Int J Environ Res (2025) 19:1
https://doi.org/10.1007/s41742-024-00668-5

REVIEW ARTICLE

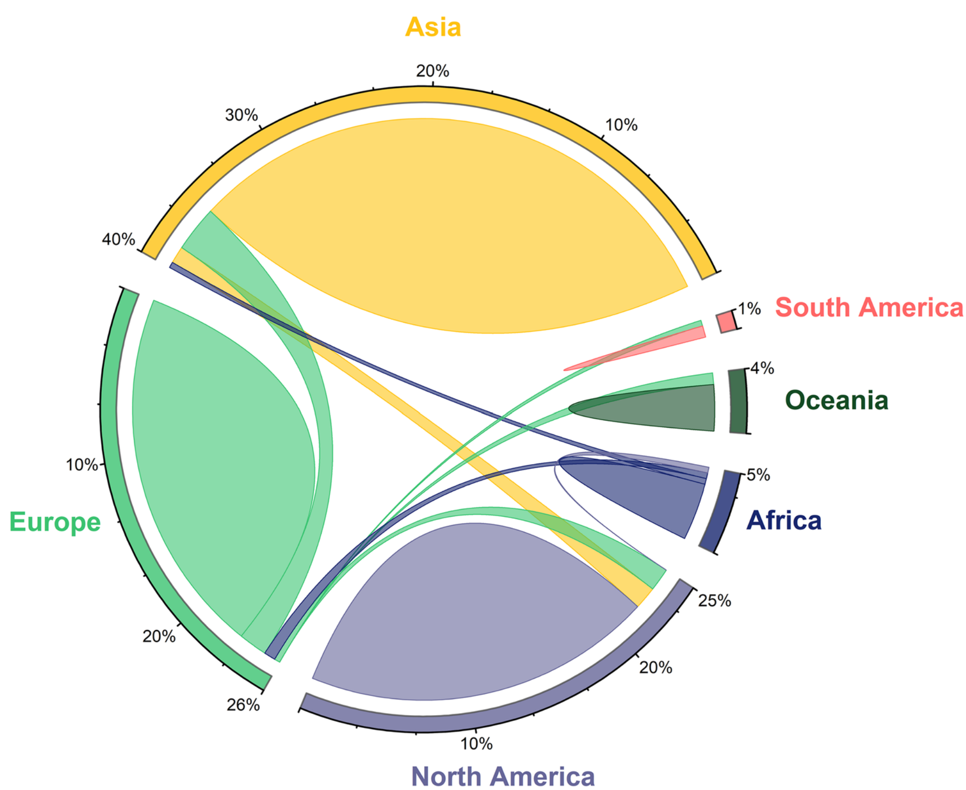
A systematic review of current AI techniques used in the context of the SDGs

Lucas Greif[1] · Fabian Röckel[1] · Andreas Kimmig[1] · Jivka Ovtcharova[1]

Received: 25 July 2024 / Revised: 16 September 2024 / Accepted: 5 October 2024 / Published online: 24 October 2024

Abstract
This study aims to explore the application of artificial intelligence (AI) in the resolution of sustainability challenges, with a specific focus on environmental studies. Given the rapidly evolving nature of this field, there is an urgent need for more frequent and dynamic reviews to keep pace with the innovative applications of AI. Through a systematic analysis of 191 research articles, we classified AI techniques applied in the field of sustainability. Our review found that 65% of the studies applied supervised learning methods, 18% employed unsupervised learning, and 17% utilized reinforcement learning approaches. The review highlights that artificial neural networks (ANN), are the most commonly applied AI techniques in sustainability contexts, accounting for 23% of the reviewed methods. This comprehensive overview of AI techniques identifies key trends and proposes new research avenues to address the complex issue of achieving the Sustainable Development Goals (SDGs).

Graphic abstract



Extended author information available on the last page of the article

Keywords Artificial intelligence · Sustainable development goals (SDGs) · Machine learning · Sustainability · Literature review

Abbreviations

AI	Artificial intelligence
ANN	Artificial neural networks
ANFIS	Adaptive neuro-fuzzy inference systems
CART	Classification and regression tree
CNN	Convolutional neural networks
CV	Computer vision
DL	Deep learning
DQN	Deep Q-learning network
DRL	Deep reinforcement learning
EU	European union
FNN	Fuzzy neural networks
GA	Genetic algorithms
GRNN	General regression neural network
LLMs	Large language models
LSTM	Long short-term memory
MDGs	Millennium development goals
ML	Machine learning
MLP	Multi-layer perceptron
NLP	Natural language processing
OLS	Ordinary least squares
PPO	Proximal policy optimization
RF	Random forest
RL	Reinforcement learning
SDGs	Sustainable development goals
SJR	SCImago journal rank
SVM	Support vector machines
UN	United nations
XAI	Explainable artificial intelligence
XGBoost	Extreme gradient boosting

