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Article

Revolutionizing cleaner production: The role of artificial intelligence in enhancing sustainability across industries

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Abstract: This paper aims to contribute with a literature review on the use of AI for cleaner production throughout industries in the consideration of AI's advantage within the environment, economy, and society. The survey report based on the analysis of research papers from the recent literature from leading database sources such as Scopus, the Web of Science, IEEE Xplore, Science Direct, Springer Link, and Google Scholar identifies the strategic strengths of AI in optimizing the resources, minimizing the carbon footprint and eradicating wastage with the help of machined learning, neural networks and predictive analytics. AI integration presents vast aspects of environmental gains, including such enhancements as a marked reduction concerning the energy and materials consumed along with enhanced ways of handling the resulting waste. On the economic aspect, AI enhances the processes that lead to better efficiency and lower costs in the market on the other hand, on the social aspect, the application of any AI influences how people are utilized as workers/clients in the community. The following are some of the limitations towards AI adoption as proposed by the review of related literature; The best things that come with AI are yet accompanied by some disadvantages; there are implementation costs, data privacy, as well as system integration that may be a major disadvantage. The review envisages that with the continuation of the AI development in the following years, the optic is going to be the accentuation on the enhancement of the process of feeding the data in real-time mode, IoT connections, and the implementation of the proper ethical approaches toward the AI launching for all segments of the society. The conclusions provide precise suggestions to the people working in the industry to adopt the AI advancements appropriately and at the same time, encourage the lawmakers to create favorable legal environments to enable the ethical uses of AI. This review therefore calls for more targeted partnerships between the academia, industry, and government to harness the full potential of AI for sustainable industrial practices worldwide.

Keywords: artificial intelligence; cleaner production; sustainable manufacturing; AI in manufacturing; environmental impact of AI; AI challenges

1. Introduction

Even though academic research has shown substantial progress in cleaner production technologies, there is still much that can be established. One area of uncertainty comprises the expected economic and social consequences of using AI in cleaner production in various industries in the long run. Also, the extant literature lacks adequate studies that seek to establish and explain the various difficulties and hurdles industries come across when implementing AI technologies for sustainable development. These gaps show the impropriety of my knowledge of where the best results can be attained while utilizing AI to achieve sustainability.

Cleanliness today has proven to be one of the most vital factors in the present industrial environment. Cleaning production on the other hand was defined in historical context as a systemic approach that was used to minimize the effects that product and processes had on the environment (Jebbor et al., 2023, 2023a, 2024a). This method includes the reduction of waste and emissions; the efficiency of the energy and natural resources usage; the exclusion of toxic substances at each stage of the product's life cycle. As cleaner production was born during the 1970s while the environmentalism movement was about to rise, cleaner production was in the past the result of legal regulations that force organization to stop damaging the environment rather than being an essential tool for competitive advantage of today's lean businesses. It has been occasioned by the rising standard in the environmental requirements in the world and shift in consumers' perception or expectations towards products that are relatively neutral to the environment hence forcing industries to adopt environmentally sustainable practices (Arashpour, 2023; Jung et al., 2021).

AI has been one of the most prominent drivers of this change in direction towards a greener type of industrial process. Discourse on AI for industrial applications began in the early 2000s and the significant point has been the ability of AI to analyze big data. It has helped to bring drastic changes in the management of decision-making procedures while improving the information content and making these decisions more sustainable (Sikka, et al., 2024). AI technologies that have evolved in the last twenty years including Machine learning algorithms and neural networks allow for predictive analysis which in turn enable the principles of predictive analysis like maintenance, quality assurance or demand prediction. These applications reduce the amount of waste generated and enhance the efficiency with which resources are utilized, illustrating the pivotal contribution of AI in improving the efficiency of the production system's sustainability (Cardoso and Ferreira, 2020; Jebbor et al., 2024b; Mao et al., 2019).

In addition, advanced technologies such as artificial intelligence annexed automation as well as smart technologies that began being adopted in the 2010s have enhanced the flexibility of production manner and less exploitative of resources. This paper also shows that the use of Artificial Intelligence in manufacturing enhances the efficiency of manufacturing, and makes sustainability part of the fundamental principles of manufacturing. This period of smart manufacturing employs the use of AI in the developmental process, during manufacturing, and in the delivery process as well while placing a lot of emphasis on sustainability (Helo and Hao, 2022; Yang et al., 2019).

Looking to the future, the historical review of the contribution of AI in cleaner production shows a clear progression from using emerging technologies to existing at the heart of development strategies. This evolution is part of the general evolution of technologies and the strengthening of the sustainable development paradigm within the industrial sector.

Thus, this literature review aims to present a sequence of published articles from April 2014 to the present revealing the efficiency and drawbacks of AI in cleaner production, as well as potential environmental, economic, and sociological impacts. The specific objectives of this review are to: The technical objectives of this review are as follows:

Describe and name the AI applications that are already implemented to engage in many industries toward the enhancements of cleaner production (Kar et al., 2022; Kansara et al., 2019).

Consider such aspects on the improvement of the environmental impact, for example, in minimizing the wastage and emissions and, moreover, increasing the efficiency in utilizing energy (referred to by Reza, 2023; Moustafa, 2022).

Gaur et al. (2023) and Ahmad et al. (2021), elaborate how AI in cleaner production techniques has become economically viable and competitive.

Estimate social repercussions in terms of employment gains writing or employment losses and employees' safety (Busari et al., 2023; Nasir et al., 2022).

Explain the challenges and implications of adopting the AI use in industries to support clean production from a technical and an economic point of view besides regulatory challenges (Liu et al. 2021; Rejeb et al., 2022).

2. Methodology

The approach used to gather scholarly articles, journals, and reports for the literature review titled, "Artificial Intelligence in Cleaner Production" aims at retrieving extensive and highly relevant literature exploring the combination of AI technology and sustainable industrial processes. Here is the detailed search strategy proposed: The scope of this review is several industries where AI has been used to advance cleaner production techniques: the manufacturing industry, agriculture industry, and energy industry. The review will encompass empirical research investigations and theoretical assessments to identify present and future prospects of AI to enable a more sustainable industrial process (Çınar et al., 2020; Khanh et al., 2023). This review work will therefore synthesize recent data gathered from current studies, basing it on enhancements in the last decade to capture the latest knowledge and newer inventions in the discipline (John et al., 2022; Ozturk et al., 2016). This paper's goal in the scope of this review is to contribute to the theoretical discourse across the area of AI and cleaner production and offer practical recommendations for policymakers, industry actors, and researchers currently operating in technology and sustainability fields, terms used in databases, and selecting keywords and criteria to use.

