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AI-Powered Innovations and Their possible effects on environmental Sustainability Aspects: Systematic Literature Review

Mohamed El Merroun
Address: Jozsef street 40 Country:Hungary

Abstract: The increasing pressure on countries and organizations to address critical environmental issues, such as climate change, energy crises, and waste management, has reached unprecedented levels. Technological progress is like a double-edged sword, it has the potential to intensify the problem or serve as a tool to mitigate environmental damage. Artificial Intelligence (AI), a cornerstone of Industry 4.0, demands particular attention due to its rapid development and widespread accessibility. This paper employs the Systematic Literature Review (SLR) methodology to analyze 110 papers discussing the utilization of AI in mitigating environmental degradation. By identifying a gap in the literature pertaining to a comprehensive analysis of specific scenarios where AI has been applied for environmental sustainability, we focus on five distinct aspects: Waste Management, Carbon Emission Reduction, Energy Management, Circular Economy (CE), and Resource Efficiency. The article aims to furnish stakeholders and organizations with valuable insights, providing clarity on how the implementation of artificial intelligence can address existing environmental concerns.

Key words: Artificial intelligence – Machine learning – Environment – Sustainability – Environmental sustainability

I. Introduction :

The advent of artificial intelligence (AI) stands out as a remarkable innovation in the scientific world, captivating the interest of nearly every discipline in academic research. Scholars are harnessing AI to address the challenge of predicting protein structures, with the potential to bring about significant advancements in the field of biological sciences. (Jumper et al., 2021). In addition, AI plays a crucial role in predicting renewable energy availability for optimizing energy consumption efficiency.(Shin et al., 2021). It is also instrumental in discovering innovative electrocatalysts to develop scalable and effective approaches for storing and utilizing renewable energy(Zitnick et al., 2020). The substantial research and notable accomplishments in applying AI across diverse domains have greatly heightened its significance. This article examines the utilization of AI in five key aspects of environmental sustainability. Before embarking on this exploration, it's essential to clarify a couple of foundational concepts.Artificial neural networks (ANN), support vector machines (SVM), genetic algorithms (GA), and fuzzy logic (FL) are AI models but can also be considered synonyms for Artificial intelligence (Chambers et al., 2018; Hong et al., 2018; Lesnik & Liu, 2017; R. Zhang et al., 2019). Machine learning and deep learning, on the other hand, are different concepts, but they are often used interchangeably with AI. Machine learning is a computer program that learns and performs progressively better over time in connection with a specific set of tasks and performance measures (Jordan & Mitchell, 2015) . This is accomplished by using algorithms that repeatedly learn from training data that is particular to the situation at hand. This enables computers to discover intricate patterns and hidden insights without requiring them to be explicitly programmed (Janiesch et al., 2021). While machine learning methods typically have fewer hidden layers, deep learning, on the other hand, often involves several hidden layers arranged in deeply nested network designs. As for processing text, pictures, videos, voice, and audio data, deep learning consistently outperforms ML methods, particularly excelling in areas with big and high-dimensional data(LeCun et al., 2015). Both machine learning (ML) and deep learning (DL) are integral aspects of AI, allowing the development of programs that autonomously learn from past data, accumulate knowledge from experience, and continuously enhance their learning behavior to make predictions based on fresh data(Holzinger et al., 2019). To clarify the relationship between these concepts, it's important to note that Deep Learning is a subset of Machine Learning, which, in turn, is a subset of Artificial Intelligenceexpressed as $DL \subset ML \subset AI$. (Goodfellow et al., 2016).

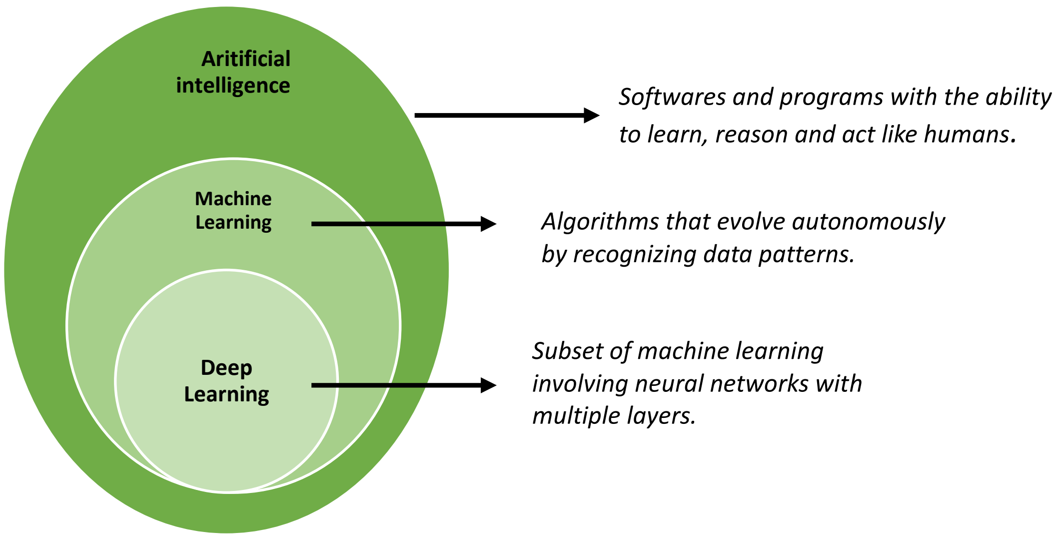


***Figure1**: The intersection of DL, ML and AI*

The application of AI in the context of environmental sustainability has garnered significant attention from both researchers and practitioners. AI possesses the potential to mitigate human emotion bias and address knowledge asymmetries, two critical challenges hindering the progress of environmental sustainability (Cullen-Knox et al., 2017). Generally speaking, innovations in digital technology promote the environment, human health, and the entire food chain (Weersink et al., 2018).

This research highlights the potential impact of digital transformation on environmental sustainability and focuses on Artificial intelligence, which has gained a lot of attention in the past couple of years. One of the critical factors that enhanced the popularity of AI is that it reached even individuals. Most readers of this article have likely interacted with AI in some capacity and understand its power, in contrast to other industry 4.0 technologies, which are typically only accessible to large corporations due to their complexity. For this reason, it is crucial to conduct research that specifically explores the use of AI to enhance key aspects of environmental sustainability.

This article will be presented as follows: Section 2 presents the literature review regarding the use of industry 4.0 technologies and AI for environmental sustainability goals; Section 3 will showcase the objectives, the questions, and the methodology followed to achieve these objectives; Section 4 will present the results of the paper; Section 5 will be the discussion; and finally, Section 6 will present the conclusion and propositions for future research areas.

II. Literature Review :

1. Industry 4.0, AI and environmental sustainability:

The Fourth Industrial Revolution encompasses a variety of technologies, including IoT, AI, Blockchain, Big Data, Cloud computing, and more. While this paper primarily focuses on AI, it's important to provide an overview of Industry 4.0 as a whole, as these technologies often complement each other in various applications. Digital transformation has demonstrated significant potential for enhancing environmental sustainability. However, there is still limited in-depth research in this area (Goralski & Tan, 2020). Industry 4.0 has transformative implications that extend beyond process optimization and efficiency concerns. It reshapes services, business models, and entire value chains, while also enhancing our understanding of the environment, economic processes, and social and individual behavior through the analysis of large volumes of data (R. Liu et al., 2019). While it is crucial to note that in most cases, the use of AI and Industry 4.0 technologies is fuelled by economic objectives, which can contribute to negative uncertainties about the effects of these technologies on environmental sustainability, it is also crucial to emphasize the potential of AI and Industry 4.0 technologies in enhancing environmental sustainability and encourage their integration into both the long and short term objectives of decision makers. Many companies are concentrating their efforts on creating a balance between sustainability goals, taking people, the environment, and profit into consideration. Industry 4.0 is shifting the game's rules, challenging the long-standing order of things, and offering the knowledge and direction needed to improve sustainability efficiency, particularly at the manufacturing level (Ghobakhloo, 2020; Nagy et al., 2018;

Tiwari et al., 2022). Many more studies have shown the positive impact of Industry 4.0 technologies on environmental sustainability if it is used correctly; (Burritt & Christ, 2016) have demonstrated through case studies of German and Chinese firms that Industry 4.0 technologies can have a substantial impact on energy efficiency and resource utilization. The circular economy concept is promoted within businesses as part of an Industry 4.0 approach to waste recycling, aligning with a roadmap proposed to encourage optimal and sustainable use of natural resources (Müller & Hopf, 2017; Stock et al., 2018). (Ford & Despeisse, 2016; Jelonek & Urbaniec, 2019) demonstrated how using technology in manufacturing (like additive manufacturing) can help save the environment, and the list goes on and on. The following table presents recent research on the relationship between industry 4.0 technologies and environmental sustainability aspects:

