents a promising pathway toward environmentally responsible and economically viable industrial operations in an increasingly resource-constrained world.*

Keywords: *Green AI, Sustainable Manufacturing, Supply Chain Management, Environmental Management Systems, Intelligent Manufacturing*

Abbreviations:
AI: Artificial Intelligence
SM: Sustainable Manufacturing
GSCM: Green Supply Chain Management
EMS: Environmental Management System
BDA: Big Data Analytics

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I. INTRODUCTION

The global manufacturing sector has experienced extraordinary growth over the past decades, accompanied by noteworthy environmental challenges. Manufacturing businesses worldwide consume approximately 54% of global energy resources, generate over 20% of global carbon emissions, and produce substantial waste streams that pose significant environmental risks. As industrial activities continue to evolve, the imperative for sustainable practices has become increasingly crucial, driving a considerable revolution in industrial approaches.

Sustainability's journey in manufacturing dates to the late 1970s and 1980s, and developed from several environmental issues and concerns about resource depletion [1]. It started with end-of-pipe solutions and compliance with regulations, and has evolved into a sustainable manufacturing approach [2] in which manufacturers consider environmental factors in making decisions throughout a product's lifecycle [3]. After the 1980s, the focus shifted from a process perspective to a product perspective, with importance and emphasis being placed on resource reduction, energy saving and creating renewable materials [4].

Driven by technological advancements, stricter environmental regulations, and shifting consumer expectations, sustainable manufacturing practices have made notable progress in recent years. Research highlights that the implementation of green manufacturing not only improves operational and economic performance but also leads to substantial improvements in environmental sustainability [5].

The development of Green Artificial Intelligence (AI) represents a notable innovation along the sustainability journey. Green AI is characterised as being environmentally conscious while being accurate by minimizing computational costs and encouraging research accessibility [6]. Besinger observes that Green AI seeks to engineer AI systems that are effective and efficient while remaining environmentally responsible, while attempting to tackle critical challenges such as climate change and depleting resources [7].

While prior research has extensively examined traditional sustainable manufacturing processes, the state of knowledge on how Green AI technologies can facilitate sustainability across manufacturing processes Has not yet been fully encapsulated [8]. The knowledge gap is even wider. Severe considering

AI's promise to optimise resource consumption, minimise waste production, and reduce environmental impacts in both contemporary and emerging economies [9].

It is essential to explore how various Green AI applications impact the different operations of manufacturing and supply chain management. This exploration will enable leaders in the industry, policymakers, and technology developers to create more effective sustainability action plans. As far as the researcher knows, there is minimal empirical research that systemically examines the application of Green AI for sustainable manufacturing across operations [10].

Therefore, this study aims to investigate the role of Green AI in enhancing sustainability in manufacturing and supply chain management, and the extent to which it can improve various functions for environmental benefits [11].

More specifically, the study addresses the following research questions:

RQ1: What is the current state of sustainability practices in manufacturing, and how has it evolved?

RQ2: What are the specific applications and measurable impacts of Green AI in different areas of manufacturing processes?

RQ3: How does Green AI contribute to sustainable supply chain management across different functions?

This paper is organised as follows. The first section presents a comprehensive literature review on sustainability in the manufacturing sector, including a discussion of the evolution of Green AI applications across various sectors. The following sections present an exploration of Green AI in sourcing and procurement, focusing on enhanced sustainable supply chain management functions applied in selected manufacturing processes. The conclusion summarises the main findings of the study and discusses the key implications for practice, highlighting the study's limitations and suggesting directions for further research.

II. SUSTAINABILITY IN MANUFACTURING

Sustainable development as a concept first appeared in the Report of the World Commission on Environment and Development in 1987. World Commission on Environment and Development [12] defined sustainable development as "coordination and harmony of nature, society, and economy under conditions of equal importance." They additionally explained that sustainable development of green manufacturing signifies "a concept of harmonious coexistence and orderly growth of humanity, people and other aspects in the production and manufacturing processes."

According to Lodhi [13], sustainable manufacturing attempts to find a balance between industrial production needs and environmental sustainability needs. Sustainable manufacturing must balance the demands of productivity with a minimization of harmful impacts on the environment.

Chan et al. [14] provided a more comprehensive definition of Sustainable Manufacturing (SM) as the "creation of manufactured products which use processes that minimize negative environmental impacts, use energy and natural resources as efficiently as possible, are safe for employees, communities, and consumers and are economically viable."