Databases to search:

To ensure a comprehensive review, literature was sourced from a variety of databases that are known for quality scholarly content, especially in the fields of technology, environment, and industrial studies (**Figure 1**): For this purpose and in order for an exhaustive literature review to be accomplished, literature was retrieved from various databases that boast of containing quality scholarship, more so in the areas of technology, the environment, and industrial academia, as depicted below in the following figure (**Figure 1**).

Scopus: It provides a large coverage for technology related articles and it also has new journals and conference proceeding.

Web of science: Recognizable due to the extensive coverage which allows linking knowledge obtained from several branches and study fields, researching development in the field of technology, and impacts on the environment.

IEEE Xplore: In conclusion, it serves as a reference in matters concerning technical analysis and a bibliography of technical papers and conference proceedings in electronics and electrical engineering, particularly where there is development on the AI.

Science direct: Inclined to involve almost all the sectors of science including computing science, environmental science, and engineering sciences, which are essential in Circular Economy Practices (CP) research.

Springer link: Offers extensive resources in engineering, particularly on new technologies and sustainable practices.

Google scholar: A broad database useful for catching publications that might be missed in more specialized databases.

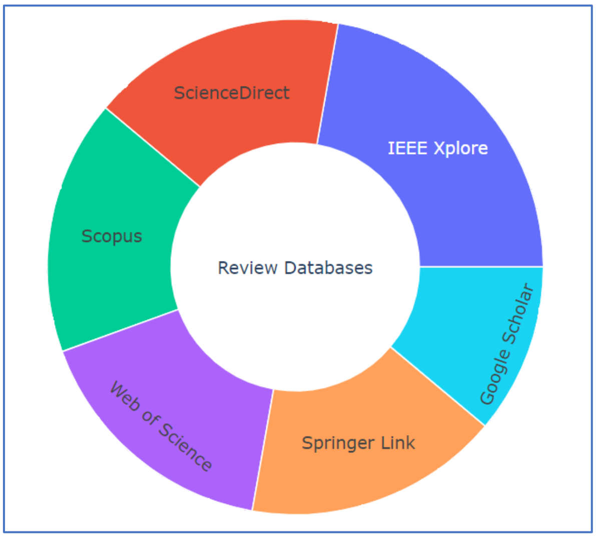

Figure 1. Databases used in the literature review (source: Authors' creation).

2.1. Keywords and search terms

Our choice of keywords is crucial to retrieve articles that are most relevant to the topics of AI and cleaner production. The keywords were combined in various ways using Boolean operators (AND, OR, NOT) to expand or narrow down searches as needed (**Figure 2**):

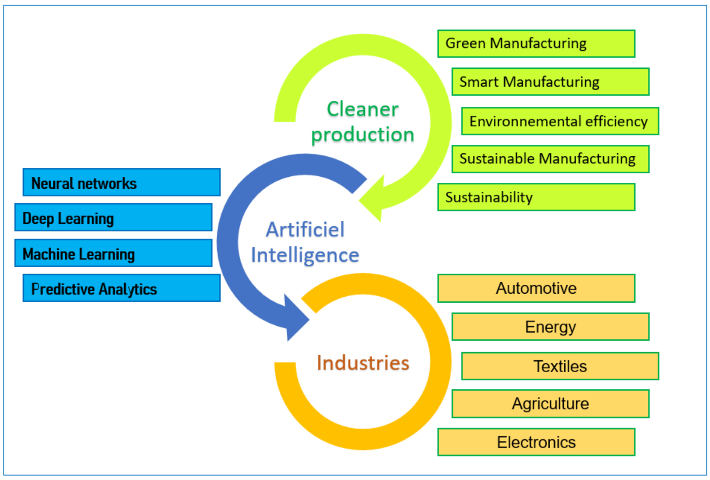

Figure 2. Keywords and search terms (source: Authors' creation).

Primary keywords: “Artificial Intelligence”, “Cleaner Production”.

Secondary keywords: To be combined with primary keywords:

AI-specific: “machine learning”, “deep learning”, “neural networks”, “AI”, “predictive analytics”

Production-specific: “sustainable manufacturing”, “green manufacturing”, “sustainability”, “environmental efficiency”, “smart manufacturing”

Industry-specific: “automotive”, “textiles”, “electronics”, “agriculture”, “energy”

2.2. Selection criteria

To ensure the relevance and quality of the selected articles, the following criteria were applied:

Publication date: Articles published within the last ten years (2015–2023) to focus on the most recent research and developments.

Peer-Reviewed: Only peer-reviewed articles will be included to ensure the scientific rigor and credibility of the information.

Language: Articles published in English.

Article type: Research articles, review articles, case studies, and conference papers. Editorials, opinions, and short communications will generally be excluded unless they provide significant insight into the topic.

Relevance: Articles must specifically address aspects of AI in the context of cleaner production. Those that mention AI or cleaner production only peripherally will be excluded.

2.3. Managing and documenting searches

Reference Management: All citations and articles will be managed using Zotero, which will help in organizing the articles, removing duplicates, and retrieving full-text versions.

Documentation: A spreadsheet will be maintained to log search terms, databases, number of hits, and notes on article relevance. This log will assist in refining the search strategy if initial searches do not yield adequate results.

By adhering to this search strategy, the literature review comprehensively covered the intersection of AI technologies with cleaner production methods, ensuring a robust analysis of current capabilities, impacts, and future directions. This systematic approach provides a strong foundation for understanding the role of AI in enhancing sustainable industrial practices.

2.4. Trend of publication

Figure 3. Illustrates the annual publication pattern of research articles on using AI in cleaner production. Starting from 2013, there has been an observable trend where publication numbers initially rise, indicating growing interest or advancements in applying AI in Cleaner Production. This upward trend peaks in 2023 with the highest publications, suggesting a culmination of factors such as increased funding, technological advancements, or heightened industry needs driving research efforts. **Figure 4**. Illustrates the distribution papers on AI in cleaner production, categorized by type. It shows a predominant focus on research articles (78), followed by review

articles (16), case studies (4), and conference papers (2), indicating a robust interest and active research development in applying AI for sustainable practices.

