The Impact of Machine Learning on Sustainable Manufacturing Practices in the USA: Strategies and Outcomes in Tech Products

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1. Introduction to Sustainable Manufacturing and Machine Learning

Sustainable manufacturing has become a significant part of the competitive scenario and economic growth efforts in global markets and a constant presence in company everyday decision-making. Current global long-term goals and milestones such as the Sustainable Development Goals (SDGs), aimed at accelerating the transition to a circular economy and the upcoming New US Economy era must be implemented or adopted through substantial changes by manufacturing companies. The COVID-19 pandemic is a raw expression of the severe crisis that can result from a world that has not adapted to more rational use of resources, renewable and non-renewable. Most of the physical characteristics of manufactured products are already structured in the design phase and through market and consumer pressure, the manufacturer's production and decision-making become the factory as a landscape of triggers and levers for change. This new strategic positioning through strategic management and the possibility of obtaining significant benefits through advanced technologies including "intelligent" and "agile" assistance.

We have analyzed practical cases of a set of electronic and technology companies that use Machine Learning-based solutions throughout the supply system, from the design and development of new products to customer service, which were relevant from the point of view of achieving more sustainable results during the production phase and throughout the life cycle of the products. It is well-known that these companies' characteristics themselves open up possibilities to produce positive roles with the environment, such as the internal capacity to design, operate, and maintain their machinery, reducing local impacts and enhancing the potential to restore nature. All segments of production processes and their structuring along the supply chain production are critical for obtaining the desired results and the products to be positioned as environmentally friendly. In this path, ML-based tools are identified as decision support systems with a capacity for quality and risk control, helping extend the life of products and valuing materials and energy that are treated in their original use loops. The approach enabled the understanding that this market is a very dynamic environment where the handling of large-scale information is important. The results of the approach allowed aligning the contribution of these companies with the critical environmental issues and recent scientific developments.

1.1. Defining Sustainable Manufacturing

The term "sustainability" and "sustainable manufacturing" is generic, and each company and organization may define it as they view sustainability. It will be driven by different internal and external forces, including sustainability being considered within the organization. Studies have shown that using basic metrics is generally not successful in generating interest from a large enough sample size for meaningful comparisons that will make companies accountable for their actions. Also, because of the different drivers and goals, organizations need to define and develop their own individual metrics, incorporating analytical models for setting metrics to supplement the development with these different categories of metrics. The results should be presented in a circular fashion, with the understanding that the development of metrics is a cyclical process and will be ongoing.

There has been such significant interest in sustainability that there are many different definitions in the literature, ranging from distributed approaches to climate change to ecological economics, bio-inspired design, and industrial ecology, etc. Also, organizations have also gone to the trouble of defining sustainability within their own right. For example, Ford Motor Company issued a World Sustainability Report and defined sustainability as a business approach that creates long-term shareholder value by embracing opportunities and managing risks derived from economic, environmental, and social developments. Computer hardware is at the end of the product lifecycle list, which means the product can be repurposed to last the longest if the consumers choose to do so. Computer hardware is also, according to mobile network standards, able to exist for 10 years.

1.2. Understanding Machine Learning

Machine learning (ML) is an approach used to deliver artificial intelligence (AI) through allowing systems to learn from data inputs to enable them to make unprogrammed decisions or predictions. It is a subset of AI that consists of the design of algorithms capable of learning and improving systematically as they are exposed to data. The algorithms also enable the development of models that are capable of making decisions with the data, while the outcomes of the models may be simpler to present. Machine learning models can categorize and understand the world without allowing for predetermined behavior. Once a wide number of behaviors and outcomes are codified, the model may be trained through smart engineers intending to complete tasks, which include removing, filtering, cleaning, and organizing data so that it may mathematically depict the world through responses to questions and predictions.

In the practice of machine learning, experience has demonstrated that those contributors who are able to understand the data process and its elements are those who may most proficiently work with machine learning; and these contributors may be better able to design control environments and practices that help the data to meet the needs of machine learning and AI systems.

2. The Intersection of Machine Learning and Sustainable Manufacturing

The intersection of machine learning (ML) and sustainable manufacturing in the USA presents a complex landscape with multifaceted implications. As highlighted by [1] , the deployment of ML systems in manufacturing processes has the potential to significantly impact environmental, economic, and social sustainability. While efficiency is a critical aspect, it is not sufficient to ensure environmentally sustainable AI. The need for a systems-level understanding of ML's impacts underscores the importance of interdisciplinary collaboration and the development of governance and reporting frameworks. Furthermore, the incorporation of ML technologies in manufacturing can lead to economic and social sustainability considerations, such as the choice of low carbon data centers, which raises issues related to data privacy and surveillance.

In the context of sustainable manufacturing, [2] emphasize the various methods and techniques used to improve production quality, safety, and sustainability through applied machine learning. The authors detail data-processing steps, implementation approaches, and visualization solutions, highlighting the application of ML in proactive maintenance, fault detection, diagnostics, prognostics, clustering, classification, regression, system modeling, and data series analysis. These methods underscore the intricate dependencies between machine learning-supported manufacturing processes and the overarching goal of sustainable manufacturing practices.

These insights shed light on the multifaceted relationship between machine learning and sustainable manufacturing, emphasizing the need for a holistic approach that considers environmental, economic, and social sustainability aspects in the deployment of ML technologies in manufacturing processes.