Jin and Chen [15] explained that green technological innovation is focused on environmental protection and aims for the coordinated development of the economy, technology, and environmental science. This holistic approach emphasises that sustainability in manufacturing extends beyond mere environmental considerations to encompass economic viability and social responsibility.

Sen et al [1] noted that the concept of sustainability emerged from a series of meetings and reports in the 1970s and 1980s, primarily motivated by environmental incidents and disasters as well as concerns about chemical contamination and resource depletion. The 1987 Brundtland Report, "Our Common Future," played a pivotal role in establishing sustainability as a formal concept.

Singh and Thakar [4] identified that from the 1980s, activities in sustainable manufacturing began to concentrate on waste reduction during production processes. Subsequently, the paradigm for sustainable manufacturing shifted from a process-oriented approach to a product-oriented one, primarily emphasizing the reduction of resources, energy, and toxic materials, along with the development and utilization of renewable materials [3].

Khan et al. [16] observed that the adoption of green manufacturing practices can result in considerable advantages regarding operational efficiency and financial performance, while also providing significant contributions to environmental sustainability. This demonstrates how sustainability in manufacturing has evolved from being viewed as a regulatory burden to being recognised as a strategic business opportunity.

Shen and Zhang [17] explained that due to the pressure of increasingly scarce resources and energy supply, along with the carrying capacity of the ecological environment reaching its limit, countries are opting to transition from a 'black development model' to a 'green development model.' Each country strives to develop effective green economic policies that enhance social welfare and promote sustainable economic growth and development. They emphasized that environmental sustainability cannot be achieved without substantial technological impetus.

According to Jin and Chen [15], the description of green product innovation is reducing environmental damage and increasing energy efficiency, the reduction, reuse, recycling, or the usage of energy efficient/made from eco-friendly/renewable materials in the design/development of new products or improvement of existing products.

From the perspective of Mao [9], green manufacturing presents the characteristics of high-level of efficiency and safety. This highlights the need for stricter environmental policies and more effective measures to prevent accidents. Green manufacturing can enhance safety and efficiency, which is crucial for process industries. It is assumed that green manufacturing will serve as a requirement of advanced economic development [18].

Innovation is a primary driver of green development, and technological advancements are essential in helping balance economic growth with environmental quality improvement [19], thereby enhancing the role of research and development

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in sustainable manufacturing.

Raju and Laxmiprasad [20] defined Green Supply Chain Management (GSCM) as the process of generating green inputs, producing end-products from these inputs, and reclaiming and reusing the outputs at the end of their productive life, thereby creating a complete sustainable supply chain. GSCM not only improves the environmental leg but also reduces costs, increases efficiency, and gains a competitive advantage in innovation. Sustainable manufacturing is also a means of improving resource utilisation, reducing environmentally harmful emissions, and fostering a better quality of life for humans [5]. This multilayered approach illustrates the impact of sustainability in manufacturing.

Gjerdrum et al. [21] illustrate how Artificial Intelligence powered energy management systems delivered significant advances in sustainably reducing energy use and greenhouses gases. Research has shown that manufacturers can meet their sustainability targets by advancing sustainable energy solutions. This research highlights how technological innovation can contribute to enhanced sustainability.

Porter and Van der Linde [22] stated that competition between firms for adequate environmental management has become a key competitive advantage and a firm can make profits. Their ground-breaking research created the business case for sustainability in manufacturing.

III. GREEN ARTIFICIAL INTELLIGENCE

Green artificial intelligence (AI) differs from traditional AI because it is both environmentally and socially responsible. It produces accurate results but without increasing computing costs, and it allows any researcher to conduct high-quality research on their laptop without the need for expensive cloud servers [6]. Green AI has made AI research accessible to everyone and has created the possibility of extending optimistic research outputs to researchers who would not be able to do anything without the power of cloud computing or supercomputers.

Bolón-Canedo [6] also noted that Green AI tries to minimize its environmental footprints with algorithms, hardware performance, and sustainable data management approaches. Green AI can be more compatible with sustainable practices, as it can offer energy-efficient solutions using cloud centres and mobile or edge devices. It has a smaller carbon footprint, better data quality, smaller models, a reduced use of computing resources and more logical transparency in producing results. It also enables trustworthy human judgment by showing how it arrived at its conclusions, thereby contributing to social sustainability as a secondary outcome.

Besingera et al. [7] showed that Green AI is made up of AI algorithms to handle environmental problems, such as climate change and resource depletion. Green AI focuses on developing AI systems that are both effective and efficient, while also prioritising ecological care. This captures the bi-part meaning of green AI; it minimizes its environmental impacts and contributes to ecological solutions.