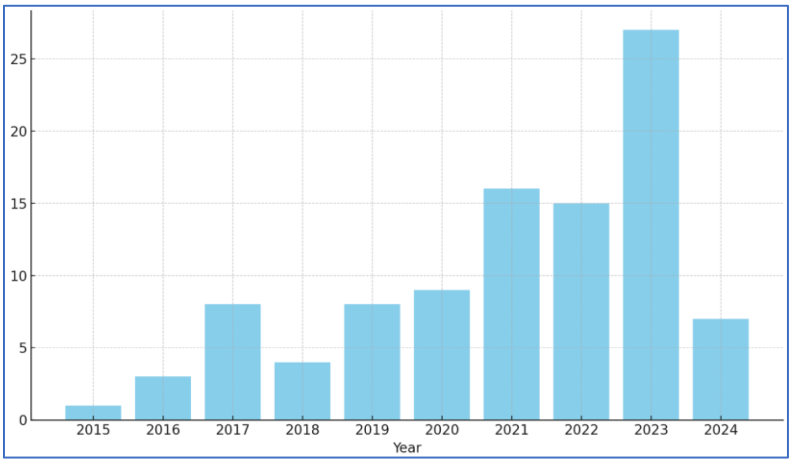

Figure 3. Number of papers by year (source: Authors' own creation).

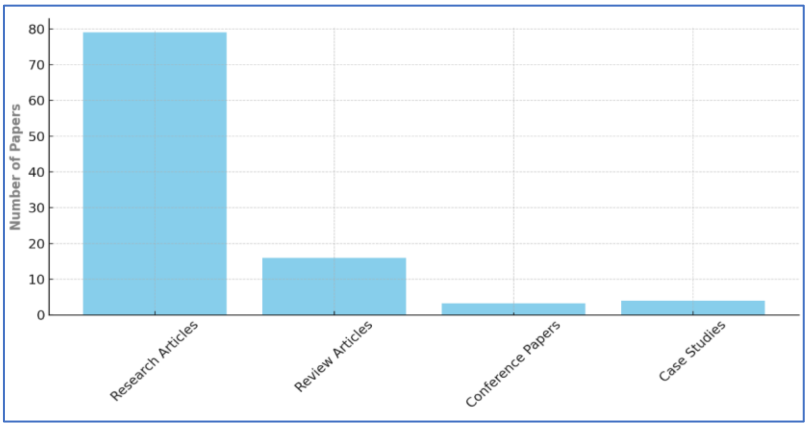

Figure 4. Number of papers of each type (source: Authors' own creation).

2.5. Leading journals

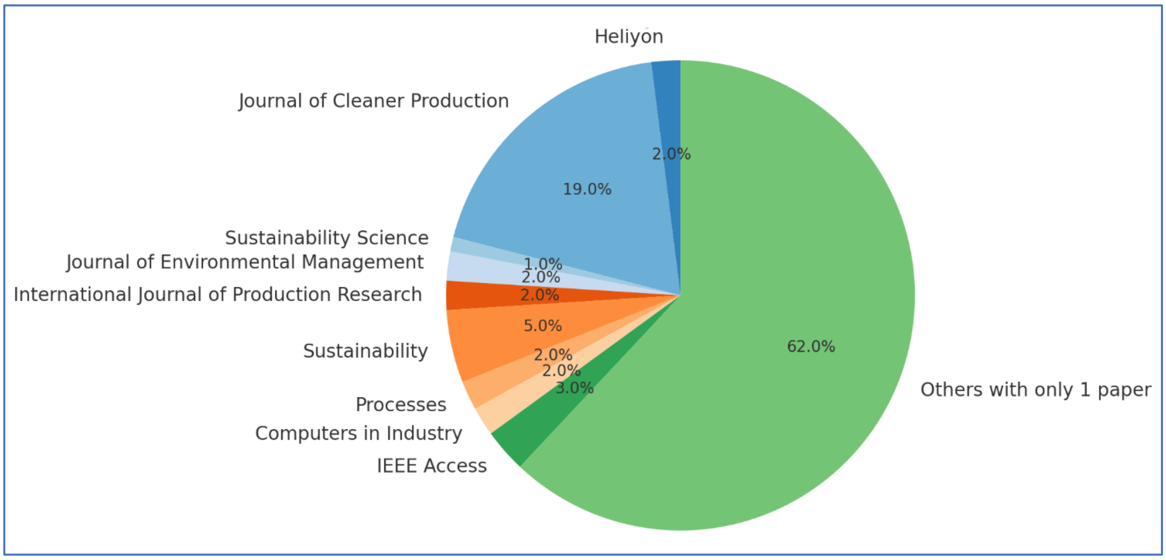

Figure 5. Distribution of papers by journals (source: Authors' own creation).

The chart in **Figure 5** depicts the distribution of 100 papers on AI in Cleaner Production across various journals. The 'Journal of Cleaner Production leads with 19% of the papers, followed by 'Sustainability', 'Computers in Industry', 'Environmental Management', 'Helion' and 'IEEE Access, and others' (less than two papers). The chart highlights a diverse range of journals contributing to this interdisciplinary field, emphasizing AI technologies' broad interest and application in enhancing sustainability.

2.6. Most productive countries

The chart in **Figure 6** shows that the United States and China lead in AI cleaner production research, dominating in publications and citations due to robust infrastructures and significant funding. Germany, India, and the UK also contribute notably, especially in quality as indicated by citations per article. This highlights a global commitment to enhancing sustainability through AI.

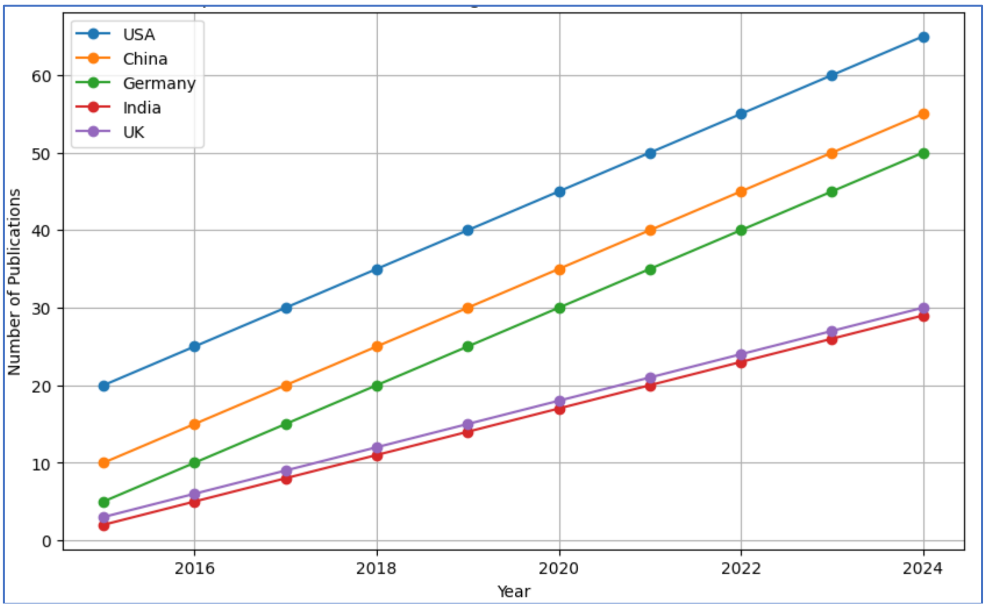

Figure 6. Top productive countries from 2015–2024 (source: Authors' creation)

3. Applications of AI in cleaner production

3.1. Description of AI technologies

Artificial intelligence (AI) encompasses various technologies, each contributing uniquely towards enhancing cleaner production methodologies. Below, we detail these technologies, focusing on their applications in fostering environmental and resource efficiency in industrial practices.