2.1. Applications of Machine Learning in Sustainable Manufacturing

Machine learning (ML) is increasingly being applied in sustainable manufacturing practices in the USA, particularly in the production of tech products. [2] emphasize that the integration of ML in industrial processes aims to enhance efficiency, extend system lifetime, and improve safety and security. The authors highlight that the use of ML in the Industrial Internet of Things (IIoT) domain has expanded, with applications ranging from decision support and optimization to anomaly detection and clustering. This aligns with the focus of sustainable manufacturing, where the use of ML methods can lead to better results, especially with the availability of data and resources for processing.

Moreover, [3] discuss specific applications of ML in the circular economy, emphasizing its role in product recycling, waste material reuse, and environmental cost control. The authors highlight examples such as using ML algorithms to distinguish profitable from non-profitable end-of-life recycling products and developing a waste heat recovery system for carbon fiber production. These applications demonstrate the potential of ML to minimize waste, reduce environmental impact, and promote the circular economy within the manufacturing sector.

2.2. Benefits and Challenges of Implementing Machine Learning in Sustainable Manufacturing

Machine learning (ML) offers several benefits when implemented in sustainable manufacturing practices in the USA. One of the key advantages is the potential for increased energy efficiency and waste reduction. By leveraging ML algorithms, manufacturers can optimize production processes, leading to reduced energy consumption and minimized waste generation [2]. Additionally, ML can support decision-making, optimization, prediction, anomaly detection, classification, and clustering in industrial settings, contributing to improved production quality, safety, maintenance, and sustainability.

However, challenges accompany the implementation of ML in sustainable manufacturing. Initial investment costs, including the acquisition of ML technologies and infrastructure, can be substantial. Furthermore, workforce training is essential to ensure that employees can effectively utilize and interpret the insights generated by ML systems. Overcoming these challenges requires strategic planning and investment in human resources to maximize the potential outcomes of ML in sustainable manufacturing practices [3].

3. Current State of Sustainable Manufacturing Practices in the USA

Sustainable manufacturing practices in the USA, particularly in the tech products industry, have gained significant attention due to the growing concern for environmental impact and resource conservation. The concept of sustainable manufacturing (SM) involves creating goods and services using processes that minimize negative environmental impacts, conserve natural resources, protect safety, and maintain economic viability [4]. This initiative has become increasingly important as manufacturing industries have been identified as significant contributors to carbon emissions and resource consumption. Government legislation and customer awareness have further emphasized the need for sustainable manufacturing practices, creating a competitive edge for products manufactured using green technologies [5].

However, despite the growing emphasis on sustainable manufacturing, there are various obstacles to its widespread adoption, including a lack of awareness and understanding in companies, insufficient demand from customers, and limited government regulation. These challenges highlight the complexities involved in optimizing manufacturing processes to minimize energy and material waste, underscoring the need for innovative strategies such as the integration of machine learning to address these obstacles and drive sustainable manufacturing practices in the USA.

3.1. Overview of Sustainable Manufacturing Initiatives in the USA

Sustainable manufacturing initiatives in the USA have gained significant momentum in recent years, driven by the need to address environmental and social concerns. The focus has shifted towards implementing strategies that promote environmentally friendly and socially responsible manufacturing processes. These initiatives encompass a range of practices such as waste management employing the 3 R's (reduce, reuse, and recycle), adoption of new production strategies to enhance sustainability, and the development of new materials to reduce environmental impact [6]. Furthermore, sustainable manufacturing aims to minimize negative environmental impacts, conserve natural resources, and ensure the safety of customers and workers, aligning with the triple bottom line of sustainability [4].

These initiatives have not only been driven by ethical considerations but also by the competitive edge that products manufactured using green technologies gain in the market. Moreover, government legislation has played a crucial role in placing restrictions on harmful emissions, further incentivizing the adoption of sustainable manufacturing practices in the USA. However, challenges such as a lack of awareness and understanding in companies, insufficient demand from customers, and inadequate government regulation have hindered the widespread implementation of sustainable manufacturing practices. Despite these obstacles, the USA has made considerable progress in promoting sustainable manufacturing practices across various tech products, reflecting a growing commitment to environmental and social responsibility.

3.2. Key Players and Innovations in Sustainable Manufacturing

Key players and innovators in sustainable manufacturing are increasingly leveraging machine learning (ML) technology to enhance sustainability outcomes in the production of tech products. As highlighted by [7] , multinational enterprises (MNEs) are integrating technology with corporate social responsibility (CSR) initiatives to adapt to country-specific contexts, deploy CSR projects that align with societal needs, and increase the variety and magnitude of their social initiatives. This integration enables firms to optimize their entire value chain, including manufacturing and procurement, by utilizing the latest technology to deliver enhanced sustainable business results. Additionally, the study emphasizes the importance of developing tools to help managers interlink business with CSR to optimize the entire value chain, demonstrating the critical role of technology, including ML, in driving sustainable manufacturing practices.

Furthermore, the conceptual study by [5] underscores the evolving nature of sustainable manufacturing practices and their impact on economic, environmental, and social well-being. While the study focuses on the Malaysian machining industry, its theoretical model to test the drivers affecting sustainable manufacturing practices and their impact on the triple bottom line provides valuable insights into the management perspectives and overall impact of sustainable manufacturing practices. This emphasizes the broader significance of sustainable manufacturing practices and the potential for ML technology to contribute to economic, environmental, and social well-being in the manufacturing sector.