The role of green AI is closely tied to a broader understanding of the development of artificial intelligence technologies. According to Shen and Zhang [17], based on their historical study, artificial intelligence was introduced in the 1950s as a new type of general-purpose technology. However, the limitations of available computer data processing methods meant that AI development was at the recognition stage for over forty years. During that time, it was again in the developmental stage, when pattern recognition and prediction became simple and easy to apply. This context can also help explain why environmental issues have only recently become a consideration in the development of AI technology.

Jin and Chen [15] reported that new intelligent technologies have helped produce industrial structure changes, which could help lower carbon footprints. Eventually, the continued advancement and adoption of green AI will be crucial for ensuring that the uses of artificial intelligence are aligned with the planet's environmental limits.

IV. APPLICATIONS OF GREEN AI IN MANUFACTURING

The incorporation of Green AI technologies into manufacturing is one of the most effective ways to foster sustainability in industrial processes. Lodhi et al. [13] noted that AI advances manufacturing by automating and optimising production processes, enabling predictive maintenance, and improving resource management. These improvements directly reduce the carbon footprint of manufacturing processes while simultaneously improving efficiency and productivity.

Further, Rojek et al. [10] noted that a critical emerging gap in the research of green energy management in manufacturing is the use of AI-driven demand forecasting to improve energy efficiency, reduce waste, and foster sustainability. Developments in machine-learning algorithms can analyse inputs from a variety of sources, including weather and climate trends, and market demand, and seamlessly integrate this real-time data to improve forecasting of demand, enabling sustainability while maintaining profitability.

Mao et al. [9] found that artificial intelligence can be used in process scheduling via optimization algorithms. These algorithms can optimize the scheduling of processes by considering system resources, process priority, and deadlines. AI facilitates predictive maintenance, condition monitoring, and the optimization of energy consumption. These capabilities enable manufacturing operations to minimize resource waste while maximizing operational efficiency.

Jin and Chen [15] mentioned that AI can help diminish carbon emissions intensity through enhanced energy efficiency. This facilitates the efficient reorganisation and rational allocation of labour, capital, and resources, enabling business transformations, propelling the rationalisation of industrial structures and structural upgrades, and promoting the achievement of carbon neutrality.

Lodhi et. al [13] explained that AI can fundamentally transform the design, production, and utilization of cutting tools, facilitating the optimization Of all the elements of their life Cycle for sustainability. AI-powered design tools can analyse extensive datasets to determine the

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most efficient and sustainable materials for cutting instruments. This enables producers to choose alternatives that strike the optimal balance between durability and environmental impact. Furthermore, AI can monitor cutting tool performance in real-time, forecasting maintenance or replacement needs, thus minimizing waste and prolonging tool lifespan.

A. Green Supply Chain Optimization

Green supply chain optimization is a critical step to enable sustainable manufacturing value chains and minimize environmental impacts over the whole lifecycle of the product [23]. Zhang et al. have identified Green Supply Chain Management (GSCM) as "the combination of sustainable methods such as green design, green purchasing, and green reverse logistics, that minimize environmental impact while still maintaining competitiveness." The whole system approach allows for the manipulation of the environmental impact throughout the complete production and distribution process [24].

Today, traditional supply chain practices typically have a lack of transparency, which leads to higher logistics inefficiencies, overproduction, and a greater carbon footprint [23]. If environmental criteria are not incorporated into the integration process, conventional supply chains can accelerate resource depletion, waste, and carbon emissions. Moin et al. [25] have demonstrated that unoptimized supply chains can account for up to 40% of the total environmental impact from the product. The following section provides a detailed discussion of the application of Green AI in supply chain management.

B. Energy Efficiency and Waste Reduction

Ensuring energy efficiency and minimizing waste is essential for reducing environmental footprints and achieving sustainability in manufacturing processes [6]. Energy efficiency is vital for minimizing environmental footprints and achieving sustainability in logistics and warehouse functions [6]. Energy consumption has a direct effect on operational costs and environmental performance, as well as compliance with regulations, so it is an essential enabler of sustainable manufacturing [26].

Conventional processes are characterized by high energy consumption, often leaving surplus waste materials due to inefficient material use and production schedules [6]. Traditional supply chains rely on non-renewable energy sources. When non-renewable sources are used for their products, traditional supply chains can generate substantial greenhouse gas emissions that result in climate change [27]. Cancela et al., [28], explored waste from traditional manufacturing models, and found that the waste from energy consumed exceeds 30% in some cases.