Table 1: Literature on industry 4.0 and environmental sustainability

Industry 4.0 / Environmentalsustainability	**Artificial intelligence**	**Blockchain**	**Internet of things**	**Additive manufacturing**
Waste management	(W. Du et al., 2022), (Amin Amani & Sarkodie, 2022) (Abdallah et al., 2020)(P. K. Gupta et al., 2019)(Ahmed & Asadullah, 2020)(Abbasi & El Hanandeh, 2016) (Coskuner et al., 2021)(Nasreen Banu & Metilda Florence, 2021) (Król et al., 2016) (Agarwal et al., 2020) (T. H. Ali et al., 2019) (Abbasi & El Hanandeh, 2016)	(Dey et al., 2022),(R. W. Ahmad, Salah, Jayaraman, Yaqoob, & Omar, 2021; Bamakan et al., 2022; França et al., 2020; P. K. Gopalakrishnan et al., 2021; P. Gopalakrishnan & Ramaguru, 2019; P. K. Gupta et al., 2019; Lamichhane, 2017; Steenmans et al., 2021) (R. W. Ahmad, Salah, Jayaraman, Yaqoob, Omar, et al., 2021; Baralla et al., 2023; Bhubalan et al., 2022; Dua et al., 2020; Sahoo & Halder, 2020; Taylor et al., 2020)	(X. Xu & Yang, 2022), (X. Chen, 2022), (Anagnostopoulos et al., 2017; Malapur & Pattanshetti, 2017; Medvedev et al., 2015; Misra et al., 2018; Pardini et al., 2019; Salehi-Amiri et al., 2022; Shyam et al., 2017; Singhvi et al., 2019) (Adam et al., 2018) (Dubey et al., 2020); (Razip et al., 2022)(Rao et al., 2020) (W.-E. Chen et al., 2018) (Rahmanifar et al., 2023) (A. Khan & Khachane, 2018) (Karthikeyan et al., 2017) (Suryawanshi et al., 2018) (Sharma et al., 2020) (Marques et al., 2019) (Hasan et al., 2017) (T. Ali et al., 2020)	(Rejeski et al., 2018) (Peng et al., 2018) (Mohammed et al., 2018) (Jiang et al., 2019) (Giurco et al., 2014) (Arifin et al., 2022) (Mehrpouya et al., 2021)
Resource efficiency	(Waltersmann et al., 2021)(Tsui et al.,	(C. Xu et al., 2018)(Xie et al., 2021)(F. Zhang et al.,	(Jagtap et al., 2021)(Jagtap & Rahimifard, 2019)(Lvovich et	(Despeisse & Ford, 2015)(Simeone et al.,

	2022)(Rentsch et al., 2015)(Brüggemann et al., 2020)(J. Li et al., 2023)(Guldner et al., 2021)	2017)(Y. Liu et al., 2020)(H. Xu et al., 2020)(Y. Liu et al., 2021)	al., 2019)(Sheng et al., 2018)(Tanveer et al., 2022)(A. Kumar et al., 2017)(Jagtap & Rahimifard, 2017)(Beier et al., 2017)(D. M. Kumar & Ghosh, 2019)(Siegel et al., 2018)(Schmitt et al., 2022)(Kaur & Sood, 2015)(Kaur & Sood, 2015)(Hossain et al., 2018)	2020)(Monteiro et al., 2022)(Craveiro et al., 2017)(Kanyilmaz et al., 2022)(Ford & Despeisse, 2016)(Lušić et al., 2015)(Girdwood et al., 2017)(Urban et al., 2018)(Kellens et al., 2011)(Barz et al., 2016)(Hegab et al., 2023) (Krol et al., 2013) (Qian et al., 2019)(Maboudi et al., 2020)(Meiners et al., 2020)(Machado et al., 2019)(Ingarao, 2017)(Walter & Marcham, 2020)(Giurco et al., 2014)
Circular economy	(Ramadoss et al., 2018)(M. Wilson et al., 2022)(Ghoreishi & Happonen, 2020)(Jose et al., 2020)(Agrawal, 2022)(Wilts et al., 2021)(Bag et al., 2021)(M. Chen et al., 2022)(Chidepatil et al., 2020)(Nañez Alonso et al., 2021)(N. M. Kumar et al., 2021)(Sankaran, 2019)(Rajput &Singh, 2019b)(Pregowska et al., 2022)(Demestichas & Daskalakis, 2020)(Noman et al.,	(Upadhyay et al., 2021)(Kouhizadeh et al., 2020)(Böckel et al., 2021)(Nandi et al., 2021)(Shojaei et al., 2021)(Yildizbasi, 2021)(Böhmecke-Schwafert et al., 2022)(Narayan & Tidström, 2020)(Kouhizadeh et al., 2023)(Basile et al., 2023)(Kouhizadeh et al., 2019)(Alves et al., 2022)(N. M. Kumar & Chopra, 2022)(Chidepatil et al., 2020)(Bhubalan et al., 2022)(Khadke	(Ramadoss et al., 2018)(Rejeb et al., 2022)(Mboli et al., 2022)(Cavalieri et al., 2021)(Nobre & Tavares, 2017)(Askoxylakis, 2018)(Reuter, 2016)(Magrini et al., 2021)(Nobre & Tavares, 2020)(Cui et al., 2021)(B. Wang et al., 2021)(Hatzivasilis et al., 2018)(AL-Khatib, 2023)(Andreopoulou, 2017)(Miaoudakis et al., 2020)	(Colorado et al., 2020)(Sauerwein et al., 2019)(Sanchez et al., 2020)(Shanmugam et al., 2020)(Hettiarachchi et al., 2022)(Ponis et al., 2021)(Romani et al., 2021)(Giurco et al., 2014)(Kravchenko et al., 2020)(Tavares et al., 2020)(Leino et al., 2016)(Priyadarshini et al., 2022)(Angioletti et al., 2016)(Tavares et al., 2023)(Sauerwein et al., 2020)(Kromoser et al., 2022)(Sigley et al., 2023)(Fitzsimons et al., 2020)(Betim

	2022)(Andono et al., 2022)(Roberts et al., 2022)(Akinode & Oloruntoba, 2020)	et al., 2021)(Hatzivasilis et al., 2021)(Erol et al., 2022)(Dounas et al., 2021)(Davidova & McMeel, 2020)(Castiglione et al., 2023)(Pakseresht et al., 2022)		et al., 2020)(R. Singh & Kumar, 2022)(Sauerwein, 2020)
Energy management	(Kuo & Huang, 2018)(Wahid et al., 2019)(Rocha et al., 2021)(Agostinelli et al., 2021)(Albarakati et al., 2021)(Alassery et al., 2022)(Jose et al., 2020)(Ma et al., 2021)(Kuzior et al., 2022)(Qela & Mouftah, 2012)(Shamami et al., 2020)(Chaouachi et al., 2012)(Hu et al., 2022)(Natsheh, 2013)(Aguilar et al., 2021)(T. Ahmad, Zhang, Huang, Zhang, Dai, et al., 2021)(Penya, 2003)(Fu et al., 2020)(Elkazaz et al., 2016)	(Miglani et al., 2020)(Van Cutsem et al., 2020)(van Leeuwen et al., 2020)(Z. Li et al., 2019)(Stephant et al., 2018)(L. Wang et al., 2020)(Kumari et al., 2020)(Yahaya et al., 2020)(Bao et al., 2020)(Bodkhe et al., 2020)(Q. Yang et al., 2021)(Nakayama et al., 2019)(Q. Yang & Wang, 2021)(Khattak et al., 2020)(L. Wang et al., 2021)(N. Ullah et al., 2020)(Kuzior et al., 2022)(Brilliantova & Thurner, 2019)(J. Li et al., 2022)(Kumari et al., 2022)	(Shrouf & Miragliotta, 2015)(Tao et al., 2016)(X. Liu et al., 2019)(Sadeeq & Zeebaree, 2021)(Ramadan et al., 2022)(J. I. Z. Chen & Lai, 2020)(Ejaz et al., 2017)(D. Wang et al., 2021)(Spanias, 2017)(Tiwari et al., 2022)(J. Li et al., 2021)(Y. Li et al., 2017)(X. Wang et al., 2021)(Shyr et al., 2018)(H. P. Nguyen et al., 2021)(Saba et al., 2021)(Golpîra & Bahramara, 2020)(Mahapatra et al., 2017)	(Y. Wang et al., 2021)(Sun et al., 2021)(Gao et al., 2021)(Magisetty & Cheekuramelli, 2019)(Peng, 2016)(Bito et al., 2017)(K. Wang, 2023)(Tarancón et al., 2022)(H. P. Nguyen et al., 2021)(Ajay et al., 2017)(Ajay et al., 2016)(Khosravani & Reinicke, 2020)(Minetola & Eyers, 2018)(Griffiths et al., 2016)

2. The barriers to Successful AI Implementation:

The imperative for firms to invest in AI has witnessed a steady escalation over time. As evidenced by an increased number of literature reviews on the subject and AI leader organizations' reports, the pressure to adopt AI is mounting, compelling firms to embrace these transformative technologies. Based on the fact that only 33% of firms made progress in the adoption of AI (IBM, 2022), the challenges and requirements to

implement AI should not be trivialized, as they represent significant bottlenecks that firms must address to fully adopt and leverage the transformative potential of this innovation.
In the upcoming paragraph, we will shed light on the five most frequently encountered obstacles faced by firms in adopting AI.

2.1- Lack of a digital strategy alongside resource scarcity:

Drawing a clear strategy that integrates technological tools as a main pillar of a firm while allocating the resources needed to implement the strategy appears to be one of the main barriers to implementing AI (Borges et al., 2021). The firm's resource profile is an important factor in determining its strategy and performance. The decisions taken by the businesses are a result of the resources and the competencies that they possess(Coates & McDermott, 2002). The financial requirements of the investment in AI differ massively depending on the nature of the AI-based application, but companies committed to including AI in their strategy would have to increase their anticipated annual capital investments(Klumpp, 2018). It is readily apparent that the capabilities needed to adopt AI create a barrier that impedes firms from merging AI within their global strategy. Implementing AI is a strategic decision, and the opposition at the executive level makes establishing a digital strategy to implement AI projects extremely challenging(Alsheibani et al., 2019). As an example, data management is one of the crucial factors that decide whether AI implementation will succeed or not.In this regard, the implementation of cloud computing, which is an essential tool for the data functioning of AI, is opposed by the majority of medium-sized companies.The genesis of this issue can be traced to the decision-makers of these companies(Bhalerao et al., 2022a).

2.2- Inadequacy of Skilled Workforce:

(Alsheibani et al., 2019),(R. P. Singh et al., 2020), (Bhalerao et al., 2022b), and (Rjab et al., 2023) all agreed that one of the primary barriers to establishing an AI strategy is a scarcity of qualified workers, as well as the need to retrain employees to match new requirements. Future workplaces will require new approaches to fit with the technological revolution, which might impact workers in a positive as well as negative manner (Smit et al., 2016). The changes in the work environment are often faced by resistance and disengagement in business organisations (Bauer et al. 2015).