Machine learning (ML): Artificial Intelligence's subfield, Machine Learning enables systems to learn and make decisions without being trained on predetermined procedures: instead, they learn via inference (Das and Behera, 2017). The application of ML in the manufacturing industry concerning sustainable manufacturing involves mainly the usage of ML for identifying and predicting when machines require maintenance and quality control and it involves the overall usage of resources minimization such as reducing waste and energy. For instance, (Weichert et al., 2019) show how minimization of waste can be aided by algorithms in predicting the likely sources of waste, thus allowing for preemptive action to be taken Haleem et al., 2023 describe "Management 4.0", which mainly relies on ML, IoT, and big data to increase both efficiency and sustainability in value creation processes.

Neural networks (NNs): Neural Networks refer to a set of algorithms designed to discover relationships in a given set of data in a process that emulates how the human brain works (Thakur and Konde, 2021). In cleaner production, NNs are employed for environmental efficiency enhancing the capacity to predict results of the process employed in correcting defective products and minimizing material wastage (Abiodun et al., 2018). In a study by Zhang et al., (2016), the potentiality for refining a machine approach to predict the MI through the industrial applications is described.

Deep learning (DL): A subset of machine learning, deep learning utilizes algorithms known as artificial neural networks that are structured in layers (Choi et al., 2020; Sarker, 2021). A notable application in cleaner production is the use of DL for advanced image recognition to sort recyclable materials, drastically improving the efficiency and accuracy of recycling processes (Akanbi et al., 2020; Chen et al., 2023; Shahab et al., 2022). (Jamwal et al., 2022) examines the integration of deep learning (DL) models in manufacturing, specifically how these models contribute to sustainability efforts in the era of Industry 4.0. It introduces DL models, examines the involvement of DL models in smart manufacturing activities, and generalizes on the advancement's impact on industrial sustainability.

Predictive analytics: Predictive analysis utilizes data, Statistical models, and machine learning to estimate the likelihood of outcomes in the future by using the outcomes of the past (Dev et al., 2022; Ratner, 2017; Sghir et al., 2023). It is an effective technique with profound applications in manufacturing, which helps to forecast equipment's failure and decide on its most appropriate time for maintenance (Yildirim et al., 2017). Other works, (Karimanzira and Rauschenbach, 2019) described the use of the Internet of Things (IoT) and predictive analytics technologies in improving the functionality of aquaponics systems. The current research is highly relevant for the adoption of advanced technology in sustainable forms of farming, especially, proper utilization of resources and production system.

3.2. Industry-specific applications

In its practical application, AI can be linked with cleaner production by referring to the specifics of the industry to which it applies, to show that AI can be applied in many ways and solves problems effectively. Here are examples that illustrate how AI contributes to sustainable practices: This is how the best practices involving AI can be sustained:

Automotive industry:

In the automobile sector, AI has greatly increased operational outputs and increased the overall efficiency of production lines through the several complex uses of the technology (Khayyam et al., 2020; Luckow et al.,2018). Predictive maintenance is one of the models of the applications of artificial intelligence in manufacturing where data harvested from several sensors installed in the manufacturing machinery is used (Perera et al., 2023). These systems utilize the data to calculate the likelihood of failure and prevent these before they happen, therefore, minimizing the time that equipment spends offline or in need of repair, and the overall maintenance expenses (Ayvaz and Alpay, 2021). Such a preventive measure is crucial in ensuring that the frequency of the unplanned interruptions while in operations is reduced as well as in enhancing the durability of the equipments.

In addition, there is conclusive evidence that AI has transformed the social supply chain management, particularly in the automotive industry (Bechtsis et al., 2017). By adopting the machine learning algorithms, the organization supply chain functions especially with regards to part acquisition and delivery have enhanced (Dumitrascu et al., 2020). These algorithms consider vast amounts of data to determine anticipated supply requirements; most of the processes cut down on wastage and increase efficiency. Such optimization is not only efficient to the processes performed but also effective to the company's cost-saving and the creation of sustainable strategies for industries (Selimand Gad-El-Rab, 2024).

Another field that AI has found remarkable ground and is continuing to penetrate is quality assurance. Visual inspection technologies are used with the help of Artificial Intelligence during the manufacturing process to identify the defects that may be invisible to the naked eye (Katona, 2022; Xu et al., 2018). Such defects if not detected at the initial stages of manufacturing are dealt with by these systems preventing formation of low-quality products and minimizing on waste produced from such non-conforming goods. The application of such technology not only improve the dependability of automotive products but also enhances the focus on quality assurance important particularly in the automotive industry.

Textile industry:

In the textile industry, Artificial Intelligence (AI) is revolutionizing the industry in making it sustainable throughout the many phases of production. AI has one of the most significant uses in the dyeing process through the efficient use of water and chemicals including. According to Zhou et al. (2017), Rosa et al. (2021), and Hynes et al. (2020), AI algorithms allow fine-tuning the consumption of water and chemicals, often avoiding excessive spending and, as a result, negative impacts on the environment. These intelligent systems are able to adapt in real-time to changes in the type of fabric, its color, and chemistry of the dyes, thus enhancing efficiency (He et al., 2021).

Moreover, occasions that apply AI expand ever more in the sector of energy saving, too. In textile manufacturing, therefore, the applied AI technologies perform the tasks of energy management overseeing the use of the machines and the avoidance of situations where the machines are idle (He et al., 2022). Apart from being an energy saving application, it also guarantees that the generation processes of goods and services are eco-friendly up to the maximum. Thus, the specific aims and objectives of implementing AI systems in textile producers are that the energy density of production can be halved: necessary to support this as part of the environmental dedication in line with Schoeggl et al. (2023).