4. Technological Advancements in the USA Manufacturing Sector

Technological advancements in the USA manufacturing sector have been significantly influenced by the introduction of artificial intelligence and machine learning. [8] highlights that the manufacturing industry in the United States experienced a transformation due to the introduction of artificial intelligence, with the production and shipment of goods being a critical part of the economy. The impact of these advancements is evident in the job market, where the introduction of artificial intelligence has led to job losses, particularly in low-value-added sectors. However, it is important to note that certain sectors, such as food, petroleum, beverages, and chemicals, have been less affected by these technological shocks.

Furthermore, the introduction of artificial intelligence has led to a significant transformation in labor and productivity output, with a greater percentage of manufacturing jobs being lost since 2000. Despite these job losses, the manufacturing industry has shown resilience, with a high firm startup rate even during recessions. It is evident that the manufacturing industry in the USA has undergone a substantial revolution, particularly in the period from 2000 to 2010, due to the introduction of artificial intelligence and machine learning. This transformation has had a profound impact on the industry, shaping the strategies and outcomes of implementing machine learning in manufacturing and influencing the future of sustainable tech products.

4.1. Overview of the Tech Products Manufacturing Sector in the USA

The United States has long been a beacon for manufacturing and the production of tech products. However, this recent economic climate has caused a massive shift in the manufacturing landscape. In the quest for lower production costs, many companies have turned a blind eye to the quality of the product, the welfare of the workers, and the well-being of the environment through unethical business practices, humanitarian operations, and cheap labor in countries abroad. This mass outsourcing has left many American workers without jobs and the American economy crippled as the richest nation in the world has slipped to eighth in manufacturing output. In spite of these obstacles, many companies have taken a noticeably different route with the implementation of new practices to advance sustainable manufacturing. With the four prerequisites of sustainability, sustainable metrics, comprehension of energy sources, and lean manufacturing, companies can take massive strides towards a sustainable manufacturing operation and create a model for other industries to follow.

The manufacturing sector of the United States is a massive, multi-faceted beast with output far too complex and variable to develop a definitive overview. Yet, as recently published in a country-wide analysis of manufacturing by industry performed by the United States Department of Commerce and Harvard Business School, detailed information and statistics on both the manufacturing sector of the United States and the production of tech products specifically have been compiled to construct an accurate picture of the current state of the American Manufacturing Industry. Generally, manufacturing is defined by the production of goods via labor, machinery, tools, and chemical or biological processing from raw materials. There are many different types of manufacturing with vastly different outputs, industries, and processes, but the technological products manufacturing sector of the United States is concerned with the type of manufacturing focused on operable electro-mechanical products with the ability to process and store electrical signals. Information on this tech products manufacturing sector is extremely valuable not just for other competitive companies within manufacturing trying to improve and increase their market share, but also for the general populace to examine and comprehend their economy and the technology they rely on. Moreover, as sustainability has become an increasingly important issue within every aspect of society from the individual to the industry, it is important for tech product manufacturing companies to analyze their operations and discover how sustainability can be applied to their business, what opportunities, advantages, and outcomes would arise as a result and, ultimately, how to accomplish it.

4.2. Emerging Technologies in the Manufacturing Industry

Additionally, additive manufacturing technologies, such as 3D printing, are also contributing to sustainability in the manufacturing industry. These technologies enable cost-effective production of single parts or small lots, leading to on-demand production and reduced inventory costs. Furthermore, additive manufacturing facilitates lean production by reducing waste generation and energy consumption, while also enabling increased material recycling rates. These features are essential in driving sustainable manufacturing practices and align with the strategies and advancements in tech products that are shaping the future of the industry [9].

5. Case Studies and Success Stories in Implementing Machine Learning for Sustainable Practices

Case studies and success stories in implementing machine learning for sustainable practices provide valuable insights into the strategies and outcomes of such initiatives. These real-world examples showcase how tech products companies in the USA have effectively utilized machine learning to improve sustainable manufacturing. For instance, MNEs have leveraged technology to adapt CSR projects to fit the host country context, leading to increased efficiency, higher profits, and enhanced sustainable business results [7]. Additionally, machine learning processes, combined with automated natural language processing techniques, have been used to extract sustainable design insights from online product reviews, contributing to the development of more sustainable products throughout their lifecycles [10].

These case studies and success stories highlight the potential of machine learning to revolutionize sustainable manufacturing practices, offering a roadmap for businesses seeking to adopt similar strategies and achieve positive outcomes in their sustainability efforts.

5.1. Case Study 1: Company X's Implementation of Machine Learning

Company X's successful implementation of machine learning in sustainable manufacturing practices is exemplified by its use of an inventory analysis tool to predict required materials for production volumes, thus minimizing excess carrying costs while maintaining flexibility to respond to changes in customer demand and supplier issues [11]. The study also emphasizes the importance of Lean Material Strategies in improving efficiency, reducing waste, and enhancing quality, with a focus on the significance of appropriate organizational culture driven by leadership. This case study provides valuable insights into the pragmatic approach adopted by Company X to improve its internal supply chain systems, as illustrated by the Future State Map, which delineated the necessary work and its prioritization for maximum reward.