2.3- Lack of quality data and poor data management:

One of the main factors of a successful implementation of AI is data quality. As a result of the interconnection of several machines, sensors, industrial systems, and facilities in AI, big data is generated (Haider, 2020). Managers may use the enormous amount of information at their disposal to put AI into effect for a sustainable future. Without better data quality, this would not have been achievable(Papagiannidis et al., 2023). According to (Kar & Kushwaha, 2021), several challenges associated with big data significantly impact the functioning of AI. Firstly, the process of data transformation in an AI environment is challenging and demanding. Given that the data generated in industries is predominantly machine data, it requires conversion into visual formats for operators and transformation into a compatible form for various smart devices. Secondly, the complexity of data integration and modeling poses a challenge. Interoperability, a core element of automation in AI, involves connecting different types of equipment. The difficulty lies in effectively combining diverse forms of generated data into a unified platform for efficient production. Thirdly, real-time access to data is crucial in AI applications. The failure to detect errors in real time within a single source of data can lead to malfunctions in the final product generated by AI. Additionally, security and privacy emerge as significant concerns in the era of big data. The rapidly increasing volume of heterogeneous data in AI, along with the migration of all data to the cloud, increases the security risk and concerns the stakeholders.

2.4- The Scarcity of Adequate Collaborative Networks:

Strategic alliances and collaborative partnerships are crucial strategic success factors in the intense competition fuelled by continual technological developments (Das and Teng 2000). The significance of collaboration and networks is particularly underlined in the context of AI (Deveci, 2023). The collaborative nature of AI presents a dual challenge. On one hand, companies unable to forge robust partnerships with organizations sharing a common vision may struggle to fully embrace AI. On the other hand, given that AI often thrives on the sharing and exchange of sensitive data, achieving data security becomes increasingly challenging, raising concerns about potential knowledge loss(Koul et al., 2022).

2.5- Low return on investment:

The historical examination of the economic and profitability benefits associated with investing in information technology has been well-documented (Brynjolfsson 1993; Osterman 1986; Stolarick 1999). With the advent of AI, uncertainties arise concerning distinct economic outcomes due to its profound implications for productivity. Beyond the financial sphere, AI exercises influence on social and environmental facets, presenting challenges in quantifying their financial implications. This paper aims to investigate the considerable environmental impact that can arise from a successful implementation of AI. However, evaluating the financial benefits of green practices remains a complex task.

III. Methodology:

The evident potential of AI to improve various aspects of the industrial world should be harnessed to achieve environmental sustainability. Therefore, presenting a systematic review that highlights the use of AI for each environmental sustainability aspect and how decision-makers can utilize AI applications to achieve environmental sustainability is crucial. The main objective of this paper is to present different cases from the literature where the use of artificial intelligence has contributed to enhancing environmental sustainability. These varied cases are intended to serve as concrete evidence and examples for decision-makers and academics, providing inspiration and a deeper understanding of the transformative potential of AI in promoting environmental sustainability. To achieve that, the following questions arise:

- *Question 1: How can AI applications enhance various aspects of environmental sustainability?*
- *Question 2: What challenges and obstacles need to be addressed for the effective utilization of AI applications in environmental initiatives?*
- *Question 3: What are the key gaps in research that require attention for the successful integration of AI and environmental sustainability, and what future research directions should be pursued?*

To achieve the paper's objective and address the research questions, this article employs a systematic literature review methodology, following the framework proposed by (Tranfield et al., 2003) and (Kitchenham, 2004). The structure suggests three main phases: planning the review, conducting the review, and reporting the review. This section presents the first two phases, while the final phase, reporting the review, will be discussed in the 'Results' section. This structure was used in many articles on industry 4.0 and information technology-related topics ((Al-Emran et al., 2018; O. Ali et al., 2018; Borges et al., 2021; S. Gupta et al., 2018; Martins et al., 2019).

1. Planning the review:

To conduct our research four databases were chosen: SCOPUS, SPRINGER, Web of Science, and Google Scholar. From the environmental sustainability side, we chose five main aspects that were mentioned the most in the literature; we used the command-line program Astrogrep to scan 458 articles from Scopus and Web of Science databases that had one of the following terms either in the title or abstract: environmental sustainability, environment, sustainability, ecology, green practices, Sustainable practices, and Eco-sustainability. The results are shown in table 2.

Table 2: *Most mentioned environmental sustainability aspects*

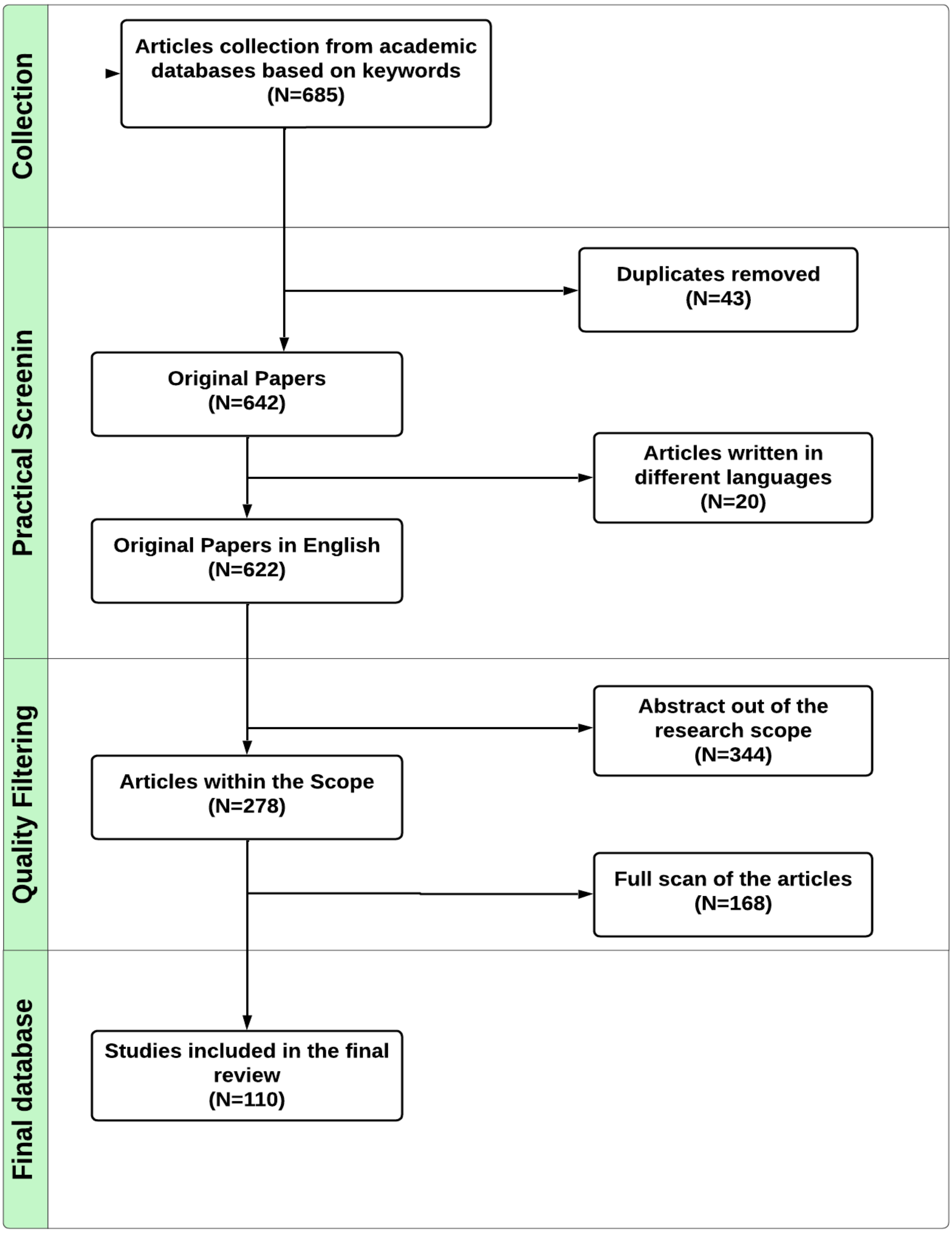
Environmental sustainability aspects	Number of mentioned out of 458 articles
Waste management	112
Resource efficiency	101
Circular economy	98
Energy management	156
Carbon emission	127
Air Quality Control	67
Water Conservation	32
Sustainable Agriculture	9
Biodiversity Preservation	2

To get these results, for every aspect, we used different synonyms (e.g., waste management, waste control, recycling, resource recovery, etc.) as illustrated in Table 3. From the AI side, we used three terms: artificial intelligence (AI), machine learning (ML), and deep learning (DL). The exclusion criteria were that if the articles were published before 2014, even if AI was invented in 1950 (Cantú-Ortiz et al., 2020), it is a technology that gets improved at a high pace, it is more relevant to examine the newest papers. The sub-section exploring AI and renewable energy is the only paragraph encompassing papers published before 2014. The significance of these papers will be elaborated upon in the dedicated section. The second criterion involved assessing whether the paper addresses the impact of AI and other technologies on environmental sustainability, with AI as the primary technology. For instance, (Sassanelli et al., 2022)introduced a cutting-edge model that integrates Cyber-Physical Systems, IoT technology, and AI to consolidate energy demand from numerous buildings while simultaneously monitoring their energy consumption. Cases like this were excluded as AI did not serve as the main technology but rather played a supportive role. However, we included instances where AI is the primary technology in conjunction with other technologies.

Following data extraction, in line with(Kitchenham, 2004; Tranfield et al., 2003),it is essential to proceed to the pivotal stage of research synthesis. This involves synthesizing, integrating, and aggregating findings from various studies that investigate the multifaceted impact of AI on environmental sustainability. We explore this intersection from multiple angles, including a business perspective, government initiatives, and the efforts of various organizations. We concentrate on how AI applications contribute to environmental sustainability in these contexts. Additionally, we categorize Artificial intelligence's roles based on their contributions to environmental goals, such as energy conservation, emissions reduction, waste management, and overall ecological well-being.