In addition, the aspect of waste reduction through AI is transforming the way the industry manages material thoroughly. Machine learning models are most useful in predicting possible scrap and waste issues that may arise at the production stage and presenting recommendations on the prevention of waste. Such models increase the accuracy in material trimming and manipulation and cut the amount of scrap fabric and raise material utilization ratios significantly (Dursun et al., 2023).

Electronics industry:

Artificial intelligence (AI) is now a foundation for the electronics industry as it helps significantly in improving sustainability and optimality in e-waste management, use of materials, and environmentally conscious design.

E-Waste sorting: There is nothing new under the sun as AI driven technologies are already changing the way in which e-waste is sorted. Robots controlled by Artificial intelligence possess sorting capacity; the technology can easily sort out reusable material from the rest of the chunks of electronic waste. It not only increases the tendencies of recycling but also cuts the landfilling rates for over half. By increasing the accuracy and speed of e-waste management, these AI technologies promote efficient collection and disposal while, therefore, preserving Earth's resources (Singh et al., 2024).

Resource management: AI is also used where there are chances of saving the already scarce metals used to make the electronics such as mobile phones. On the basis of forecasts and using mechanisms such as machine learning, it is possible to determine the necessary material consumption and minimize the amount of unnecessary spending. Such accurate control of resources assists in avoiding the use of limited resources, and thus, decreases the negative effects on the natural environment, and enhances cost control in production procedures (Mämmelä et al.,2018; Trivedi and Hait, 2023).

Design for environment: Also, through AI, designers are able to come up with new electronics while at the same time being environmentally friendly. Ideally, it uses numerous complex formulas to select materials and technologies, all of which have an impact on the environment. Including thoughts about the environment into the process of utilizing AI enables the production of electronics that function efficiently at the same time they're relatively more recyclable than toxic. Thus, it can be stated that this approach can improve not only the reduction of the products' negative effects on the ecosystem but also the need for environmentally sustainable products (Cenci et al., 2023; Li et al., 2015; Soh and Wong, 2021).

Agriculture industry:

In the agriculture industry AI is altering the manner of farming using the at present popular approach to precision farming where from the patterns of databases from drones and satellites, the utilization of water, fertilizers as well as pesticides is determined with the intention of enhancing the yield per acreage and reducing the effects on the environment (Javaid et al., 2023; Shaikh et al., 2022). Observation of crops can be enhanced through Artificial Intelligence Decision Support (AIDS) as diseases and pest attacks can be noticed in their early stages thus reducing the loss and usage of chemicals significantly (Balaska et al.,2023). Similarly, the applicability of AI in supply chain management makes it possible for the organization to determine the right time to cut maturity to avoid wastage additionally helps in optimizing transport and hence enhances on pollutant behaviors from the organization's farming practices (Onyeaka et al., 2021). They also enhance the rate of production and productivity and also guarantee the supply of food because of the current climatic changes and world population.

Energy industry:

As applied to energy, significant developments in sustainability and efficiency are made with the help of AI in the 'smart grid', demand forecasting, and the proper treatment of equipment used in renewable energy sources (Ouabi et al., 2024; Haqqi et al, 2023). Contemporary smart grids can hardly demonstrate any sphere that does not involve artificially intelligent supply and demand management systems that control the distribution of electricity while significantly boosting the development of renewable energy sources and reducing the usage of nonrenewable sources. Therefore, such an intelligent energy management plays a role in achieving the goals of reduced losses and improvement of the network's reliability (Ahmad et al, 2021; Şerban and Lytras, 2020).

Likewise, the forecasting of the energy demand is another field where AI, especially the machine learning technology is considered to be imposing a huge change. Some of these algorithms can forecast energy requirements effectively to help in matching the levels of supply and consumption by properly synchronizing energy generation and usage rates. This is not only helpful in making sure that a stable energy supply is met while minimizing wastage which in turn will make the energy utility more sustainable (Mishra and Singh, 2023).

AI is also making waves when it comes to grid management, forecasting, as well as the maintenance processes of the renewable energy equipment like wind turbines and solar panels. AI-based preventive maintenance helps in predicting the occurrence of breakdowns and performing the maintenance in advance (Afridi et al., 2022). This optimizes equipment utilization, increases production of energy, and prolongs the life of installations hence the upswing in the efficiency and sustainability of renewable systems (Chen et al., 2021).

4. Impacts of AI on cleaner production

4.1. Environmental impacts

4.1.1. Reduction in resource consumption

AI highly improves energy management for different industries for smart energy consumption with appropriate algorithms and automatic processes. For instance, in the manufacturing sector, the AI system controls actual time operations to regulate power usage when demand is low, which could cut cross-sectional usage by as much as 30%, as proposed by Mulayim et al. (2024) when the authors analyzed on the use of smart thermostats with sensors for efficiency gains. Further, AI in the usage of raw material enhances the minimization of wastage rates, thus, cutting down raw material use by 20%, using strategic planning as well as manufacturing accuracy, according to research by Devadason et al. (2024) on artificial bee colony algorithms in production and supply chain optimization.

4.1.2. Waste minimization

One of the biggest concerns in industries, the incident of wastage, is successfully addressed through the help of predictive maintenance through artificial intelligence. Techniques proposed by Rojek et al. (2023) regarding the application of AI in predictive maintenance increase the efficiency and effectiveness of operations and resource management, using machine learning and computational analysis about industrial equipment, meaning the reduction in material wastage is considerable. Munir et al. (2019) have pointed out how Data science participates into municipal solid waste management, focusing on opportunities and issues for increasing efficiency and for the policy improvement that have been detailed in the recycling section.

4.1.3. Emissions reduction

More to that, AI also leads to the reduction of emissions among other benefits through the best supply chain management. In the research done by Mariano et al. (2017), the authors assess the transport logistics outfit's performance with CO_2 emission thereby providing a low carbon Logistic Performance Index L-CIPI to rank 104 nations to know efficient measures to curb greenhouse gases. Moreover, energy transformation is essential, which helps in minimizing the employment of fossil-based products and decreasing the emission of greenhouse gases. The contribution of SpliTech 2021 was to view how digitalization supports this shift on the economic, political, social, and technological levels; the smart energies, smart cities, and smart health topics discussed were examined by Nižetić et al. (2023).