Introduction

Sustainable development is one of the most pressing challenges of the 21st century, underscored by global initiatives such as the 2030 Agenda of the United Nations, which outlines 17 SDGs aimed at tackling critical issues such as poverty, inequality, environmental degradation, and climate change (United Nations 2015). Complementing this, the European Union announced the Green Deal in 2019, with the aim of reducing greenhouse gas emissions and climate neutrality by 2050, with an interim goal of a reduction 55% below 1990 levels by 2030 (European Commission 2019). However, achieving these goals faces significant obstacles due to escalating anthropogenic pressures such as over-extraction of groundwater, deforestation, urbanization, and agricultural expansion, which can strain water resources at regional levels. In addition, climate change is intensifying these challenges globally, with rising temperatures accelerating evaporation rates, altering precipitation patterns, and increasing the severity and frequency of extreme weather events such as floods and droughts. For example, water resource management is becoming increasingly challenging, particularly in arid and semi-arid regions. In these regions, the rising occurrence and severity of extreme hydro-climatic events, including heavy rainfall, flooding, and droughts, have negatively impacted the hydrological cycle (Kumar et al. 2022). Studies, such as those conducted in the Upper Betwa River basin in central India, demonstrate that climate change combined with changes in land use can lead to significant reductions in rainfall, surface runoff and groundwater percolation, further exacerbating water scarcity and complicating sustainable water management strategies (Kumar et al. 2023). Furthermore, an assessment of the current progress in achieving the SDGs reveals that economy-related goals, such as SDG 8 (decent work and economic growth), SDG 9 (industry, innovation, and infrastructure), and SDG 12 (responsible consumption and production), are showing promising progress, with some regions nearing the objectives. However, significant challenges remain in other areas, particularly SDG 4 (quality education), SDG 11 (sustainable cities and communities), and SDG 13 (climate action), where progress has been slow and many regions are far from meeting their targets. In addition, the study highlights significant regional disparities in progress. Developed countries are generally closer to achieving many goals, particularly those related to economic growth and infrastructure. In contrast, regions such as Sub-Saharan Africa and South Asia face serious challenges, particularly in addressing poverty, hunger, education, and inequality. Climate action (SDG 13) and sustainable urbanization (SDG 11) are global issues that require more urgent attention in all regions to ensure that the 2030 targets are met (Halkos and Gkampoura 2021). This study highlights the need for innovative tools and strategies to drive progress toward the SDGs. AI has emerged as a transformative technology with the potential to address the SDGs. Its evolving capabilities in data analysis, pattern recognition, and predictive modeling make AI a powerful tool to optimize resource use, improve energy efficiency, and improve environmental monitoring (Sætra 2021). This capability of AI is evident in various applications that address a spectrum of sustainability challenges such as water conservation (D'Amore et al. 2022; Mehmood et al. 2020), urban sustainability (Damiani et al. 2021), clean energy (Ahmad et al. 2021, 2022; Krzywanski 2022), and waste management (Aniza et al. 2023; Naveenkumar et al. 2023). Figure 1 underscores the growing interest in the application of AI to achieve the SDGs by showing the annual number of new published studies from 2000 to 2024 related to AI and the SDGs, obtained from Google Scholar. The search was performed on 31st August 2024, indicating that publications for the year 2024 are still being processed, with the total expected to increase. The search utilized the keywords "AI" AND "SDG", and the publication count per year was recorded.

Despite its promise, AI's role in sustainability is not without challenges. The environmental cost of developing and deploying AI models, particularly in terms of energy consumption and carbon emissions, presents a paradox that must be addressed (Strubell et al. 2019). Moreover, concerns about algorithmic bias, transparency, and fairness raise ethical questions that need careful consideration (Fox et al. 2022). As a result, responsible integration of AI into sustainability efforts requires a balanced approach that maximizes its benefits while mitigating its risks. This review seeks to provide a comprehensive examination of the current role of AI in advancing sustainability. Therefore, this study explores current AI methodologies and their applications in various sustainability domains, highlighting their impact on SDG achievement. The novelty of this review lies in its detailed analysis of how AI can be leveraged as a catalyst for innovation, while also offering insight into the ethical implications and systemic challenges that accompany its integration into sustainability frameworks. By providing a structured overview of AI applications, challenges, and future directions, this review aims to contribute valuable knowledge to the growing discourse on sustainable development in the age of AI. The rest of this paper is structured as follows: Sect. 2 aims to elucidate key AI and sustainability terminology, ensuring a shared understanding of the terms used throughout the review. Section 3 explains the methodology of this review. The core of the review, located in Sect. 4, organizes the literature on AI methodologies, examining their application in various scenarios related to SDGs. Each subsection delves into applied AI methods, their implementation, and quantified outcomes, illustrating the efficacy of these methodologies in achieving sustainability goals through empirical evidence and numerical data. Section 5 synthesizes the main findings and considers their implications for addressing sustainability challenges and identifying prospective avenues for future research. Section 7 culminates in a summary of key insights.