2. Conducting the review:

Figure 1: *The article's methodology*



We conducted the search on the SCOPUS, SPRINGER, Web of Science and Google Scholar databases using the final search queries from Table 3. To effectively locate and synthesize the distributed literature regarding the use of AI to enhance environmental sustainability, a multilayered approach for systematic literature review was used as suggested by (Kitchenham, 2004; Tranfield et al., 2003). As a result, the selection process followed the steps outlined in Figure 1 and adhered to the methods listed below:

- *Key terms were searched within the titles, keywords, and abstracts of the papers, with duplicate files subsequently eliminated based on the titles.*
- *Inclusion and exclusion criteria were applied, resulting in the exclusion of articles not written entirely in English.*
- *A final assessment determined the relevance of articles, leading to the discarding of non-relevant ones. The remaining articles underwent analysis, and data extraction took place.*

Table3: *Search Keywords for Data Retrieval*

The topics	Search parameters
Environmental sustainability aspects	TITLE-ABS-KEY (“Environmental sustainability” OR “Environmental protection” OR “Environmental preservation” OR “Environmental restoration” OR “Waste management” OR “Waste disposal” OR “Waste handling” OR “Waste control” OR “Waste reduction” OR “Waste treatment” OR “Waste mitigation” OR “Resource recovery” OR “Environmental sanitation” OR “Energy management” OR “Energy conservation” OR “Energy efficiency” OR “Energy optimization” OR “Energy control” OR “Energy monitoring” OR “Energy savings” OR “Power management” OR “Energy utilization” OR “Energy” OR “Resource efficiency” OR “Resource optimization” OR “Resource conservation” OR “Sustainable resource use” OR “Efficient resource utilization” OR “Resource management” OR “Circular Economy” OR “Carbon emissions” OR “Gas emissions” OR “Air pollution” OR “Pollution gases”
Artificial intelligence	TITLE-ABS-KEY (“Artificial intelligence” OR “Deep learning” OR “ Machine learning” OR “ Neural Network” OR “Fuzzy Logic” OR “Genetic Algorithm” OR “Decision Tree Algorithm”)

IV. Results:

1. Descriptive analysis:

The number of papers included in the research database are 110, in which 22 of them are published prior to 2014, the remaining are published after 2014.

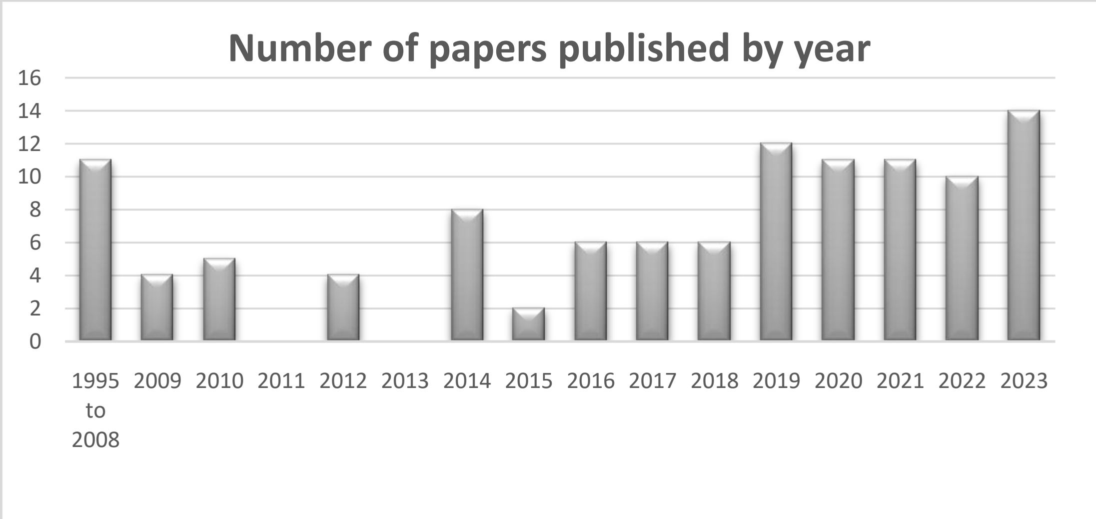


***Figure 2**: Year of papers included in the research*

It is not a surprise that in the last five years, the number of research studies showing interest in Artificial Intelligence and environmental sustainability has grown exponentially, as shown in **Figure 2**. Even when focusing on contemporary articles in one section of this research, which explains the presence of articles published before 2014, there is a notable trend. From 1995 to 2008 (spanning 13 years), only 11 articles were found, a number that falls short of the papers published in 2019, for example.

Regarding the bibliographic distribution, the journals displayed diversity and independence, with the largest share of 14% attributed to the Journal of Cleaner Production. Google Scholar was also employed throughout the research period, but focusing solely on reputable publishers such as Scopus, Springer, and IEEE. Among the 110 publications cataloged, 104 were authored by distinct individuals. The significant number of contributors highlights the active involvement of the scientific community in these topics.

2. Content examination and thematic integration of AI and environmental sustainability.

Table 4presents the main papers focusing on the practical aspect of AI. Here, "practical" means involving experiments, trials, or case studies to validate conclusions based on tangible evidence where authors applied AI models to improve aspects of environmental sustainability. On the other hand, **Table 5** includes papers exploring the theoretical application of AI in promoting environmental sustainability. Both tables provide insights into the primary environmental aspects investigated and the significant research outcomes, and the AI models employed in the case of practical studies. The number of AI models can be estimated to be in the hundreds, if not thousands, by the time this article is written, but the most used models include Decision Trees for decision-making based on input features, Neural networks for pattern recognition and decision-making, Fuzzy Logic for handling uncertainty, and attention-based models like Transformer models(Kuzior et al., 2019). If, in any case, an article has focused on multiple aspects of environmental sustainability or other objectives unrelated to environmental sustainability (e.g., cost, safety, social), these outcomes have been added to the 'key results' section. The citation column indicates how many times the article has been cited up to the date of writing this paper. The citation data are extracted from the original publisher of each specific paper. In this sense, this research focuses mainly on articles that treat one aspect of environmental sustainability (e.g., waste management). Articles that study sustainability or the environment as a whole were not included and filtered in the "Quality screening" step, as illustrated in **Figure 1**. However, If the research focuses on one environmental sustainability aspect but mentions outcomes related to other aspects, it is included, with additional outcomes highlighted in the tables.

Table 4: *Summary of the papers focusing on the practical use of AI on environmental sustainability.*

Publication Date	Title	Environmental Aspect	AI-model used	Key results	Citation Count	Reference
2023	Towards intelligent building energy management: AI-based framework for power consumption and generation forecasting	Energy management	Convolutional long short-term memory &Percepton	AI model was used to accurately predict the energy generation and consumption	23	(S. U. Khan et al., 2023)
2023	Prediction of Carbon Emission of the Transportation Sector in Jiangsu Province-Regression Prediction Model Based on GA-SVM	Carbon emission	Genetic Algorithm	Development of an AI model that can accurately estimate CO2 emission and the peak time for CO2 emissions.	3	(Huo et al., 2023)
2023	AI-guided design of low-carbon high-packing-density self-compacting concrete.	Carbon emission	Machine Learning	Development of an AI based model for the self-compacting design that showed a 57,2% reduction in carbon emission compared to the traditional way	0	(Cheng et al., 2023)
2023	Development of hybrid surrogate model structures for design and optimization of CO2 capture processes: Part I. Vacuum pressure swing adsorption in a confined space.	Carbon emission	Hybrid model	Development of an AI model that demonstrated a reduction on CO2 concertation going from 1000 ppm to 399 ppm in a confined space.	1	(J. Du et al., 2024)
2022	eco2AI: Carbon Emissions Tracking of Machine Learning Models as the First Step Towards Sustainable AI	Carbon emission	Python	Development of an open-source library to measure the carbon emissions of any AI-based application	41	(Budennyy et al., 2022)

2022	Design and simulation of global model for carbon emission reduction using IoT and artificial intelligence	Carbon emission	Decision Tree Algorithm	Presentation of an AI based model that could achieve a 21% reduction in carbon emissions in residences	5	(Alpan et al., 2022)
2022	Artificial intelligence enabled efficient power generation and emissions reduction underpinning net-zero goal from the coal-based power plants.	Carbon emission	Vector Machine & Extreme Learning Machine	AI model development that can reduce the carbon emission in a coal plant by 210KG tons annually.	17	(Muhammad Ashraf et al., 2022)
2021	Digitalization, Circular Economy and Environmental Sustainability: The Application of Artificial Intelligence in the Efficient Self-Management of Waste	Circular economy	Convolutional Neural Networks and image identification	AI can assist in distinguishing between glass and plastic based on 1000 images, a crucial process to achieve CE in relevant sectors. The results showed that the application provide a 90% reliability.	29	(Nañez Alonso et al., 2021)
2021	AI-Assisted approach for building energy and carbon footprint modeling	Energy management	Deep learning technique of long short-term memory	The study relied on AI to estimate energy consumption in office building. The model showed a high estimation ability.	14	(C.-Y. Chen et al., 2021)
2020	Edge computing enabled production anomalies detection and energy-efficient production decision approach for discrete manufacturing workshops	Resource efficiency	RecurrentNeuralNetwork	The creation of a Long Short-Term Memory (LSTM) in order to detect manufacturing errors. The experiment showed a 21% increase in product quality.	17	(C. Zhang & Ji, 2020)
2020	From Trash to Cash: How Blockchain and Multi-Sensor-Driven Artificial Intelligence Can Transform	Circular economy	Multi-sensor data-fusion algorithms	Presentation of ongoing attempts to sort plastics by type and to increase the accuracy of information about recycled plastics using blockchain supported by multi-sensor data-fusion algorithms	148	(Chidepatil et al., 2020)