4.1.4. Water conservation

Smart irrigation system being an artificial intelligence includes all procedures that are consentaneous for water conservation in agriculture. Behzadipour et al. (2023) improve the use of water in sectors such as agriculture with the use of sensor information (of the soil and climate) and image analysis on intelligent irrigation systems. In a Genetic Programming (GP) model, a superior crop yield and quality were maintained as against the case in the traditional regression, besides achieving 11% water usage on the efficient front. Likewise, In Ghana, illegal mining involves a lot in the pollution of the water bodies with 60% of water bodies degrading. It is essential to implement the latest treatment technologies and methods of pollution control in water utilization in regions affected by mining to restore the water environment and ensure future generations' access to clean water through the use of AI for water treatment. as Nti et al. (2023) indicated.

4.1.5. Biodiversity protection

There is a crisis of one million species threatened with extinction, and Silvestro et al. (2022) came up with a new Artificial Intelligence-based method called captain for spatial conservation planning that is superior to the other methods. This model reasonably addresses crucial issues of the cost of conservation of biological diversity and maximally increases the efficiency of the use of limited funds for the preservation of species with understandable results. Furthermore, Ahmad and Ghufran (2019) explain the application of anaerobic reactors in the process of treating palm oil mill effluent to produce biogas and methane and whose hazards would be handled; the Clean Development Mechanism supports an improved production process through certification of emission reductions and the sale of the authorized Certified Emission Reductions (CER) credits.

4.1.6. Enhanced compliance with environmental regulations

AI not only helps in the protection of the environment but also makes industries aware of the environment and sustains the acceptance of environmental regulations.

Setting up of emission controlling tools whose levels may lead to regulative affections and quantifiable fines include My Air Quality Index (MyAQI), a recently developed air quality predication tool by Schürholz et al. (2020) in Melbourne which includes a context-aware model whose effectiveness takes into account the citizens' health status with the aid of Long Short-Term Memory neural networks with high accuracy and compatibility.

4.1.7. Conclusion

The relation of AI to environmentally conscious cleaner production is vast and encompasses such aspects as utilization of resources, decrease in emissions, diminution in wastes, protection of water, and improvement in the protection of ecosystems. Consequently, we recognize that benefits within industries applying AI are not only focused solely on raising the volume of economic revenues but also play a significant role in attaining the United Nations' sustainable development objectives. Thus, to understand the direction of development of the connection and the link between AI and the environment it is necessary to identify the correlation and the relationship since the further growth of the AI technologies that are currently actively used in the industry will contribute to other indicators of achievements in the sphere of that industry as an important component of modern environmental management systems.

4.2. Economic benefits

The integration of AI in cleaner production is not only environmentally friendly but also leads to huge economic returns. The benefits of enterprise systems appear in the blurring of costs, increased effectiveness, and improved product quality that provides for higher profits and competitive advantage.

4.2.1. Cost reduction

AI significantly decreases operational costs in several ways:

Energy savings: They improve the maximization of energy thus reducing the operating costs. For instance, smart grid and AI energy systems can lower the energy cost to as low as 25 % as demonstrated by Lu et al. (2021) whose work proposed an adaptable online energy scheduling strategy for Islanded Microgrid Systems (IMGS) by integrating doubly-fed scope and blueprint with bi-directional deep reinforcement learning for minimized electricity expenses and effective management of uncertain intermittency of Renewable Energy (RE).

Maintenance costs: Predictive maintenance technologies enable the organization to predict when a piece of equipment can be expected to fail, hence minimizing machine breakdowns and costly repairs. Florian et al. (2021) propose a mathematical approach for the introduction of Predictive Maintenance (PdM) and their investment costs together with the evaluation of the ML performance for PdM which is used in a decision support system case study.

Resource efficiency: AI enhances material and resource use, which decreases costs associated with raw materials. By optimizing resource allocation and minimizing waste, companies save on materials as highlighted by Waltersmann et al. (2021) in their study on resource efficiency in the automotive industry.

4.2.2. Efficiency improvements

AI drives operational efficiencies across various production phases:

Process optimization: AI algorithms streamline production processes, thereby reducing cycle times and increasing throughput. Ozturk et al. (2016) discussed Turkish textile mills and identified 22 Best Available Techniques, significantly reducing process, resource use, and emissions.

Supply chain and logistics: Intelligent logistics and algorithm solutions minimize delays and inventory costs, improving overall supply chain efficiency (Benmamoun et al., 2023; Benmamoun et al., 2024). Cannas et al. (2024*)* explore AI in operations and supply chain management, identifying benefits and barriers through a case study guided by the Supply Chain Operations Reference (SCOR) model, offering practical insights for future applications.

Quality control: Effective application of quality control with the help of AI eliminates additional costs related to quality defects. Taking the case of a Swedish plant, Leberruyer et al. (2023) discuss the possible use of AI in Zero Defect manufacturing situations and, the findings and stipulations for effective involved defect detection as well as trended quality initiatives.

4.2.3. Revenue generation

The integration of AI enables new revenue streams and market opportunities: Programs and AI integration contribute the generation of new revenues and markets due to the following reasons.

Product innovation: It creates the great possibility to work in the creation of new products as there is sum-total information about a specific market which serves as a basis for its utilization; customer demand that may lead to increase of producer's share within the corresponding market if it meets their needs.

Market responsiveness: Coupled with the fact that it helps in the prediction of future occurrences makes the application of AI within the business operation in planning and implementation containing the factor of faster produced in responding to changes within the market to try and match the rate of production for goods with the demand to avoid oversupply.

4.2.4. Competitive advantage

Companies employing AI in their production processes gain significant competitive advantages: When using the AI in the production processes it takes up the role of a major competitive advantage for companies using the said strategy:

Agility and flexibility: thus, he found that the use of AI integrated systems provides condition responsiveness to organizations and firms' ability to meet new market conditions.

Customer satisfaction: Therefore, with the help of the lead time and the quality of the products, AI assists in increasing the degree of satisfied customers.

Brand reputation: Thus, the integration of sustainability through the help of AI shows the positive impact on the company image, especially for those customers who are conscious about the concept of sustainability.

Conclusion:

The economic impacts of AI in cleaner production are profound, offering tangible benefits that enhance companies' bottom lines and competitive positions. These benefits extend beyond mere cost savings, influencing entire operational frameworks and strategic approaches. As industries increasingly pivot towards sustainability, AI's role becomes central, not just in fostering ecological benefits but also in driving economic success.

4.3. Social implications

That is why the integration of Artificial Intelligence (AI) in cleaner production does not only affects the current and future shape of the environment and the economy but also has deeper social consequences. These implications affect patterns of human interactions, the health of the public, and the well-being of the communities which have twofold gains that are attributed to technological advancements. From the preceding section, an understanding is gained and discussed of the extent and nature of the impacts of AI in cleaner production on the social aspects.