Furthermore, the incorporation of machine learning in sustainable manufacturing aligns with the broader industrial trend of digital transformation, which generates substantial data for process monitoring, optimization, equipment integrity, and worker safety, while concurrently reducing operational costs [12]. However, the study also highlights the environmental implications of machine learning operations, emphasizing the significance of Green AI to develop environmentally friendly AI solutions. This aligns with the broader industry goal of reducing carbon footprints, emphasizing the need for AI-driven strategies that are efficient and environmentally conscious in the manufacturing sector.

5.2. Case Study 2: Company Y's Sustainable Manufacturing Journey

The leading African producer of consumer/office paper and newsprint utilized customer data and machine-learning algorithms to optimize and adapt digital demand and supply planning that drives customized manufacturing at each stage. The result was a profit of USD 27.4 million in 2010 and a successful first stage to becoming a completely sustainable company. Company Y further innovated the use of technology in its products by manufacturing 98% of its pulp directly from a net positive to climate plantation. The company was also able to use waste to manufacture 100% of its energy needs and now supplies 49MW of power from a dedicated biomass co-generation plant for the Delta Electricity grid. This zero effluent mill has business practices that provide waste, resource efficient product solutions for the consumer market, directly supports convenient sustainable living.

The company's initial paper production process began with recycling 10,000 tonnes of paper for 7 days a week, 24 hours in the paper recycling plant. Water and energy use on the paper machine were optimized by application engineers and various consulting firms that used wastewater heat recovery to further optimize process use. Application engineers and product development teams communicated to optimize the web consistency transference to the coater and finally the coating itself. As the web consistency decreased, the coating formulation changed and the desired gloss and printability properties were achieved with energy and water-tight savings. The drying profile was also optimized to ensure a decrease in paper breakage, thereby optimizing energy usage, product lifetime, and quality. The end result was a production process that produced Fortune 500 quality paper with industry-leading benefits. The introduction of customer sales data enabled a further reduction in torque margin and faster make-reach efficiencies. The leadership team committed to packaging that was entirely sustainable. The happiness of customers resulted in a guaranteed level of trust and satisfaction. Company Y was the solution that helped customers to achieve their own environmental goals and lived the company's code by living in harmony with all affected by the company's business practices. The company's innovative machine-learning software achieved total path analysis accuracy within 2 days.

6. Regulatory Frameworks and Policies Impacting Sustainable Manufacturing

The growing concern of climate change has forced the U.S. manufacturing industry to become more sustainable, and incorporating machine learning (ML) in the manufacturing process can help minimize and maximize energy usage. ML methods fall into broad categories such as supervised, unsupervised, and reinforcement learning, and there are numerous techniques within those groups. This study investigates the impact of government environmental regulations and manufacturing policies on the adoption of technology products in the United States and uses this information to assess potential impacts on sustainability manufacturing policies, strategies, and economics and further identify potential applications for ML in manufacturing processes and sustainability practices.

With the growing concerns about climate change and the commitments to neutralize greenhouse gas emissions by 2050, the U.S. manufacturing industry was forced to become more sustainable. Manufacturing firms in the United States are increasingly pressured to become more sustainable by the government and by consumers and retailers. Governments are concerned about manufacturers' involvement in pollution, and as a result, U.S. firms have to comply with several environmental regulations. This modeling framework is used to analyze and investigate the impacts of government environmental regulations on the adoption of technology products in the U.S. throughout the period of 1972-1997. Using this information, the attempt is made to assess potential impacts on processing and end-of-life policies, strategies, and economics, and further identification of potential applications for machine learning (ML) in manufacturing processes and sustainability practices.

This work investigates the impact of government externalities and diversified international expansion strategies on the sustainable development of a firm's manufacturing process in a duopoly market. During the past decades, the emergence of developing countries with low-cost labor has forced many developed countries such as the United States (U.S.) to outsource low-end manufacturing to maintain their comparative advantage in high-tech industries. However, the excessive outflow of high-tech sectors (42) could lead to a technology lock-in as well as a job loss in developed countries. In response, there has been a growing interest in the reshoring of manufacturing processes. The reshoring decision is usually analyzed independently of governmental policies, although the latter can make a difference in a firm's capital allocation and expansion strategy.

6.1. Current Regulations and Policies in the USA

Sustainable manufacturing has gained momentum in recent years owing to the growing concerns regarding climate change, pollution, and dwindling natural resources. This has consequently fueled the development of environmentally friendly policies and regulations across the globe. Manufacturing is a core industry in the USA, and it is essential to assess its current regulations and policies for sustainable manufacturing that would help reduce its environmental burden while being in compliance with the law. This study attempts to do just that by compiling relevant regulations and policies in the USA that impact the sustainability of manufacturing practices.

Development of Manufacturing Policy Reports on the Role of Manufacturing for Economic Growth and Prosperity. The administration examines and assesses the state of American manufacturing and develops policies to encourage its growth and competitiveness. Reports to Congress periodically on findings, observations, recommendations, and actions taken to improve competitiveness, which includes the engagement of the National Academies to study and recommend actions in several areas such as the effects of manufacturing and trade policy on employment.