AI supports the creation of predictive models to predict energy demand and better match energy generation with energy consumption [6]. Sparse training approaches and energy-aware pruning help lower the energy used by artificial intelligence systems themselves [26]. By creating forecasting models for renewable energy, forecasting models help better integrate energy into the grid and lower emissions [28].

AI-enabled automation enables production workflows to dynamically modify to lower waste energy dynamically dynamically dynamically dynamically dynamically [27]. AI-enabled optimizing control of IIoT, Cyber-Physical Systems, and Smart Manufacturing increases energy use efficiencies for production [29]. Pervasive digital twins and AI predictive models reduced energy consumption by 7%. Supporting evidence from public spaces, as cited by Morán-Fernández et al., claims that cloud-based systems reduce greenhouse gases by 50%. TPUs have energy efficiencies that are 2-5 times that of GPUs, which were described by Alonso-Betanzos et al. [27]. Research by Nozari [29] recognized industry themes of Industry 4.0 and lean manufacturing that adopted AI as a priority in achieving green manufacturing goals.

C. Predictive Maintenance and Resource Management

Predictive maintenance and resource management are crucial for reducing downtime, enhancing the effectiveness of equipment, and minimising waste associated with employees in manufacturing processes. Moin et al. [25] defines predictive maintenance as a concept that minimizes sudden and unplanned breakdowns, minimizing downtime and optimizing resources. Predictive maintenance provides timely maintenance and, in turn, replaces resources when the resources should not be replaced earlier, but prevents unplanned breakdowns [31].

On the other hand, maintenance practices typically performed on fixed schedules or even unplanned intervals (e.g. upon failure) have some possibility of delaying repairs or replacing resources at an earlier-than-necessary time, which leads to increased waste of various resources [25]. Maintenance practice is typically rigid and does not consider the condition of the equipment, unlike condition-based maintenance. As a result, maintenance practices usually lead to the replacement of unnecessary parts or increased waste. Krishnan et al [31] proved that the traditional mode of maintenance of parts could lead to up to 30% waste in replacement parts.

AI-based predictive maintenance improves operational efficiency, as it permits repairs based on real-time data rather than a fixed schedule [25]. Automated monitoring systems can identify problems with machinery in real-time, allowing for reduced downtime and maintenance scheduling [30]. AI models also enhance the accuracy of fault detection, thereby improving operational efficiency and reducing material waste.

AI-based demand forecasting allows energy consumption and production schedules to align to minimize surplus energy use and emissions [31]. AI-driven predictive analytics allow for a more efficient demand forecasting, leading to a reduction of wasted resources of 15% and fuel consumption of 20% [32].

Ejjami et al. [33] confirm that AI improves labor structure upgrades, management optimization, and regulatory compliance. Mao et al. [9] found that AI-based predictive maintenance reduced unplanned downtime between 30 and 50% and increased resilient machinery by 40%, leading to reduced resource use and waste. Manufacturers that implement AI-driven maintenance report increases in operational efficiency.

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D. AI and Carbon Emission Reduction

A significant consideration for sustainability initiatives in manufacturing is the reduction of carbon emissions related to climate change and compliance. Chen et al. [8] asserted that carbon emissions must be reduced

for manufacturing to become environmentally sustainable. To meet the current pressures from tighter emissions regulations and to adequately address the need to reduce emissions in all manufacturing processes, carbon management is critical [15].

Current manufacturing practices have a continual dependence upon fossil fuel energy, thereby producing excessive carbon emissions [8]. Most traditional manufacturing methods are energy and carbon intensive, processing fossil energy since they were not designed to consider the total life stage burdens of carbon emissions [15]. Jedidah et al. [34] support the idea that conventional manufacturing processes can produce up to 30 percent more carbon emissions because of fundamental inefficiencies in the processes.

With advancements from AI-led operational optimizations, energy efficiency can be improved by eliminating wasteful scheduling of production timing and utilizing predictive maintenance [8]. In addition, AI can link green product innovation and optimize industrial products and lead to reduced carbon emissions [15]. AI will also be a significant part of the way green supply chains are reinvented through logistics management, vehicle routing optimizations, and emissions reductions [34].

AI implementations such as transportation routing and inventory management have achieved reductions in transportation emissions from 5% to 12% [34]. AI can also drive low-carbon innovation through deploying green energy solutions and intelligent process automation [35].

Varela et al. [34] showed that AI-enabled industrial reforms can lead to improvements in energy management and a reduction in emissions. Parekh et al. [36] established that AI-enabled optimized approaches in manufacturing processes can lead to up to 15 to 25% reduction in carbon emissions in comparable production without lowering the output. Chen et al. [8] found that companies employing carbon reduction methods assisted by AI have also improved their operations by not only positively affecting their environmental performance, but also, improving their efficiency of operation.