4.3.1. Workforce transformation

Job creation: Mainly the industries that adopt AI will need novel forms of skill sets and consequently employ people for high-tech jobs. These are specialized professionals such as artificial intelligence specialists, data analysts, and system managers. However, using emerging economies' workforce, Nabi (2019) observed potential employment threats with AI while creating novel employment opportunities primarily in the developed world.

Job displacement: on one hand, AI creates new forms of occupations, on the other—it eliminates traditional occupations due to the rising of automated systems such as robotization in the manufacturing industry. Authors such as Medaglia et al. (2023) have written a Special Issue based on the topic of AI in Government covering policy worldwide drives and trends, further research, and future key concerns which include; governance and trustworthy AI.

Workforce upskilling: The increase in the use of artificial intelligence and robotics in industries results in the requirement for a skilled population in artificial intelligence and robotics. The review of the literature is performed by Zirar et al. (2023) in which various themes such as worker distrust, and requirements for AI coexistence in workplaces are discussed, and potential areas of future studies are revealed.

4.3.2. Health and safety enhancements

Safer work environments: AI's inferential abilities enhance productivity when it comes to the identification of risks within work environments; as well as timely maintenance of company assets, in a bid to avoid accidents. Employing the redeca framework, Pishgar et al. (2021) aim to discover how AI is implemented in the areas of Occupational Safety and Health (OSH) in different sectors while outlining one of a kind uses and research directions for the integration of OSH and AI.

Health monitoring: there is an increased level of risks in workplaces that fall under sensitive industries for instance the chemical manufacturing industries; with the help of AI based systems, the environment that such industries expose their employees to can be constantly checked for any dangerous level and prevented, thus minimizing the annual health risks.

4.3.3. Community well-being

Environmental health: The use of cleaner production techniques that are promoted by AI greatly decreases pollutants and emission levels which in turn enhance the nature of air and water that surrounds several communities. According to Masood et al. (2021), the betterment of health among the communities is cited as a positive impact caused by lowered industrial pollution.

Economic stability: the businesses that come under artificial intelligence can help to balance the economies by providing the high-quality employment and can improve the efficiencies of industries. This economic upliftment translates to improved social services and quality of life as most often realized in areas with such industries.

4.3.4. Ethical and equity considerations

Bias and inequality: This can present the major danger of the perpetration of existing biases by the new AI systems in case they are not well developed and supervised. Challen et al. (2019) brief on the application of AI in bias and clinical safety.

Access and inclusivity: thus, equal opportunities and fair access to the improvement in education and health that AI offers must be defended. This involves advocacy for policy measures to avoid the formation of situations whereby certain groups of people are the only ones who reap benefits from AI solutions in cleaner production.

4.3.5. Cultural impact

Cultural sensitivity: AI has to be implemented in production systems about cultural aspects taking place, especially in the global markets. AI integration thus has to work with acceptance of the local culture to be effective.

4.3.6. Legal and regulatory implications

Compliance with laws: it is important that various usage of AI be integrated such that it complies with the regulations which may have necessitated the writing of new laws to portray new upcoming issues in AI. This comprise of factor like employment relations safety issues and implication to the privacy.

Data privacy: Since data is a primary element of any Artificial Intelligent system, privacy of the users is very crucial. These regulations suggest that lawyers should be willing to deploy hardline positions in combating data leakage in a style that keeps everyone as informed as needed of the various proceedings and engage in business activity that is compliant with the various regulations. In its turn, Kingston (2017) notes that General Data Protection Regulation (GDPR) has introduced new severe penalties and compliance standard; it leverages checklists, risk assessment, and breach reporting by applying rule-based approach.

4.3.7. Conclusion

There are numerous social repercussions of AI when it comes to cleaner production; these cut across the different areas and spheres in life and in society. The use of AI can bring about massive social benefits as seen in the opportunities section but at the same time it does present risks which have been seen in the challenges section and therefore AI needs to be managed well through policy, education and ethics. Thus, to manage these implications fully it is crucial to consider all the sides to help improve the human experience with the help of AI and avoid any possible negative consequences.

5. Challenges and future directions

It is, therefore, worth pointing out that incorporation of Artificial Intelligence (AI) in cleaner production comes with several difficulties. In its turn, transnational IPV is portrayed as a problem that cuts across the technical, economic, social, and regulatory domains. There is a need to know these barriers and the possibility of their overcoming for using AI to the maximum in the sphere of sustainable activities. Moreover, it is possible to explore various trends that might occur in the future of AI as a result, similar to the approach that was made in other research works to predict further developments in this active area of science.

5.1. Technical and economic barriers

5.1.1. Technical barriers

Data quality and quantity: AI systems' efficiency depends on the data that is put into the system, which validates the fact that great artificial intelligence systems are made great by feeding them with great information. Indeed, in many sectors including healthcare, manufacturing, transport and especially in the developing world the lack of rich abundant datasets of good quality can slow down the progress to and training of good AI systems.

Integration complexity: the incorporation of different industrial AI systems in to current working environment is difficult among the following reasons for instance current industries were built with existing infrastructure and it is always hard to accommodate modern AI industries' facilities into the existing infrastructure.

Scalability: There are also difficulties in transferring the pilot project to the large-scale implementation one with AI; one gets requests for huge investments and has to work with higher system's intricacy.

5.1.2. Economic barriers

High initial costs: Some of the initial costs that maybe incurred in the adoption of AI include the costs of the technology, the costs of training, and the integration cost which can be offloading for most organizations particularly those of the Small and Medium-sized Enterprises (SMEs).

Return on Investment (ROI) uncertainty: AI projects in many organizations can have unpredictable ROI ratios meaning that in industries where operating profit line is nearly negligible, using AI may well be impossible unless the big brains come up with a magic solution that has a near zero effect on the operating profit line.

Job displacement concerns: that is why, the meanings which AI has for the economic world primarily for the workforce, such as the consequences of job loss because of automated systems, cause negative reactions in the organizational environment and among the population, therefore becoming the barriers to implementation of AI.

5.2. Future trends in ai for sustainable practices

Increased adoption of IoT and AI: IoT is going to be even tighter with connected devices to control production tweaking it by itself with the help of AI to minimize energy and material usage.

Advancements in AI algorithms: Further works that would be developed on the improvement of the algorithms will enable the optimization of the use of Artificial Intelligence in manufacturing contexts.