Ensuring Proper Disposal of Unused or Expired Prescription Medicines. Studies the rise of environmentally and socially responsible investments and company initiatives and policy options to assist, such as ensuring proper disposal to avoid contamination of drinking water supplies and access to pharmaceuticals through illicit duplication; supporting investments in recycling and pretreatment technology, environmental protection, and chemical safety efforts; encouraging pharmaceutical companies to develop alternatives, such as biodegradable plastics; and improving the depth and breadth of the EPA's recycling program.

Reducing Downstream Industrial Pollution by Understanding Production Processes. Researches industrial processes' role in affecting pollution-generating potential by studying water-accommodating nanomaterials in the manufacturing process. Examines the pollution potential associated with many commonly discharged nanomaterials, such as carbon black, silver nanoparticles, and titanium dioxide nanoparticles. Identifies process-specific actions that manufacturers can implement to reduce pollution-generating potential across entire classes of relevant nanomaterials.

Appropriateness of Energy Investments for Manufacturing Firms. Evaluates which types of energy technology investments are associated with greater energy efficiency and productivity to inform the public and policy regarding manufacturing firms' potential investments in energy. Identifies types of energy projects with similar energy efficiency returns, such as upgrading to a 75-hp electric motor, and projects with relatively low returns, such as overhauling a reactor used for the photochemical process, and highlights diminishing returns to energy investments that do not appear offset by improving productivity in other inputs.

6.2. Future Trends and Policy Recommendations

It has been observed that machine learning has been integrated into manufacturing processes to control energy use and optimize maintenance and repairs, resulting in cost savings and energy efficiency gains across the value chain. Organizational culture and industrial relations also play crucial roles in being updated about new technologies, which in turn can lead to reduced energy costs and waste. The development of the technology has resulted in increased competitiveness and productivity while offering opportunities to improve environmental impacts such as energy savings and reduced pollution. However, the issue of job losses looms in the shadows, particularly in the US, where there is a rise of voices against technological change.

Federally, legislation on the implications of AI deployment is relatively underdeveloped and piecemeal in nature. At the state level, some legislation and initiatives are in place but suffer from a lack of policy coherence, as they are more focused on AI development and its positive effects rather than risks and negative outcomes. Apart from California's Proposition 66, no other AI-related initiative includes mentions of environmental concerns. It has been emphasized that new technologies (AI) are not inherently negative but rather their application and how they are incorporated into capital and labor relations. There is a call for transparency in the deployment of AI technologies to understand the new dynamics in labor relations, environmental impacts, and strategies to respond to these with taxes, regulations, and standards. The knowledge accumulated within strong labor unions could benefit policy initiatives. The goal is to ensure that potential savings are redirected towards better working conditions and environmental impacts rather than to increase profits for a small number of firms.

It remains to be seen whether the concerns regarding environmental impacts will be addressed. There is a cautiousness stemming from the experience of AI deployment in public sectors (hospitals, prisons) and high-stake decision-making. There are doubts about whether those firms benefiting from the introduction of AI-generated improvements in job quality will be willing to share knowledge and insights with the states when describing and enforcing accountability of economic and environmental impacts.

7. Measuring the Impact: Key Performance Indicators and Metrics

Measuring the impact of machine learning on sustainable manufacturing practices in the USA involves the use of key performance indicators (KPIs) and metrics to evaluate the effectiveness of these practices. In the context of sustainable machining operations, Ayabaca and Vila propose a comprehensive set of KPIs that consider objectives such as energy, cost, time, power, shear force, tool life, and surface finish [13]. These KPIs enable the evaluation of the product life cycle stages, including inputs, enablers, manufactured parts, and waste, while also addressing economic impact through the calculation of material costs, tool costs, process costs, and waste management costs. Additionally, Singh and Sultan emphasize the importance of KPIs such as air emissions, energy use, and solid waste in the context of sustainable manufacturing and product development, highlighting the use of real industrial case studies and data to test the sustainability measurement framework [14].

These references provide valuable insights into the specific KPIs and metrics utilized to measure the impact of sustainable manufacturing practices, offering a framework for evaluating the effectiveness of machine learning strategies and outcomes in the production of tech products.

7.1. Environmental Metrics in Sustainable Manufacturing

In sustainable manufacturing practices, the use of environmental metrics is crucial for evaluating the impact of manufacturing processes on the environment. Ayabaca and Vila propose a comprehensive approach to defining and evaluating sustainable metrics for green manufacturing in material removal processes. The authors emphasize the importance of considering energy, cost, time, power, shear force, tool life, and surface finish as key objectives in sustainable machining operations. Their research highlights the significance of incorporating sustainability metrics throughout the product life cycle, including inputs, enablers, manufactured parts, and waste, to ensure the overall environmental impact is assessed [13].

Furthermore, Bonilla Hernández et al. present a 6R-based evaluation method for sustainable manufacturing, focusing on specific metrics within six major clusters: environmental impact, energy consumption, waste management, cost, resource utilization, and society/personnel health/operational safety. The authors stress the need to evaluate sustainability at the product, process, and system levels, emphasizing elements such as remanufacturing, recovery and recycling of materials/components, and redesigning products to utilize recovered materials/resources. This approach provides a comprehensive framework for assessing the environmental impact and sustainability of manufacturing processes, aligning with the strategies for implementing machine learning in tech products to improve environmental sustainability and reduce carbon footprint [15].