E. Green Packaging

Optimized packaging can lessen waste, which offers sustainability improvements in the entire supply chain [37]. Sustainable packaging design considers things like materials selection, structural efficiencies, recyclability, as well as options for disposal, which all contribute towards a packaging solution that uses less harmful packaging materials, but still protects products and remains functional whether used for groceries or other products [40]. Packaging is known to add a significant amount of material to the manufacturing waste stream [41].

Traditional packaging uses too much packaging material and creates a lot of unrecyclable waste [37]. Conventional approaches also tend to marginalize sustainability and focus on cost and protection, resulting in excessive packaging; use composite materials that are difficult to recycle, and can contribute to a significant amount of waste [38]. Madushika and Rangani et al., [39] showed that traditional approaches can lead to packaging waste, which would contribute up to 30% more excessive packaging material.

Research from Pirarththan [37] indicates that AI-enabled design software creates sustainable packaging through the ability to assess material consumption. In packaging plants, automated systems can eliminate 15-20% material waste, as shown by [41] .AI optimizes packaging dimensions for best shipping efficiency and lower emissions generated through transportation emissions [41]. Additionally, machine learning algorithms help identify sustainable material substitution without losing performance [38].

Research by Madushika et al. [39] also provides evidence that packaging optimization using artificial intelligence can have tangible benefits from an environmental impact perspective. Research by Pirarhtthan et al. [37] produced no less than 15-20% material reduction in automated packaging systems utilizing AI while maintaining or enhancing product protection. Sah et al. [11] noted significant improvements in transportation efficiency and customer and stakeholder satisfaction for companies that put an AI-driven packaging design in place.

F. AI in Sustainable Scheduling and Resource Optimization

Scheduling and resource allocation optimization yield operational efficiency benefits that translate to environmental benefits in manufacturing [42]. A well-planned schedule reduces idle time, saves energy during periods that are not productive, and consumes resources most efficiently throughout the production process [43]. Kalla and Brown [42] established that scheduling optimization is a route to reduce the environmental impact of manufacturing operations.

Manual scheduling results in inefficient use of resources and has high rates of emissions [42]. Existing conventional scheduling methods lead to non-optimal production sequences with high levels of changeovers and inefficient resource allocation, which results in waste generation and excessive energy consumption [43]. Research from Kalla indicates that conventional scheduling methods result in energy consumption with waste levels as high as 15-25%, compared to optimal scheduling methods.

AI applications, including Genetic Algorithms and Artificial Neural Networks, produced efficacies in scheduling and energy consumption in manufacturing settings [42]. Scheduling decisions using AI would account for many variables simultaneously, including energy costs, equipment efficiency, and availability of resources to develop the best scheduling plan to produce and reduce environmental damage [43]. Research by Kalla and Brown suggests that AI tools can minimise energy consumption within manufacturing by synchronising intake and resources with energy use in In an innovative manner.

AI applications in sustainable manufacturing have increased in research publications by 281% since 2015, illustrating that their significance and acceptance as a legitimate option are on the rise [42]. Evidence by Kalla and Brown indicates that AI-driven scheduling can use 10-15% less energy than conventional scheduling. According to Kalla [43], manufacturers using AI Scheduling has improved productivity while mitigating their environmental footprint.

G. Reverse Manufacturing and Recycling

Recycling and material recovery are critical elements of an approach based on the circular economy [1]. Reverse manufacturing is an efficient closure of material loops, reducing the extraction of virgin material, and reducing landfill waste, thereby contributing to sustainability and resource needs [43]. Shrivas et al. [44] identified effective material recovery as a tool to decrease the overall environmental footprint of manufacturing.

Inefficient recycling weighs inefficiently by creating even more waste [1]. Traditional recycling often involves manual sorting, which is limited in its ability to recognise materials. Mixed materials are challenging to recognize manually, leading to contamination [46]. Modi et al. [45] found that traditional recycling could miss up to 30% of recyclable materials at the sorting stage.

Sen et al. [1] identified several benefits that result from Green AI. AI-enabled systems increase material recovery rates and optimize recycling pathways [1]. They also found that machine learning and computer vision lend themselves to more effective sorting of recyclable material, which increases the quality of the recycled outputs [44]. AI models can also aid in identifying the optimal disassembly sequence for complex products, thereby enhancing the effectiveness of material recovery operations.