	Circular Economy of Plastic Waste?			powered by artificial intelligence. The result showed a precise separation of commingled plastic waste.		
2020	Artificial Intelligence-Based Emission Reduction Strategy for Limestone Forced Oxidation Flue Gas Desulfurization System.	Carbon emission	Neural Network	Reduction of 35% of Sulphur Dioxide (SO2) AND a 42% reduction of Mercury (Hg) is possible by integrating AI in a 2*660 MW supercritical coal-fired power plant.	20	(Uddin et al., 2020)
2019	Deep learning in material recovery: Development of method to create training database	Waste management	Deep Convolutional Neural Networks	The identification of paper and cardboard with an accuracy of 61.9% to 77.5%	30	(Vrancken et al., 2019)
2019	Content-based image retrieval system for solid waste bin level detection and performance evaluation	Waste management	Gray-level aura matrix	Detection of the bin overloading level with an accuracy of 95% and the differentiation between different type of wastes.	32	(Hannan et al., 2016; Rajamanikam & Solihin, 2019)
2019	Assessment of waste characteristics and their impact on GIS vehicle collection route optimization using ANN waste forecasts	Waste management	Artificial Neural Network	An optimization within the waste collection route by 19.9% compared to the non-modified composition	90	(Vu et al., 2019)
2017	A novel integration of hyper-spectral imaging and neural networks to process waste electrical and electronic plastics	Waste Management	Artificial Neural Network	The identification of Plastic material within e-waste with a 99% accuracy	30	(Tehrani & Karbasi, 2017)
2017	Smart Technologies in Reducing Carbon Emission: Artificial Intelligence and Smart Water Meter	Carbon emission	Artificial Neural Network & Hidden Markov Model & Dynamic Time Warping	Presentation of an AI model that can manage water cycle to reduce carbon emission	12	(K. A. Nguyen et al., 2017)

2017	New artificial intelligence technology improving fuel efficiency and reducing CO2 emissions of ships through use of operational big data	Carbon emission	Human-centric AI Zinrai	Calculation ofvessel performance in actual sea conditions with a margin of error of no more than 5%.	28	(Anan et al., 2017)
2016	An automatic classification method for environment: Friendly waste segregation using deep learning	Waste management	Deep Convolutional Neural Networks	The improvement of the timing of the waste sorting, enhance the workers safety and improve efficiency.	73	(Sudha et al., 2016)
2016	How to improve WEEE management? Novel approach in mobile collection with application of artificial intelligence	Waste management	Fuzzy Logic and Genetic Algorithm	Mobile phone-based application to collect waste in the easiest and most efficient way.	73	(Król et al., 2016)
2015	A Multi-Criteria Decision Support System for a Routing Problem in Waste Collection	Waste management	Genetic Algorithm	Maximizing the volume of the collected waste while optimizing the journey distance	28	(Ferreira et al., 2015)
2014	Prediction of the compression ratio for municipal solid waste using decision tree	Waste management	Quinlan's M5 algorithm	The anticipation of waste compression with a coefficient of 0.92	20	(Heshmati R et al., 2014)
2014	Comfort-based fuzzy control optimization for energy conservation in HVAC systems	Energy management	FuzzyLogic	Comparison of the traditional control system with an AI-based system showed that AI model achieved a reduction of 16.1% in the energy consumption	84	(Hussain et al., 2014)
2010	Estimation of static formation temperatures in geothermal wells by using an artificial neural network approach	Energy management	Artificial neural network	Introduction of an Artificial neural network that can be used to predict the static formation temperature	83	(Bassam et al., 2010)
2010	ANN and ANFIS models for performance	Energy management	Adaptive Neuro-Fuzzy Inference System	The AI model was used to evaluate the Vertical Ground Source Heat	82	(Esen & Inalli, 2010)

	evaluation of a vertical ground source heat pump system			Pumps (VGSHP)		
2010	Fuzzy Control for an Oceanic Structure: A Case Study in Time-delay TLP System	Energy management	Fuzzy Logic Control	The AI model showed promising results regarding reducing the impact of ocean waves.	152	(C.-Y. Chen et al., 2010)
2010	Genetic Programming for Sea Level Predictions in an Island Environment	Energy management	Artificial neural networks	AI models were used to forecast the sea level variation.	20	(Ghorbani et al., 2010)
2008	Evaluation of genetic algorithm based solar tracking system for photovoltaic panels	Energy management	Genetic Algorithm	The use of AI in the solar system can optimize solar tracking for improved photovoltaic and improve the design of a Solar Water Heating System	36	(Mashohor et al., 2008)
2005	Using decision tree-based data mining to establish a sizing system for the manufacture of garments	Resource efficiency	Decision Tree	Development of an AI model to identify human body size patterns for clothes and determined the amount of fabric needed for clothing patterns	108	(Hsu & Wang, 2005)
2004	Nonlinear regression fits for simulated cycle time vs. throughput curves for semiconductor manufacturing	Resource efficiency	metamodeling approach	Streamline simulation work for semiconductor manufacturing systems to and improve numerous parameters such as semiconductor production efficiency	26	(Johnson et al., 2004)

In **Table 4**, we have grouped 32 papers focusing on the practical side of AI, outnumbering the papers that explore the theoretical side (27 papers) in Table 5. This intentional emphasis on practical cases aims to concretely showcase the potential of AI in addressing environmental sustainability.

In our analysis of practical and theoretical papers in Table 4 and Table 5, we observed distinct patterns across environmental aspects. For practical studies, there is a notable concentration on waste management (8 papers), carbon emission (9 papers), and energy management (8 papers). However, resource efficiency and circular economy receive comparatively less attention, with 3 and 2 papers, respectively.On the theoretical side, a different trend emerges. While waste management (2 papers), carbon emission (5 papers), and energy management (5 papers) continue to be explored, there is a substantial shift towards resource efficiency and circular economy, with 6 and 8 papers, respectively. This difference points to a clear contrast in the research emphasis between practical and theoretical studies.

In terms of AI models utilized, Neural Network and its various types were the most used in practical articles, being employed in 11 articles, while Fuzzy Logic and Genetic Algorithms were utilized in 4 articles each. Decision Tree, on the other hand, was employed in 2 articles.

Table 5: *Summary of the papers focusing on the theoretical aspect of AI on environmental sustainability.*

Publication Date	Title	Environmental Aspect	Key results	Citation Count	Reference
2023	Assessing the role of financial development in natural resource utilization efficiency: Does artificial intelligence technology matter?	Resource efficiency	AI technologies can improve natural resource utilization efficiency based on data from 30 province in China.	3	(K. Wang, 2023)
2023	Artificial intelligence, resource reallocation, and corporate innovation efficiency: Evidence from China's listed companies	Resource efficiency	AI applications directly boost firms' innovation efficiencybased on 3185 Chinese firms.	25	(C. Li et al., 2023)
2023	Using Artificial Intelligence to Tackle Food Waste and Enhance the Circular Economy: Maximising Resource Efficiency and Minimising Environmental Impact: A Review	Circular economy	The exploration of how AI can tackle food waste and enhance the circular economy.	5	(Onyeaka et al., 2023)
2023	Enabling artificial intelligence for sustainable food grain supply chains: an agri 5.0 and circular economy perspective	Circular economy	The identification of key factor that enables the adoption of AI in food grain supply chain, empowering circular economy in India.	4	(Das et al., 2023)
2023	Revolutionizing Solar Energy: The Impact of Artificial Intelligence on Photovoltaic Systems	Energy management	Exploration of the significant breakthroughs in solar panel technology brought about by AI-driven innovations	27	(Mohammad & Mahjabeen, 2023)
2023	Artificial intelligence for carbon emissions using system of systems theory	Carbon emission	A demonstration of how AI can both negatively and positively impact the carbon emission issue and how to encourage the AI society to create efficient AI models	12	(Gaur et al., 2023)
2023	Method and evaluations of the effective gain of artificial intelligence models for reducing CO2 emissions	Carbon emission	The examination of the dual impact of AI on carbon emission	13	(Delanoë et al., 2023)
2023	Is artificial intelligence associated with carbon emissions reduction? Case of China	Carbon emission	Based on data from 30 provinces in China, the author showed that the development of AI reduces carbon emissions with a spatial spillover effect.	3	(Ding et al., 2023)
2022	Artificial intelligence in support of the circular economy: ethical considerations and a path forward	Circular economy	Highlighting the crucial role of AI in transitioning from the traditional economy to the Circular economy	16	(Roberts et al., 2022)
2022	Machine Learning and Artificial Intelligence in Circular Economy: A Bibliometric Analysis and Systematic Literature Review	Circular economy	Revealing that Artificial intelligence is one of the most powerful and promising technologies for leading the shift in CE from linear to circular based on bibliometric analysis followed by a comprehensive literature review.	12	(Noman et al., 2022)

2022	Do Artificial Intelligence Applications Affect Carbon Emission Performance? — Evidence from Panel Data Analysis of Chinese Cities	Carbon emission	Examination of the relationship between AI and carbon emission. The result showed that the development of AI by 1% can directly contribute to a carbon intensity reduction of 0.0027%.	27	(P. Chen et al., 2022)
2021	Advanced recycling technologies to address Australia's plastic waste	Waste management	Detection, classification, and waste sorting immediately after the discard in Australia	11	(King, S & Hutchinson , SA, 2021)
2021	The impact of artificial intelligence on labor productivity	Resource efficiency	Based on a sample of 5257 companies, the authors demonstrated how AI and robotics can enhance the productivity and resource efficiency in SMEs	102	(Damioli et al., 2021)
2021	Artificial Intelligence Applications for Increasing Resource Efficiency in Manufacturing Companies—A Comprehensive Review	Resource efficiency	A systematic literature review based on 70 articles to analyse deeply the connection between AI and resource efficiency	40	(Waltersmann et al., 2021)
2021	ARTIFICIAL INTELLIGENCE TO INCREASE THE EFFICIENCY OF SMALL BUSINESSES	Resource efficiency	AI applications empower organizations to execute labor-intensive tasks in trade stores, warehouses, and establishments which contribute to high resource efficiency	13	(Otabek Ali, 2021)
2021	Applications of machine learning algorithms for biological wastewater treatment: Updates and perspectives	Circular economy	A review of the state of the art of the circular economy of wastewater and nutrient recovery from municipal wastewater based on machine learning algorithms	58	(Sundui et al., 2021)
2021	An Exploratory State-of-the-Art Review of Artificial Intelligence Applications in Circular Economy using Structural Topic Modeling	Circular economy	Based on 220 articles, a deep analysis was performed regarding the applications of AI models in the implementation of CE practices.	24	(Agrawal et al., 2021)
2021	Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities	Energy management	A state-of-the-art review of the use of AI in the energy sector.	339	(T. Ahmad, Zhang, Huang, Zhang, Dai, et al., 2021)
2021	Artificial intelligence and energy intensity in China's industrial sector: Effect and transmission channel	Energy management	An investigation of 16 AI-powered robots installed in 16 Chinese manufacturing divisions showed that the increased application of AI can considerably reduce energy intensity	38	(L. Liu et al., 2021)
2020	Artificial Intelligence for Smart Renewable Energy Sector in Europe—Smart Energy Infrastructures for Next Generation Smart Cities	Energy management	The exploration of recent developments in the AI adoption for the RE sector in the European Union (EU).	125	(Serban & Lytras, 2020).
2020	The carbon impact of artificial intelligence	Carbon emission	Analysis of tools to measure the carbon cost of machine learning algorithms and by moving to a sustainable artificial intelligence network.	202	(Dhar, 2020)