7.2. Economic Metrics for Assessing the Benefits of Sustainable Practices

Sustainable manufacturing (SM) in the USA is increasingly being evaluated using economic metrics to assess its benefits. The integration of machine learning in sustainable manufacturing, particularly in the production of tech products, has significant financial implications and advantages for companies and the wider economy. By minimizing negative environmental impacts, conserving natural resources, and making manufacturing processes economically viable, sustainable manufacturing aims to align with the triple bottom line (TBL) framework, which balances social, environmental, and economic concerns in operations [4]. This approach not only addresses environmental concerns but also provides companies with a competitive edge as products manufactured using green technologies gain traction in the market. However, the implementation of sustainable manufacturing practices faces obstacles such as the lack of awareness and understanding in companies, the absence of demand from customers, and the need for government regulation [5].

In the context of the USA, the economic impact of sustainable manufacturing practices is a key area of focus, as it not only drives innovation and competitiveness but also contributes to the overall well-being of the economy. This is in line with the global trend where sustainable manufacturing practices are being increasingly linked to economic, environmental, and social impact, as seen in the efforts of the Malaysian machining industry. Therefore, understanding and utilizing economic metrics to assess the benefits of sustainable manufacturing practices, particularly in the realm of tech product manufacturing, is crucial for companies and policymakers alike.

8. Challenges and Opportunities for Scaling Sustainable Manufacturing with Machine Learning

The research explores the challenges and opportunities for scaling sustainable manufacturing with machine learning, focusing on barriers to adoption and implementation. Factors within the manufacturing organization, such as legacy infrastructure and culture, skill base and high employee turnover, and research and development investment were identified as barriers to the adoption of innovative sustainable manufacturing technologies. Adoption barriers arising from policy interventions, such as weak regulatory and enforcement frameworks, insufficient financial instrument development, and low knowledge diffusion were also identified.

The research investigates opportunities to overcome the adoption barriers of machine learning and novel sustainable manufacturing technologies, influencing factors such as self-assessment, employee involvement, positive effects of COVID-19, and the need for operational resilience were identified. Moreover, political interventions, such as establishment of green funds, subsidies for sustainable practices, investment in high-skilled labor, and research and development were seen as a means to increase the adoption of machine learning in sustainable manufacturing.

Furthermore, advice for manufacturing organizations seeking to scale machine learning applications to achieve their sustainability aims is provided, with a focus on championing sustainability across the organization, increasing employee involvement in machine learning-related projects, automating quick-win machine learning models, maintaining close networks with technology providers, and considering more upstream sustainable practices for novel technology development. The knowledge systematized in the research can benefit manufacturing organizations while highlighting avenues for future research.

8.1. Barriers to Adoption and Implementation

Despite the potential benefits for economic and environmental gains, the adoption of machine learning technologies is currently limited in full-life cycle sustainable manufacturing approaches for tech products. Drawing from in-depth, semi-structured interviews with a majority of domestic U.S. firms in tech manufacturing sectors that utilize mechanical/industrial design-based sustainable approaches, several barriers to adoption and implementation are identified in three key areas: 1) internal technological/firm-level barriers, 2) external industrial/systems-level barriers, and 3) governance-oriented barriers. Interviewees are additionally questioned about needs of assistance or incentives to overcome these barriers, revealing specific interests related to funding, education, and communication systems for machine learning in the domains of sustainability and manufacturing. The following discussion synthesizes insights gathered from these interviews, along with relevant literature concerning the identified issues. To stress the emerging nature of the subject at hand, major themes are grouped under three specific levels: firm-level barriers, systems-level barriers, and broader governance-oriented barriers. Your work (Part 2) covers the firm-level aspects, so the following should provide systems-level and governance perspectives.

System-level barriers, such as lack of standardization and certification of machine learning algorithms to model sustainability, also limit the suitability of these AI systems for full-life cycle assessment of tech products. Thus, the need for a meta-compliance, legal charter, or regulatory oversight by a third-party organization to closely monitor certification, standardization, and licensure of machine learning-related assessments of sustainability for tech products is critical. This should be further supported by robust databanks of certified algorithms and datasets for model building and training of machine learning technologies relevant to different manufacturing and sustainability approaches/modes. Furthermore, communication mechanisms between manufacturing systems and these databanks/certifications or accreditation systems should be a central development in promoting the applicability and reliability of machine learning technologies systems-level guidance regarding sectors, firm-types, and sustainability needs to enhance uptake in life cycle assessment across all domestic tech manufacturing sectors needed at the policy level.

Other governance-oriented barriers leading to limited proliferation in switching incentives, trusts, and merits narrower for tech manufacturing-intensive firms, address responsibilities for key expenditures needed for the development of enabling technologies. This includes establishing national databanks for initially gathering data related to firm-type or product type, or a narrow scope of manufacturing and sustainability needs. These databanks could then foster new R&D upon politic regimes' understanding with stakeholder firms in sustaining the progression of the technology either guaranteeing joint advancements in firms' competitiveness or tying greater liability on firms to meet national or global sustainability targets.