Modi et al. [45] found that the enhanced recovery rates offered by AI-enabled machines and systems support improved overall material recovery rates. Sen et al. [1] show that AI-enabled recycling systems yield between 15 - 25% increased material recovery, while also decreasing the energy consumption in recycling by 10 - 20%. Sen et al. noted that AI-enabled reverse manufacturing systems can lead to potential improvements in both resource recovery rates and overall efficiency.

V. GREEN AI FOR SUSTAINABLE SUPPLY CHAIN MANAGEMENT

A. Environment Management System (Ems) In Green Supply Chain Management (GSCM)

Environmental Management System (EMS) is an integrated system that enables organizations to share resources and comply with environmental standards to enhance supply chain activities [23]. The introduction of an environmental management system (EMS) within supply chain management can facilitate collaborative efforts towards achieving ecological goals with other organisations, standardise practices, meet compliance obligations, and maintain reasonable operational performance.

Conventional supply chain management without an EMS framework has not taken even an initial step toward environmental coordination, leaving opportunities for redundancies and inefficiencies, as well as the possibility of ecological harm [24]. The lack of structured identification of environmental impacts results in non-standard practices, poor resource utilization, as well as inadequate engagement [23]. The traditional supply chain management process can lead to increased emissions, waste, and non-compliance with regulations.

The rise of Big Data Analytics (BDA) and Artificial Intelligence (AI) (BDA-AI) may significantly facilitate the implementation process of EMS. At the same time, it also enhances environmental visibility and supports comprehensive decision-making. Zhang et al. [23] define Green Supply Chain Management (GSCM) as "the strategic integration of sustainable approaches in purchasing and procurement, reverse logistic approaches, which collectively seek to minimize environmental impact and regulatory concern while improving competitive advantage."

AI-enhanced supply chain management supports logistics planning, which drives transportation emissions down and increases efficiency [25]. Use of AI with green warehousing and inventory management plays a tremendous role in minimizing energy consumption and resource waste [24]. AI-facilitated forecasting enhances demand prediction and timely supply of goods by minimizing overproduction, while AI-enabled transparency helps firms align with visible carbon policies, optimizing logistics and resource allocation further down the chain [23].

The empirical results show that BDA-AI enhances the interdependence between GSCM and EMS for improved market competitiveness [23]. As supported by the findings from Gao et al. [24], AI-powered upgrades are lowering emissions through optimized carbon emission strategies while demonstrating improved competitiveness. Similarly, Khan et al. [16] established that leveraging artificial intelligence within an environmental management system could reduce environmental impacts of businesses informal settings to maintain bargaining power or improve performance compared to the competition.

B. Energy Efficiency in Supply Chain Operations

The efficient use of energy is an essential aspect of reducing environmental footprints and attaining sustainability in logistics and warehouse operations [6]. Energy efficiency in the supply chain affects operational costs, environmental performance, and legal compliance. Therefore, it is an essential aspect of sustainable business practices [26]. Energy efficiency as a function of sustainability has been described as a primary driver in the optimization of a sustainable supply chain and manufacturing by researchers [28].

Traditional supply chains rely on fossil fuels, which generate substantial greenhouse gas emissions [6]. Conventional manufacturing takes up energy and produces a considerable amount of waste, also because of inefficiencies in production planning and material use [27]. More studies have been conducted, such as by Nozari [29], which agrees that the traditional perspective of energy management approaches to supply chain processes contributes to climate change and depletes natural resources.

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Bolón-Canedo et al. stated that AI can offer various improvements to energy efficiency through time-series predictive models for energy demand forecasting, enabling the planning of future energy demand and coordination between energy production and consumption. Morán-Fernández et al. [6] employed sparse training methods and energy-aware pruning that reduces the energy consumption in the AI process itself. Cancela et al. [28] reiterated that AI helps with grid management by developing renewable energy forecasting models that help minimize emissions.

The management of inventories and supply chains using machine-learning algorithms provides each site and operation with the means to reduce the amount of excess energy they use, through automatically adjusting operational flows [27]. AI-based optimization of IIoT and hybrid systems, as well as cyber-physical systems, improves energy efficiencies in an industrial production context [29]. Based on the studies conducted by Cancela et al. [28], energy consumption is reduced via the use of AI-enabled predictive models, achieving reductions of 7%. Material use is improved through AI-enhanced analytics that decrease production waste and improve sustainability [6].