2020	Artificial intelligence applications in solid waste management: A systematic research review	Waste management	Presentation of a deep systematic literature review based on 85 papers that examine the use of different models of AI to manage the waste from various aspects, including; forecasting of waste characteristics, waste bin level detection, process parameters prediction, and vehicle routing.	122	(Abdallah et al., 2020)
2019	Industry 4.0 model for integrated circular economy-reverse logistics network	Circular economy	The authors analyze based on Mixed integer linear Programming the optimization of cost and maximization end of life of product relying on AI and other I 4.0 technologies.	37	(Rajput & Singh, 2019b)
2018	Artificial intelligence for the real world	Resource efficiency	Different surveys were performed to highlight the ups and downs of AI in the business world	1146	(Davenport & Ronanki, 2018)
2018	Artificial intelligence and Internet of Things enabled circular economy	Circular economy	The authors studied the use of AI in CE and stated that AIwill enable a "factory of the future" paradigm in which prices will fall, efficiency will grow, and high-quality, rapid turnaround "batches of one" will be possible.	59	(Ramadoss et al., 2018)
2016	A review on performance of artificial intelligence and conventional method in mitigating PV grid-tied related power quality events	Energy management	Investigation of the use of AI in the energy sector. The paper showed that AI methods usually outperform conventional methods in terms of response time and controllability of energy systems.	156	(Kow et al., 2016)

V. Discussion:

1. Waste management and AI:

The global increase in waste generation can be attributed to the effects of rapid urbanization, population growth, and economic expansion. Recent statistics highlight a substantial rise in municipal solid waste (MSW) generation, reaching 2.01 billion tons in 2016. Projections suggest this figure could surge to 3.40 billion tons by 2050(World Bank, 2018). In response, there has been a notable shift in waste management practices toward sustainability and profitability. This transformation is driven by innovative technologies and intelligent systems(Abdallah et al., 2020). Many studies have focused on categorizing waste materials for use in autonomous sorting systems, eliminating the need for manual waste segregation. (Tehrani & Karbasi, 2017)employed Artificial Neural Networks (ANN)and Multispectral Imaging to identify plastic materials within e-waste, achieving an impressive accuracy of 99%. (Vrancken et al., 2019)utilized Deep Convolutional Neural Networks (CNNs), a specific type of ANN, achieving accuracy rates ranging from 61.9% to 77.5% in identifying paper and cardboard among various waste types, despite a limited training dataset of 24 images. Relying on the same technique, (Sudha et al., 2016)utomated waste sorting with CNN, significantly improving sorting efficiency compared to manual methods. (Heshmati R et al., 2014)employed Quinlan's M5 algorithm, a supervised Machine Learning subfield, to anticipate waste compression ratios crucial for municipal landfill design. The results were impressive during testing, with a coefficient of 0.92. The algorithm, fed with various solid wastes, including biodegradable fractions, dry density, and water content, demonstrated its predictive capabilities.

Another aspect of waste management that can be improved by artificial intelligence is the detection of bin levels. The AI-based applications are created to anticipate the fill level of waste containers, which could potentially be utilized efficiently to prevent inaccurate waste disposal and waste bin overloading (Abdallah et al., 2019). In this regard, (Rajamanikam &Solihin, 2019) have presented a model that generates the image texture of a 120-liter waste bin. The model showed an accuracy of 95% in generating images from the bins. The method used in the case study is known as the gray-level aura matrix (GLAM). AI technologies detect more than simply bin fullness since the algorithms can differentiate between various types of waste when the bins are loaded. (King, S & Hutchinson, SA, 2021; Yigitcanlar & Cugurullo, 2020), demonstrated how an intelligent waste bin employs machine learning to detect, classify, and sort waste immediately after it is discarded.

Waste collection often accounts for 70 to 85% of total waste management costs for numerous municipalities (D. Singh & Satija, 2018). Although smart collection of waste is still developing, new solutions for AI-based smart waste collection are being designed and implemented (Król et al., 2016; Popa et al., 2017). (Vu et al., 2019)integrated the ANN waste forecasting approach with waste collection route optimization using a geographic information system (GIS) based on 36 scenarios. The research demonstrates how the compositional characteristics of waste materials influence the optimum truck route duration, distance, and air emissions. When compared to the non-modified composition, the indicated differences in trip distance of up to 19.9%.(Król et al. 2016) used genetic algorithm (GA), to optimize routes during the collection of domestic electronic waste. Due to the optimized route distance, number of collection trucks, and staff, the usage of GA lowered collection expenses. Similarly, (Ferreira et al., 2015) employed cellular GA to maximize the volume of waste collected and the number of areas visited while optimizing journey distance and vehicle usage.

2. Resource efficiency and AI:

AI plays a crucial role in assessing, identifying, and implementing performance-enhancement techniques in manufacturing firms(Damioli et al., 2021). Digitized knowledge is critical for leveraging existing information within an organization for AI applications, thereby creating an enhanced knowledge base(A. S. Ullah, 2020). The effectiveness of AI in improving resource efficiency is contingent upon explicitly defining this goal during AI development and applicationphase. Resource efficiency, viewed as a sub-goal of sustainability and SDG 12, may offer a limited contribution to overall sustainability, yet it remains a crucial aspect(Waltersmann et al., 2021).

Numerous studies highlight that AI enables organizations to automate mid-range monitoring tasks, leading to a flatter organizational structure and contributing to significant economic efficiency(Bloom et al., 2014; Davenport & Ronanki, 2018).(Otabek Ali, 2021)argues that AI applications empower organizations to execute labor-intensive tasks in trade stores, warehouses, and establishments, such as ordering and record-keeping of purchases from various vendors, up to three times faster. These applications support decision-making in production resources by mining firms, gathering information on facility construction, and analyzing data on electricity revenue, resulting in substantial resource reductions.

In a statistical analysis using the fixed-effect model and IV-GMM,(K. Wang, 2023)demonstrates that AI technological innovation significantly improves natural resource utilization efficiency.(Mehmood et al., 2019)assess the significance of AI technologies in construction and sustainability, stating that integrating AI and big data technologies can significantly improve the cost-effectiveness of construction projects. They contend that AI has a clear U-shaped influence on green efficiency. Increasing AI capacities in resource-rich locations can accelerate green total factor productivity (GTFP) and eliminate the resource bottleneck(P. Zhao et al., 2022).(Wehle & Dietel, 2015) provided a technique for optimizing maintenance procedures by assessing real-time images of potential production defects. This technique allows defects to be repaired as effectively as possible, restoring scrap and increasing production efficiency.(C. Li et al., 2023)used a Python web crawler method to analyze how AI affects firms' innovation efficiency based on 3185 Chinese firms. The results showed that AI applications directly boost firms' innovation efficiency. (Johnson et al., 2004)employed non-linear regression to develop a more accurate meta-model and improve numerous parameters such as semiconductor production efficiency.Based on a database of measured information, they developed a decision tree, which is a model used in AI for decision-making, to identify human body size patterns for clothes and determined the amount of fabric needed for clothing patterns that contributed directly to the fabric consumption efficiency (Hsu & Wang, 2005). (C. Zhang & Ji, 2020) created aLong Short-Term Memory (LSTM), which is a type of recurrent neural network (RNN) architecture in artificial intelligence and machine learning approach for detecting manufacturing errors. The case study yielded a 21.3% increase in product quality.In industrial electronics, (Jónás et al., 2014)employed Markov Chains, a model used for tasks like modelling dynamic processes in AI. As a result, the probability of particular steps and the time necessary for repair may be estimated, enhancing process management and product quality while preserving resources.

3. Circular economy and AI:

Emerging as a transformative economic development paradigm, the circular economy necessitates the redefinition and modernization of economic systems in alignment with the principles governing material circulation and energy flow in the natural ecological system (Shen et al., 2019). With the increasing acceptance of circular economy concepts by national and local governments, particularly within the context of the Paris Agreement, the adoption of circular strategies at the city level becomes pivotal for addressing various environmental challenges(Christis et al., 2019). The application of circular economy principles has the potential to enhance global sustainability(M. Yang et al., 2023).

The circular economy and optimization processes benefit significantly from innovative machine learning and artificial intelligence approaches at each phase, accelerating organizations' regenerative strategies(Rajput &

Singh, 2019a). Machine learning algorithms demonstrate the ability to anticipate unpredictable performances across a range of operations, monitor processes in real time, and identify defects in circular structures(Sundui et al., 2021). AI has the capacity to drive the development of visual tools offering a coherent depiction of data flows related to goods, resources, and processes. These tools facilitate the exploration of previously undiscovered benefits within a circular economy(Bianchini et al., 2019). According to (Onyeaka et al., 2023), the application of artificial intelligence (AI) in the food industry is gaining prominence to reduce food waste and strengthen circular economy strategies. The authors highlight numerous potential benefits associated with AI-supported circular economy initiatives, including heightened energy efficiency, prolonged product lifespan, and improved decision-making processes.