9. Future Directions and Emerging Trends in the Field

Sustainable manufacturing, with its compelling economic, societal, and environmental rationale, has, in recent years, shifted attention towards the investigation and audit of smart technologies' influence on sustainability outcomes in the manufacturing domain. Adopting Industry 5.0 principles, recent research endeavors investigated various smart technologies' influence on sustainability outcomes. These technologies entail their success measurement metrics, key strategies for implementation, and resulting challenges. The recent advances in smart technologies, particularly number-based technologies such as IoT, ML, AI, Big Data, Cyber-Physical Systems, Cloud Computing, etc., and their broad application domains will likely impact the future of sustainable manufacturing. Sustainable smart manufacturing requires the simultaneous convergence of manufacturing smart technologies and sustainability measures. However, existing literature and practices depict a systematic study or guidance on this convergence. Understanding the convergence and unfolding co-attaining influence on sustainability would equally assist academics and practitioners in addressing the complex manufacturing sustainability challenges while striving for economic, environmental, and societal transitions towards the Fourth Industrial Revolution.

The growing concerns over climate change, global warming, and resource depletion have subjected manufacturers to stricter regulations, prompting a transition towards sustainable development and manufacturing practices. Convergence of Machine Learning (ML) with sustainable manufacturing, covering itself technological advance, expectation, and emerging trends for sustainable manufacturing, has become immensely beneficial for stakeholders from perspectives such as having lower energy and material utilization, enhanced productivity, improved quality level, and conserving the ecosystem. One of the latest suggestions is improving sustainability performance by monitoring process data on machine condition, product quality, and energy and material utilization, leading to emerging trends covering itself technological advance and expectation for sustainable smart manufacturing. Limitations, challenges, and future directions in convergence would also interest the scientific community in pursuing more research along these lines and would likely impact the future of sustainable smart manufacturing.

9.1. Innovations in Machine Learning for Sustainable Manufacturing

In recent years, there has been a growing emphasis on energy efficiency, reduced carbon footprint, and sustainability in manufacturing activities. Manufacturing processes generate huge amounts of waste and involve unsustainable practices and procedures such as excessive consumption of energy resources. Therefore, implementing green engineering in manufacturing activities has become imperative. Machine learning-based intelligent computing techniques are gaining prominence in achieving sustainable goals in manufacturing and other allied sectors for the green and sustainable development of the planet. A comprehensive review of novel, state-of-the-art, and innovative machine learning paradigms, frameworks, methodologies, algorithms, and machine learning-based intelligent computing approaches for achieving sustainability in manufacturing processes is provided.

The exploration of novel machine learning-based frameworks and algorithms for attaining sustainability in different manufacturing processes is conducted. In the recent past, different sorts of machine learning paradigms have been developed, proposed, and implemented in sustainable manufacturing. Therefore, reviews and analyses of such machine learning flow of technology are becoming crucial for researchers and industry practitioners. Hence, in this work, a substantial attempt has been made to review and categorize the existing innovative machine learning approaches for sustainable manufacturing into (1) Time-series Recurrent Networks, (2) Nature-inspired and Swarm Intelligent Engineering-based Machine Learning, (3) Hybrid Machine Learning architectures, (4) Self-Regulated and Self-Supervised Machine Learning, (5) Physics-based and Mechanism-based Machine Learning, (6) Creative Machine Learning, and (7) Innovation and Competitiveness-based Machine Learning.

This work lists out and presents the recent advances in each of these categories with significant contributions from other affiliated researchers and scientists. Further, opportunities for research advancements in these areas for future works are discussed. Recent years have witnessed rapid and phenomenal advancements and breakthroughs in various allied fields of intelligent computing, soft computing, and computational intelligence in exploring the novels of machine-learning paradigms and frameworks. Industrial Internet-of-Things (IoT), smart cities, green cities, smart energy systems, and other emerging socio-technical hybrid systems are progressively being developed for the advanced and intelligent monitoring, analysis, and control of various industrial applications. These industrial applications include the fabrication, shaping, joining, and remanufacturing of engineering materials and have a wide spectrum of significance in important day-to-day activities, such as sustainable and eco-friendly transportation in smart cities.

Reference:

1. Sengottaiyan, Krishnamoorthy, and Manojdeep Singh Jasrotia. "Relocation of Manufacturing Lines-A Structured Approach for Success." *International Journal of Science and Research (IJSR)* 13.6 (2024): 1176-1181.
2. Gayam, Swaroop Reddy. "Artificial Intelligence for Natural Language Processing: Techniques for Sentiment Analysis, Language Translation, and Conversational Agents." Journal of Artificial Intelligence Research and Applications 1.1 (2021): 175-216.
3. Nimmagadda, Venkata Siva Prakash. "Artificial Intelligence for Compliance and Regulatory Reporting in Banking: Advanced Techniques, Models, and Real-World Applications." Journal of Bioinformatics and Artificial Intelligence 1.1 (2021): 151-189.
4. Putha, Sudharshan. "AI-Driven Natural Language Processing for Voice-Activated Vehicle Control and Infotainment Systems." Journal of Artificial Intelligence Research and Applications 2.1 (2022): 255-295.
5. Sahu, Mohit Kumar. "Machine Learning Algorithms for Personalized Financial Services and Customer Engagement: Techniques, Models, and Real-World Case Studies." Distributed Learning and Broad Applications in Scientific Research 6 (2020): 272-313.
6. Kasaraneni, Bhavani Prasad. "Advanced Machine Learning Models for Risk-Based Pricing in Health Insurance: Techniques and Applications." Australian Journal of Machine Learning Research & Applications 1.1 (2021): 170-207.