Cloud-based platforms can reduce GHG emissions by up to 50%, as shown in the study by Morán-Fernández et al. [26]. Also, Alonso-Betanzos et al. [27] have shown TPUs currently achieve energy efficiencies that are between 2 and 5 times more efficient than conventional GPU-based systems. The intersection, as indicated by Nozari [29], of the fourth industrial revolution and lean manufacturing with AI are key indicators for achieving the objectives of green manufacturing.

C. Waste Reduction in Supply Chain

Reducing waste provides cost savings and conserves resources in supply chain operations (Ejjami et al., 2022). Waste reduction achieves a decrease in the environmental impact of production, disposal, and more effective resource use, which is an essential element of sustainable supply chain management (Sah et al., 2024). Begum et al. [46] show that companies can improve the sustainability and profits of their operations through waste management strategies.

Conventional methods of undertaking supply chain operations cause excess material usage and wastage due to ineffective planning [33]. Conventional waste management approaches promote reactive rather than preventative actions, resulting in greater usage of landfills, increased transportation emissions from landfill disposal methods, and inefficient raw material consumption [46]. Shahjalal [47] demonstrated that conventional waste management practices contribute significantly to environmental degradation.

According to Ejjami et al. [33], Green AI contributes to waste reduction through AI-enabled systems that optimize inventory and predict demand to minimize waste. Real-time machine learning algorithms reduce the spoilage of perishable goods through logistics optimization, as demonstrated by Sah et al. [11]. Generative design techniques minimize material use in packaging and products according to research by Begum et al. [46]. AI-driven demand forecasting aligns resource consumption with production needs.

Shahjalal [47] has also shown that machine learning with generative design techniques reduces the use of carbon-intensive materials like cement and steel. Ejjami et al. [33] have documented specific percentage reductions in material waste, with some implementations achieving 15-20% reductions in packaging material waste through AI-powered design tools. According to Sah et al. [11], companies employing AI-driven waste reduction approaches have described significant developments in resource efficiency and environmental performance.

D. Transparency in Supply Chain

Enhanced transparency within supply chains increases compliance and supports ethical sourcing. Transparency allows stakeholders to follow materials and products throughout the supply chain and observe compliance with environmental standards, ethics in labour practices, and regulatory considerations [31]. Poorani [32] points out that supply chain transparency is particularly relevant when meeting consumer expectations and regulatory requirements.

Traditional systems lack the capability for real-time tracking, leading to inefficiencies and increased emissions. Organizations with little to no visibility have difficulty determining or tracking environmentally concerning hotspots, determining the accuracy of sustainability claims, and ensuring compliance with environmental rules and regulations, further complicating efforts with supply networks [29]. Sah et al. [11] demonstrate that traditional methods of supply chain management discount environmental impacts.

According to Ejjami. [33], AI systems provide real-time analytics and blockchain technology to ensure compliance with environmentally friendly standards. AI traceability leads to the improved tracking of raw material supply chains and enhanced traceability with supply chains [31]. AI hashing enables verification of claims of sustainable sourcing or ethical practice [32]. The real-time monitoring systems enabled by AI can identify anomalies that signify a potential breach of environmental compliance [29].

Shahjalal [47] has documented the advantages of predictive AI tools (PCDD) at significantly improving visibility of sustainability within supply chains. Modi et. al [45] incorporated blockchain based AI systems e.g., traceability, as permanent tamper-proof public records of relevant environmental compliance documenting, for robustness with stakeholder trust, and sustainability reporting. Begum et al. [46] explained that AI enabled track and trace transparency provided for 30-40% compliance risk reduction and engendered stakeholder confidence for ESG compliance.

E. Resource Optimization

Reduction in resource usage is advantageous from both a sustainability and a cost standpoint [25]. Resource optimisation balances production needs with ecological impact by reducing waste. extraction of virgin materials and waste. Research by Mishra et al. [30] indicates that resource optimization is the Foundation of sustainable manufacturing practices.

An unplanned approach to resource consumption results in excess product waste and emissions [25].

Conventional resource management relies on historical usage rather than current, real-time consumption [30], which can result in underselling or overstocking due to resource waste through lack of use and misallocation of
excess resources across the production process. Ejjami et al. [33] found that conventional resource management practices produce, on average, 15-25% excess material usage.

Moin et al. [25] defines Predictive maintenance is a strategy that reduces unexpected breakdowns, resulting in reduced downtime, which ultimately represents optimised resource usage. According to Abd Moin [25], AI predictive analytic capabilities can represent a 15% reduction in waste resources through optimized demand forecasting and a 20% reduction in fuel consumption.