In their study on AI's role in the food grain supply chain in India,(Das et al., 2023) reveal that AI technology enables better production with more efficient resource utilization by enhancing predictive analysis, crop health management, quality, traceability, and, consequently, circular economy practices. Additionally,(Chidepatil et al., 2020) present ongoing efforts to sort plastics by type and improve the accuracy of information about recycled plastics using blockchain smart contracts supported by multi-sensor data-fusion algorithms powered by artificial intelligence. The results demonstrate the precise separation of commingled plastic waste based on physicochemical factors, potentially enhancing circular economy practices within the industry.

(Agrawal et al., 2021) focus on AI research in the circular economy, covering areas such as sustainable development, algorithmic AI and circular economy, CE-based economic development, industrial strategy, CE in logistics, network management, and waste management. Their bibliometric and Structural Topic Modeling (STM) methodology results indicate that AI is a powerful technology facilitating the transition from a linear to a circular economy. In agreement,(Ramadoss et al., 2018) state that artificial intelligence will enable a "factory of the future" paradigm, influencing prices, and efficiency, and enabling high-quality, rapid turnaround production. Similarly, (Roberts et al., 2022) assert that AI will be critical in transitioning from a linear to a circular economy, aiding in the design and maintenance of circular products and the development of circular business models.

(Noman et al., 2022) employ a bibliometric analysis and literature review to analyze the advancement of artificial intelligence systems in realizing circular economy sustainability. The research underscores that AI is a powerful technology leading the shift from linear to circular economy practices. The study identifies the prevalent use of AI methods such as fuzzy logic, unsupervised, supervised, and reinforcement learning, neural networks, and image recognition in various aspects of circular economy practices. Additionally, (Nañez Alonso et al., 2021) study how AI assists in distinguishing between glass and plastic based on 1000 images, a critical process for achieving circular economy goals. The results show that the application provides 90% reliability, significantly surpassing human achievement. Lastly, (M. Wilson et al., 2022)examine the use of AI for circular economy, particularly for reverse logistics, highlighting considerable benefits across all reverse logistics functions and activities. The study emphasizes that different forms of AI (mechanical, analytical, and intuitive) are applied to various reverse logistics functions.

4. Energy management and AI:

In the last half-century, the development of AI gained a large interest in creating experimental machines to execute various types of intelligent behaviour in the energy sector(T. Ahmad, Zhang, Huang, Zhang, Dai, et al., 2021). Artificial Intelligence (AI) technologies have the potential to support the energy management business in capitalizing on new possibilities brought about by the Internet of Things (IoT) and the integration of renewables(Sodhro et al., 2019).The traditional power grid was not intended to handle the incorporation of renewable energy sources (RES). Changes in the properties of RES (e.g. geothermal, hydrogen, wind, solar) provide issues in complying with the power grid's shifting loads(B. Yang et al., 2019).AI innovations such as machine learning, deep learning,big data, etc, are reshaping the energy industry.Many countries already implemented AI technology to perform various operations related to energy management such asforecasting,controlling, and efficient power system operations(Kow et al., 2016).

More concretely, based on a study that investigated 16 AI-powered robots installed in 16 Chinese manufacturing divisions from 2006 to 2016 to explore both the implications of AI on energy efficiency and the channel by which this effect circulates, the increased application of AI can considerably reduce energy intensity. This reduction is achieved by simultaneously increasing output value and decreasing energy consumption, particularly for high quantile energy levels. The primary effect of AI on energy management is the acceleration of technological advancement, accounting for 78.3% of the overall effect (L. Liu et al., 2021). Similarly, (Huang et al., 2017)used data from 30 Chinese provinces from 2000 to 2013, and the findings showed that AI contributed most significantly to a reduction in energy intensity, with a 1% rise in China's R&D capital base resulting in approximately a 0.07 decrease in energy consumption.Several studies, on the other hand, suggest that, while technical development could decrease energy consumption while enhancing energy efficiency, reduced effective prices produce an energy rebound effect, which may result in a disproportion fall in overall energy consumption(Grant et al., 2016; Lin & Zhao, 2016; Shao et al., 2014). Besides China, the European Union is one of the leaders in the energysector around the globe, particularly in the renewable energy sector(A.

B. Wilson, 2018).The European Union established a strategy called "Europe 2020," which assumed a 20% increase in energy efficiency, a 20% rise in the share of energy from sources of clean energy, and a 20% rise in total energy consumption by 2020. The objectives were met by 2020, and a new goal was set for 2030 called the "2030 Energy Strategy," aimed at raising the share of renewable energy sources to 32% of total energy consumed in the EU(Kacperska et al., 2021).In the European Union, AI has been extensively employed at a microeconomic level, with its presence evident in microgrids, intelligent storage systems, and centralized control systems. The utilization of modern technological assets, exemplified by the efficacy of transformation processes and changes in the structure of renewable energy facilitated by highly trained workers, serves as both a precursor and a requisite for the development of AI(Serban & Lytras, 2020).

The utilization of AI, both in general and within the realm of environmental sustainability, has become an increasingly prominent focus in recent years. The literature on this subject has experienced exponential growth, as seen in the case of AI and renewable energy, which surged from 482 publications in 2017 to 2728 in 2021(L. Zhang et al., 2022). Noteworthy studies, such as the one conducted by(T. Ahmad et al., 2022), showcase how AI can be advantageous for renewable energies. Their findings affirm that AI holds significant benefits for solar and wind stakeholder groups, including remote examination, troubleshooting and maintenance, ultrasonic receivers and transmitters, onshore solar and wind farm optimization, effective solar panel examination, autonomous drones with real-time AI, and technologies expediting due diligence.Additionally,(Mohammad & Mahjabeen, 2023), assert that AI contributes to the more efficient operation of solar farms, increased energy generation, and enhanced overall performance through cutting-edge algorithms and data analytics.

While discussions of renewable energy, unlike those of CO2 emissions dating back to the second industrial revolution in 1896, are relatively recent, the integration of AI in renewable energy was among the initial subjects explored following the emergence of AI capabilities(Baum, 2019).Contemporary research (10 to 30 years old) plays a significant role in exploring AI's application in renewable energy. The subsequent paragraphs highlight various contemporary studies examining the use of AI in different renewable energy sources, including Geothermal, Ocean, Wind, Hydro, Solar, and Hydrogen.

In the realm of geothermal energy,(Bassam et al., 2010)utilized a type of AI known as BPNN (Backpropagation Neural Network) to predict the static formation temperature (SFT) of a geothermal well. Similarly,(Esen & Inalli, 2010)employed an Adaptive Neuro-Fuzzy Inference System (ANFIS), another type of AI, to evaluate Vertical Ground Source Heat Pumps (VGSHP), a crucial variable in the geothermal energy analysis, ANFIS demonstrated more accurate predictions than BPNN methods in terms of energy and energy rates.

Turning to ocean energy, (C.-Y. Chen et al., 2010)utilized a Fuzzy Logic controller, a type of AI, to reduce the impact of ocean wave force, showing high stability.(Ghorbani et al., 2010)employed Artificial Neural Networks and Genetic programming to forecast sea level variation at the Cocos Islands in the Indian Ocean, demonstrating high accuracy with Genetic Programming.

In the field of wind energy,(Colak et al., 2012; Foley et al., 2012; Lei et al., 2009; Tascikaraoglu & Uzunoglu, 2014)presented a summarized review of the use of AI. Most studies focused on predicting wind power and speed using AI's neural learning algorithms(Mabel & Fernandez, 2008, 2009).(G. Li & Shi, 2010) have used three different AI methods (BPNN, RBFNN ADALINE) in order to predict the wind speed from two different locations. The methods showed tremendous accuracy with BPNN as the best performance in one location (minimum root mean square error of 1.254) and RBF showed the best performance in the second location with a minimum RMSE of 1.444). Other AI methods were also used to estimate the wind speed, such as the fuzzy logic that was used by (Monfared et al., 2009; Simoes et al., 1997), this methodology was tested in a wind generation system (3.5 kW), the results showed a satisfactory level of accuracy. Hydropower has also been a subject of extensive study, with, (Kishor et al., 2007; Nourani et al., 2014) have presented a full review of the combination of AI and hydropower. Several study cases have been presented in the contemporary literature using different types of AI, for example (Smith & Eli, 1995) have used the Backpropagation Neural Network (BPNN) to estimate the discharge of a rainfall-runoff of linear and non-linear reservoirs. The results have shown that the BPNN method is more accurate at predicting the highest discharge in non-linear reservoirs and excels in predicting the time it takes for discharge to peak in linear reservoirs.(Kişi, 2004) also used BPNN and the results were compared to the autoregressive (AR) method, a statistical model used to analyse time-series data, the AI-based route has shown more accurate results than the AR method. Many other AI methods were also used in the hydroenergy context, (Chang & Chang, 2001; Uzlu et al., 2014) used Adaptive Neuro-Fuzzy Inference System (ANFIS). (Chang & Chang, 2001) used this method to predict the water release in the Shihmen reservoir in Taiwan, the results of the AI-based method were compared to the M-5 rules curves, a set of rules used in hydrology resource management. AI and solar energy were reviewed by (Dounis & Caraiscos, 2009; Mellit, 2008; H. Zhao & Magoulès, 2012). (Rehman & Mohandes, 2008) forecasted the Global solar radiation between the years 1998 and 2002 using the BPNN method. The method successfully predicted the Global solar radiation for the year 2002. Similarly, (Mubiru & Banda, 2008) used BPNN to estimate the monthly average daily global solar irradiation, and the results showed a 0.97 correlation between the predicted and the actual solar irradiation.

(Mashohor et al., 2008)conducted an experiment using Genetic Algorithm (GA) to optimize solar tracking for improved Photovoltaic (PV) system performance. The best GA-Solar system, with an initial population size of 100, 50 epochs, and crossover and mutation probabilities set at 0.7 and 0.001, demonstrated a low standard deviation (1.55) in generation gain, highlighting a consistently efficient system. Additionally, GA proved effective in the optimal design of a Solar Water Heating System, showcasing its versatility in enhancing various solar applications.