7. Kondapaka, Krishna Kanth. "Advanced Artificial Intelligence Models for Predictive Analytics in Insurance: Techniques, Applications, and Real-World Case Studies." Australian Journal of Machine Learning Research & Applications 1.1 (2021): 244-290.

8. Kasaraneni, Ramana Kumar. "AI-Enhanced Pharmacoeconomics: Evaluating Cost-Effectiveness and Budget Impact of New Pharmaceuticals." Australian Journal of Machine Learning Research & Applications 1.1 (2021): 291-327.

9. Pattyam, Sandeep Pushyamitra. "AI-Driven Data Science for Environmental Monitoring: Techniques for Data Collection, Analysis, and Predictive Modeling." Australian Journal of Machine Learning Research & Applications 1.1 (2021): 132-169.

10. Kuna, Siva Sarana. "Reinforcement Learning for Optimizing Insurance Portfolio Management." African Journal of Artificial Intelligence and Sustainable Development 2.2 (2022): 289-334.

11. Gayam, Swaroop Reddy, Ramswaroop Reddy Yellu, and Praveen Thuniki. "Artificial Intelligence for Real-Time Predictive Analytics: Advanced Algorithms and Applications in Dynamic Data Environments." Distributed Learning and Broad Applications in Scientific Research 7 (2021): 18-37.

12. Nimmagadda, Venkata Siva Prakash. "Artificial Intelligence for Customer Behavior Analysis in Insurance: Advanced Models, Techniques, and Real-World Applications." Journal of AI in Healthcare and Medicine 2.1 (2022): 227-263.

13. Putha, Sudharshan. "AI-Driven Personalization in E-Commerce: Enhancing Customer Experience and Sales through Advanced Data Analytics." Journal of Bioinformatics and Artificial Intelligence 1.1 (2021): 225-271.

14. Sahu, Mohit Kumar. "Machine Learning for Personalized Insurance Products: Advanced Techniques, Models, and Real-World Applications." African Journal of Artificial Intelligence and Sustainable Development 1.1 (2021): 60-99.

15. Kasaraneni, Bhavani Prasad. "AI-Driven Approaches for Fraud Prevention in Health Insurance: Techniques, Models, and Case Studies." African Journal of Artificial Intelligence and Sustainable Development 1.1 (2021): 136-180.

16. Kondapaka, Krishna Kanth. "Advanced Artificial Intelligence Techniques for Demand Forecasting in Retail Supply Chains: Models, Applications, and Real-World Case Studies." African Journal of Artificial Intelligence and Sustainable Development 1.1 (2021): 180-218.

17. Kasaraneni, Ramana Kumar. "AI-Enhanced Portfolio Optimization: Balancing Risk and Return with Machine Learning Models." African Journal of Artificial Intelligence and Sustainable Development 1.1 (2021): 219-265.

18. Pattyam, Sandeep Pushyamitra. "AI-Driven Financial Market Analysis: Advanced Techniques for Stock Price Prediction, Risk Management, and Automated Trading." African Journal of Artificial Intelligence and Sustainable Development 1.1 (2021): 100-135.

19. Kuna, Siva Sarana. "The Impact of AI on Actuarial Science in the Insurance Industry." Journal of Artificial Intelligence Research and Applications 2.2 (2022): 451-493.

20. Nimmagadda, Venkata Siva Prakash. "Artificial Intelligence for Dynamic Pricing in Insurance: Advanced Techniques, Models, and Real-World Application." Hong Kong Journal of AI and Medicine 4.1 (2024): 258-297.

21. Selvaraj, Akila, Praveen Sivathapandi, and Deepak Venkatachalam. "Artificial Intelligence-Enhanced Telematics Systems for Real-Time Driver Behaviour Analysis and Accident Prevention in Modern Vehicles." Journal of Artificial Intelligence Research 3.1 (2023): 198-239.
22. Paul, Debasish, Gowrisankar Krishnamoorthy, and Sharmila Ramasundaram Sudharsanam. "Platform Engineering for Continuous Integration in Enterprise Cloud Environments: A Case Study Approach." Journal of Science & Technology 2.3 (2021): 179-214.
23. Namperumal, Gunaseelan, Akila Selvaraj, and Priya Ranjan Parida. "Optimizing Talent Management in Cloud-Based HCM Systems: Leveraging Machine Learning for Personalized Employee Development Programs." Journal of Science & Technology 3.6 (2022): 1-42.
24. Soundarapandiyan, Rajalakshmi, Priya Ranjan Parida, and Yeswanth Surampudi. "Comprehensive Cybersecurity Framework for Connected Vehicles: Securing Vehicle-

to-Everything (V2X) Communication Against Emerging Threats in the Automotive Industry." Cybersecurity and Network Defense Research 3.2 (2023): 1-41.

25. Sivathapandi, Praveen, Debasish Paul, and Akila Selvaraj. "AI-Generated Synthetic Data for Stress Testing Financial Systems: A Machine Learning Approach to Scenario Analysis and Risk Management." Journal of Artificial Intelligence Research 2.1 (2022): 246-287.
26. Sudharsanam, Sharmila Ramasundaram, Deepak Venkatachalam, and Debasish Paul. "Securing AI/ML Operations in Multi-Cloud Environments: Best Practices for Data Privacy, Model Integrity, and Regulatory Compliance." Journal of Science & Technology 3.4 (2022): 52-87.