AI-optimised predictive maintenance improves productivity by allowing machinery to be serviced based on data and not discrete intervals [30]. Automated monitoring systems can continuously monitor machines in real-time to identify machine failure, reducing downtime, and improving maintenance scheduling [28]. AI models improve the precision of failure detection to keep operations efficient and reduce wasted material [25].

AI-supported demand forecasting enables energy loads to be met in line with production schedules, reducing unnecessary energy consumption and emissions [48]. Krishnan et al. [31] have shown that resource optimization using AI improves logistics and operational efficiency. Poorani [32] illustrates several implementations which document percentage improvements in resource utilization, with some areas improving material use by 15-20% using AI-supported inventory management systems and production planning. Manufacturers that have adopted AI-supported resource optimization systems have also documented significant cost savings and reduced their environmental footprint [30].

VI. CONCLUSION

This review presents an extensive exploration of the three research questions that guided the study, which focuses on linking Green AI technologies to sustainable manufacturing and sustainable supply chain management. The evaluation has shown that sustainability in manufacturing is an evolving concept that differs substantially from the conceptualisation that originated in the 1970s and 1980s. Initially framed as an end-of-pipe and regulatory compliance perspective, sustainability is evolving to incorporate environmental issues at every stage of the product lifecycle [1].

The shift from process-oriented to product-oriented strategies in research and practice is characterised by a growing focus on resource and energy reduction strategies, as well as the development of renewable materials. Sustainability practices reflect enhancements in manufacturing, including green supply chain management, integrated Environmental Management Systems (EMS), energy-efficient production systems, resource optimisation strategies, and the circular economy. This evolution of thinking stems from the growing recognition that sustainable manufacturing is a competitive advantage, not simply an environmental obligation, as explained by Porter and Van der Linde [2].

Green AI has become a powerful facilitator of sustainability, through its various supply chain capabilities: by enabling better environmental management systems via Big Data AI and analytics, helping create predictive models or decision tools for energy demand forecasting and renewable energy integration, inventory optimization and waste reduction, supply chain visibility via real-time analytics and blockchain, resource optimization using predictive analytics, and carbon emissions management through route optimization and inventory solutions.

The existing research demonstrates various quantifiable benefits resulting from manufacturing operations. Some of these include 10-15% reductions in emissions through optimized supply chains, 7% energy savings with improvements in energy efficiency, 30-50% reduction by predictive maintenance of unplanned down time, extending cutting tool life by 25-35% for sustainable tool manufacturing, waste reduction by packaging material of 15-25%, 20% carbon emissions reductions through emissions monitoring, and better material recovery in recycling increased by 15-25%.

While this review attempts to be comprehensive, a few limitations need to be considered. With the changing landscape of AI and sustainability, it is possible that some of the new advancements may not have been included in this study. The papers discussed primarily report expected or theoretical benefits of Green AI applications. While some studies provide empirical results of long-term implementations, the discussion of implementation challenges, failed projects, and potential negative ramifications of adopting Green AI is not considered.

The results provide several important practical implications for manufacturing companies. First, all manufacturing companies need to strategically integrate AI technologies within their existing Environmental Management Systems (EMS) to achieve enhanced visibility, monitoring, and decision-making capabilities. Companies must also adopt an overall approach to sustainability that encompasses energy use efficiency, waste reduction, and carbon emissions management, as AI can incentivise eco-efficiencies, which ultimately improve sustainability.

Companies should ascertain their data capability to implement AI technologies effectively. This can require people, processes, and facilities, including sensors, IoT infrastructure, and data software. Organisations will need to develop cross-functional teams comprising sustainability experts, data scientists, process engineers, and operations experts to leverage the possibilities of AI in sustainability.

Several further research possibilities emerge from this review. Additional studies may examine the synergy between Green AI and emerging technologies, including blockchain, digital twins, and advanced robotics. There is also an urgent need for research that examines

The scaling of Green AI solutions from small pilots To company-wide implementations. In summary, Green AI presents a progressive and transformational opportunity for sustainable manufacturing, ultimately leading to environmentally responsible, economically viable, and socially responsible industrial practices.

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Divyanshu Ray is a student at Navrachana International School, Vadodara. He is currently pursuing Grade 12 and is planning to pursue mechanical engineering going forward. Divyanshu has a deep interest in sustainable manufacturing and the intersection of mechanical engineering with emerging technologies. His literature review on Green Artificial Intelligence and its applications in manufacturing and supply chain systems made him aware of the potential role of technology in addressing complex industrial sustainability challenges. These insights motivated him to further explore the integration of AI and automation in mechanical engineering to create efficient, scalable, and environmentally responsible systems for the future.