Finally, hydrogen energy has also a decent share in the contemporary literature, (Ho et al., 2008) used BPNN and eleven algorithms in order to predict the impact of hydrogenic car engines on the emission of CO, NOx, hydrocarbons, and CO2, the results showed a 100% accuracy in the prediction of CO emission. Another study used BPNN to predict the characteristics of a hydrogen engine, the study focused on NOx emission, air pressure, exhaust gas and engine temperature, NOx emission, and mass airflow. The AI database was fed mainly through the engine speed and the throttle position.

One of the most targeted areas of AI in the context of energy management is the building sector. This sector produces the largest percentage of total energy consumption (40%) and energy-related carbon dioxide (CO2) emissions (30%), posing a global risk of climate change(C. Wang et al., 2020). For this reason, we can find many studies that use AI applications to manage the energy in buildings. In this context, (C.-Y. Chen et al., 2021), used an AI model referred to as a deep learning technique of long short-term memory (LSTM) to predict the energy consumption and the related CO2 emissions of different types of office buildings based on the data from 2016 to 2018. The result of the LSTM application showed a high estimation ability and minimal variation across the different types of buildings. Similarly, (S. U. Khan et al., 2023) used a hybrid AI-based model to accurately predict the energy generation and consumption following three key steps, going from pre-proceeding to using a convolutional long short-term memory (ConvLSTM) that learn past patterns and finally passing to an AI algorithm called Percepton to perform the estimation, the results showed that this model has decreased the errors of 0.012 and 0.045 of the mean square error (MSE) on hourly data in comparison to the state of art recently published. (Hussain et al., 2014) compared the traditional ON and OFF control system with the AI model fuzzy logic through simulation experiments. The authors found that the AI-based model achieved a reduction of 16.1% in energy consumption and 18% in the cooling and heating periods.

5. AI and Carbon emission reduction:

The global commitment and efforts to solve climate concerns are increasing. More than 70 countries have committed to reaching net zero emissions by 2050 and strengthening their global climate commitments as part of the Paris Agreement. China, the world's largest energy consumer and carbon producer, has established a clear goal of achieving maximum carbon emissions by 2030 and carbon neutrality by 2060(Kolpakov, 2020). The research on the implications of AI on carbon emissions is divided, for this reason, there is an intense effort to use AI in a green way. Roel Dobbe and Meredith Whittaker, co-founders of the AI Now Institute, published an article on AI and climate change in October 2019 in which they called for seven policies that might pave the way for "tech-aware environmental policy, and climate-aware tech policy." Two main policies were: reducing the use of AI to extract fossil fuels and investigating the influence of AI on climate change(Dhar, 2020). AI has the capacity to both benefit and negatively impact the environment, and it is critical to prioritize sustainable AI practices throughout the AI lifecycle(Gaur et al., 2023). (Delanoë et al., 2023) demonstrated the dual impact of AI on CO2 emissions. Their study focused on AI applications developed in Brazil, Tunisia, and Sweden, examining both positive and negative effects. Solely considering positive impacts, the models showed a 34%, 73%, and 9% reduction in CO2 emissions, respectively. However, when accounting for negative impacts, the detrimental effects sometimes outweighed the positive ones. However, according to common opinion, AI has overall beneficial effects on carbon reduction (Aghion et al., 2017). Although AI applications themselves contribute to indirect carbon emissions, they are easily tracked and controlled. For instance,(Budennyy et al., 2022) developed an open-source library that measures the carbon emissions of any AI application and it is open to the public. The model uses Python and calculates the RAM, CPU, and energy consumption. According to a report published collaboratively by Microsoft and PwC, "the use of AI technology for environmental preservation is expected to raise global GDP by 3.1 to 4.4 percent by 2030 while cutting global greenhouse gas emissions by 1.5 to 4.0 percent" (C. M. Liu et al., 2019). Many studies have proved that these predictions are correct.(P. Chen et al., 2022) employed a two-way fixed effects model using temporal and area-level fixed variables to investigate the relationship between AI development and carbon emissions magnitude. The results showed that the development of AI by 1% can directly contribute to a carbon intensity reduction of 0.0027%, which is a high percentage.(Ding et al., 2023) used a database from 30 provinces in China from 2006 to 2019 to study the relationship between AI and carbon emissions. The study has shown that the development of AI reduces carbon emissions with a spatial spillover effect, this reduction is realized especially by promoting environmentally friendly practices and improving the technological aspect of the industrial sector. Similarly, (Cheng et al., 2023) based their study on Chinese manufacturing firms listed on A-share between 2012 and 2021 to examine the correlation between AI and carbon emissions using a fixed-effects regression model. Relying on carbon emission data of Jiangsu Province in China from 2002 to 2020, (Huo et al., 2023) used an AI model called genetic algorithm (GA-SVM) to predict the carbon peak time. The results demonstrated that the model incorporating the support vector machine and the genetic algorithm can accurately estimate CO_2 emissions and the peak time for CO_2 emissions.

(Alpan et al., 2022) presented a model based on AI (decision tree algorithm) and IoT technology to control residences' carbon emissions. The model's preliminary simulation achieved a 21% reduction in carbon emissions. As a result, the annual average dropped from 41.48 to 32.56 kg CO2e. (K. A. Nguyen et al., 2017) have developed a model called "Autoflow" based on the Artificial Neural Network (ANN), Hidden Markov Model (HMM), and Dynamic Time Warping (DTW) algorithm that manages the water cycle to reduce carbon emission. The proposed model has shown great potential, for instance, during the water treatment process, the model can provide the water suppliers with a full report of the origin of the used water, as an example of this, the authors presented a report extracted from 300 households revealed six different end-use types, including shower (37%), tap water (17%), clothes washer (17%), dishwasher (1%), toilet (20%), irrigation (5%) and bathtub (2%). The model can help water suppliers optimize the size of the treatment plans and the amount of treatment chemicals used that can contribute to a high carbon emission reduction. The study revealed that corporate AI adversely affects the intensity of carbon emissions. Additionally, advancements in green technology, management, and product innovation amplify the constraining impact of enterprise AI development on corporate carbon emissions. (Cheng et al., 2023) used both machine learning and compressible packing models to address the carbon emission issue of the Self-compacting concrete design that needs a large number of experiments, incurring increased material, time, and labor expenses. The self-compacting design generated by the AI model showed a 57,2% reduction in carbon emission. (J. Du et al., 2024)developed an AI-driven hybrid model to optimize CO_2 capture in a confined space using Vacuum Pressure Swing Adsorption (VPSA), integrating a Hybrid Surrogate Model (HSM). The AI model showed a reduction in CO_2 concertation going from 1000 ppm to 399 ppm and following an optimized air purification operation, the energy consumption per unit product (ECP) drops by 38.5% to 99.7 kJNm 3 air. (Muhammad Ashraf et al., 2022) focused their study on a 660MW coal power plant, by integrating AI and response surface methodology (AI-RMS) to achieve emissions efficiency in the coal plant. In the plant, two algorithms were trained: Support Vector Machine (SVM) and Extreme Learning Machine (ELM). The study showed that it is estimated that the AI model will reduce annually CO_2 by 210 kg tons, CH_4 by 23.8 tons, and Hg by 2.7 Kg. Similarly, (Uddin et al., 2020) carried out their studies on a 2*660 MW supercritical coal-fired power plant. The AI-based model developed by the authors was used in the Limestone Forced Oxidation (LSFO) Flue Gas Desulfurization (FGD) system to reduce different toxic emissions. The experiment showed a possibility of a 35% reduction of Sulphur Dioxide (SO_2) AND a 42% reduction of Mercury (Hg). (Anan et al., 2017) applied the Fujitsu AI model (Human-centric AI Zinrai) to calculate vessel performance in actual sea conditions with a margin of error of no more than 5%. The authors used data from several trips of a test ship from the Tokyo University of Marine Science and Technology (TUMSAT). The findings revealed that leveraging Human-centric AI Zinrai can lead to a substantial reduction in CO_2 emissions, allowing for the identification of the optimal route and achieving a notable 5% reduction in fuel consumption.

VI. Conclusion and future directions:

The main goal of this systematic literature review is to showcase various scenarios where AI has positively influenced different aspects of environmental sustainability. After applying deep filtering steps, we identified 110 articles, with 86 of them published between 2014 and 2023. The remaining articles were specifically considered in the renewable energy section to highlight the relevance of this topic in contemporary literature. In the analysis phase, we extracted relevant information from the most significant papers, presenting key details in Tables 3 and 4, including publication dates, paper results, and other important information. These tables aim to facilitate rapid and clearer access to the paper's findings.

The present SLR examined the use of Artificial intelligence for environmental sustainability, investigating different aspects and scenarios:

- The effects of Artificial Intelligence on different environmental sustainability aspects.
- AI has double effects on different environmental sustainability aspects, especially in carbon emission issues, AI application developments are responsible for carbon emissions by themselves. We showed in our study that a targeted use of AI will have a largely more positive impact on carbon emission reduction than it will negatively impact it.
- AI has great potential in identifying the materials of wastes (plastic, metal, organic…) to facilitate the sorting phase which is a critical step in waste management.
- Waste collection is also one of the tasks that AI can facilitate massively.
- The AI feature of taking over automated tasks results in great resource efficiency.

- The construction industry significantly contributes to high energy consumption. The AI features of big data analysis, capable of accurately predicting various variables, make AI a highly valuable tool for mitigating unnecessary energy consumption and formulating effective strategies for constructing energy-efficient buildings.

Artificial intelligence is an adaptable tool with applications in various contexts, making it challenging to encapsulate in just a couple of papers. Its potential uses are limitless, it's like attempting to cover all aspects of the internet within a specific topic.
Similar to a superhuman with high learning ability, AI, given well-organized data, can rapidly learn about a particular subject and become an expert within a few weeks. Following this idea, there are endless possibilities for AI to enhance and advance multiple industries.
Therefore, a substantial number of papers are essential to explore AI's potential and provide focused directions to make the most use of AI applications and not get lost in all these possibilities.We suggest that future research concentrates on specific aspects of environmental sustainability, such as energy management and AI integration. Additionally, exploring specific AI models, such as Artificial Neural Networks, and their applications across scenarios could further contribute to a positive environmental impact.

VII. Reference:

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