Expansion of predictive maintenance: More general and widespread applications of predictive maintenance other than equipment will be accurate for system maintenance other than the energy-saving and low-emission category.

Growth in AI ethics and governance: Eventually, as the usage of AI enhancement and utilization rises in the global market, there will be frameworks to foster the usage of AI. This involves a code of ethics to minimize the influence of bias in AI to ensure that new technologies benefit everybody through employment and others through privacy including but not limited to.

Cross-sectoral AI applications: The use of AI in sustainability will extend beyond industries like manufacturing to industries such as agriculture whereby; AI can be used to enhance the usage of water, and pesticides in farming amongst other things, and urban planning in relation to the development of sustainable cities.

Collaborative AI systems: Thus, the future may witness the occurrence of collaborative AI, in which systems integrated with different domains or regions can exchange information and results and come closer to the most suitable and efficient ideas and actions toward sustainability.

Despite the challenges, there is a clear and rather promising map for AI developments in the contribution to cleaner production to enhance economic efficiency, save the environment, and improve welfare for people. To overcome such challenges, there's a need for governments, industries, and academia to try to come up with advanced sustainable solutions for innovations. Furthermore, as different technologies advance, the main emphasis in advancing AI is going to be in its improvement for different ends beyond the financial one with an evident intention of reaching the worldwide sustainable development goals.

6. Conclusion

AI into cleaner production is a groundbreaking step, which asserts that sustainability in industries is possible. This literature review has systematically discussed the various effects of AI solutions including the environmental, economic, and social effects within the various domains as outlined by the literature The paper has also highlighted the major technical challenges and economic hurdles to the advancement of artificial intelligence. The conclusions drawn reemphasize the inclusive solutions of AI vis-à-vis operations for attaining environmental protection and favorable social change.

Summary of findings:

Environmental benefits: Notably, when it comes to resource use, energy, and in some cases, some of the raw materials used in production, AI is effective in reducing the negative impact that an organization's production processes have on the environment. Management of waste and the utilization of the environment via such methods as; Predictive maintenance and smart waste enhances a reduction in waste and pollution levels once AI integrations cut the use of energy and logistics by a significant percentage.

Economic advantages: AI technologies increase impact cleaner production in a positive manner as it minimizes the cost of energy, maintenance as well as materials proving to be a booster to the economy. It also enhances the utilization of production capacity and quality hence enhancing the competition within the market and financial revenues.

Social implications: With the help of artificial intelligence, people can be replaced in production lines, but at the same time new positions will be created, related to AI systems. AI reduces the employees' and community's interactions with workplace hazards and environmental pollutants to improve the quality of life.

Challenges: There is a possibility for some barriers in the use of AI within business and technical factors; for instance, quality data, integration processes, and growth issues have to be addressed properly. Thus, the specific levels of AI investment from the economic point of view consist of two components that are important: The cost that is necessary for implementing AI and the enviable rate of return that is characterized by the fact that SMEs are more susceptible to business risks that may hinder the achievement of optimal outcomes.

Future trends: While AI promotes its algorithmic responsibility, IoT implementations, and sensor technology, it will contribute to the sustainable practice's idea of better acceptance and regulation of the utilization of AI in the future. The level of implementation of Predictive maintenance will rise more and more, and AI's applicability will also grow more in the field of compliance, and the management of waste.

Recommendations for stakeholders:

To stakeholders across the spectrum of industry, academia, and policy-making, the following recommendations are offered to harness the potential of AI in cleaner production effectively:

- Investment in AI research and development:

There is a need to call on industries with constant AI production so that they take their time to enhance their AI research and development to come up with better and more sophisticated AI systems appropriate for their industries. Emphasize the need to create new AI developments that can be easily incorporated into current environments.

- Enhancing data infrastructure:

Establish strong data acquisition and storage procedures capable of providing large and diverse volumes of data for AI's improvement and learning.

Ensure the protection of data to maintain ethical practices and trust from the consumers.

- Policy and regulatory framework:

Thus, to prevent situations where "AI models are trained on data gathered disproportionately from long-suffering minorities and operating under optimization metrics that reflect the biases of society's power structure", there is the need for policymakers to develop good policies and regulations on correct usage and proper application of AI in industrial practices equally in relation to the safety, ethic and environmental concerns on the merits without any favor.

Encourage industries to apply efficient and intelligent technologies in programs pertaining to cleaner production by offering tax credits, subsidies, and grants.

- Stakeholder collaboration:

Promote communication between developers of technology and its consumers along with the legal systems to ensure the development of AI matches the demands in the market as well as legal requirements.

Introduce policies aimed at encouraging public and private cooperation to build an environment suitable for creating innovations for sustainability.

- Workforce development:

Reskill the workforce with the kind of knowledge and skill that is required to operate and manage the AI systems in organizations.

The social policies should comprise transitional programs for the workforce particularly in sectors that employ the use of AI automation in performing tasks.

- Community engagement:

Talk to local people to hear their fears and expectations that they have about the change that is being driven by AI in industries.

Select AI systems that serve the economic and technical value for the firm and the society and environment.

Addressing limitations:

Despite the focus on the beneficial research directions, this review also points out several shortcomings. In the first place, it is critical to conduct more long-term researches that consider the consequences of AI implementations within the parameters of the economy and society. Also, the differences that certain industries and some regions have in terms of technology adoptions can present difficulties in generalizing the AI approaches. Lastly, the possible ethical issues as well as the data privacy issues concerning the use of AI are well understood to warrant constant checks and solid legislation to prevent foul plays and to ensure that the improved results go around and are not monopolized.

Final thoughts:

As AI continues to evolve and its applications within industrial contexts grow, stakeholders must proactively address the associated challenges through strategic investments, regulatory updates, and inclusive policies. The ultimate goal is to achieve a harmonious balance between technological advancement and sustainable development, ensuring that the benefits of AI in cleaner production are realized fully and equitably. By adhering to these recommendations, industries can move towards more sustainable practices that not only boost economic growth but also enhance societal well-being and protect the environmental integrity.

Our research shows that ‘AI integration’ is more robust as compared to ‘traditional industrial practices’. Future research may look into “AI’s long-term economic and society’s effects” and ways to develop “contextual AI solutions for industries and geographical areas”. Besides, such activities as identifying “ethical guidelines for data protection and AI application”, “carrying out the cost-to-benefit analysis for AI adoption in SMEs", and promoting the "multidisciplinary approaches" could also complement the use of AI in cleaner production. A feature of policy impact studies is also the need for policy improvement that, however, should be based on empirical findings.

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