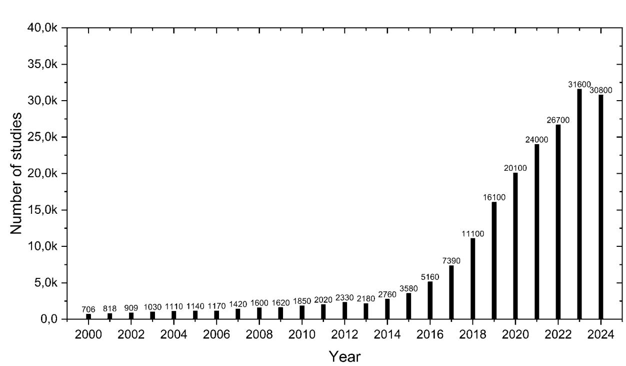


Fig. 1 Analysis of pulished paper over the last 24 years

Theoretical foundations and related work

AI is increasingly recognized for its potential to drive sustainable development in multiple domains. The integration of AI in digital education enhances the sustainability of educational management systems by improving educational outcomes through personalized learning, adaptive learning platforms, intelligent tutoring systems, and natural language processing (NLP). Predictive analytics identify at-risk students, allowing timely interventions.

The ethical implications and responsible integration of AI are vital for its successful implementation, as these factors ensure that AI technologies are used in ways that align with societal values, fairness, and transparency. Ethical concerns, such as bias, discrimination, privacy violations, and the potential for misuse, must be proactively addressed to prevent harm and build trust. In addition, responsible integration of AI involves creating frameworks and policies that guide the development, deployment, and use of AI in ways that prioritize human well-being, accountability, and sustainability (Suryanarayana et al. 2024). For example, ensuring explainability, safeguarding data, and promoting equitable access to AI tools are essential practices that contribute to an ethically sound and socially responsible AI landscape.

The optimization of supply chains through blockchain and AI improves sustainable development by improving transparency, traceability, and accountability. Blockchain supports responsible sourcing and fair-trade practices, while AI's predictive capabilities improve resource allocation, minimize waste, and facilitate informed decision-making.

Policy recommendations are provided by a range of stakeholders, including governmental agencies, international organizations, think tanks, academic researchers, and industry experts. These entities collaborate to ensure that digital innovation is aligned with sustainability objectives. For instance, governmental bodies such as the United Nations, the European Union, or national governments may draft guidelines and regulations that promote the responsible use of digital technologies in ways that reduce environmental impact. Academic researchers and think tanks contribute by conducting studies that highlight the relationship between digital technologies and sustainability, providing data-driven insights to inform policy. Additionally, industry leaders and non-governmental organizations (NGOs) often play a key role by advocating for best practices, supporting green innovation, and promoting corporate social responsibility in tech development (Hong and Xiao 2024).

The integration of AI in ecosystem management focuses on modeling complex ecological interactions and predicting changes, aiding conservation efforts. AI monitors biodiversity and ecosystem health, focusing on interdisciplinary approaches to effective management.

The challenges and solutions related to AI-based personalized e-learning systems address data privacy, bias in AI algorithms, and the digital divide. The benefits of personalized education through AI include improved student engagement and learning outcomes. Solutions for effective AI implementation are proposed based on literature reviews and case studies (Tripathi et al. 2024). Various technologies, including AI, contribute to sustainable development in sectors such as agriculture, energy and manufacturing. Sustainable technology policies and frameworks are crucial, with case studies highlighting significant improvements in sustainability through technology (Coccia 2024). The role of AI in urban planning focuses on achieving SDGs by optimizing land use, transportation systems, and infrastructure development. AI-driven urban planning improves sustainability by reducing carbon footprints, enhancing green spaces, and improving the overall quality of life of residents. Case studies demonstrate how cities have successfully integrated AI to solve urban challenges, from traffic congestion to waste management, showing practical applications and the benefits of AI-driven urban planning (Regona et al. 2024). The application of AI in optimizing renewable energy systems highlights the role of AI in enhancing the efficiency and reliability of renewable energy sources, predictive maintenance, and energy management. Case studies and quantitative analysis of AI applications in renewable energy illustrate how AI technologies, such as machine learning (ML) and artificial neural networks (ANN), can predict energy production from renewable sources such as wind and solar, optimize energy storage and improve grid management, contributing to a more sustainable and resilient energy infrastructure (Raman et al. 2024). AI applications in agriculture promote sustainability through AI-driven precision agriculture, resource management, crop monitoring, and pest control. Reviewing and analyzing case studies on AI implementations in agriculture reveal how AI helps farmers make data-driven decisions to optimize yields, reduce waste, and use resources more efficiently, demonstrating AI's transformative impact on agricultural sustainability (Coccia 2017). Finally, AI innovations in healthcare support sustainable development by improving diagnostics, treatment plans, patient management, and healthcare delivery efficiency. Reviews and case studies in healthcare settings illustrate how AI-powered diagnostic tools, personalized treatment plans, and predictive analytics for patient care management can improve healthcare access, reduce costs, and improve patient outcomes. The potential of AI to revolutionize healthcare and contribute to sustainable health systems is significant (Jauhiainen 2024).

Sustainability

Sustainability is a broad concept that refers to the ability to maintain or support a process continuously over time. It encompasses ecological, social, and economic dimensions, ensuring that activities or processes do not deplete resources or harm ecological and social systems beyond their capacity to recover Brown et al. (1987). Therefore, sustainability can be thought of as the goal or the end state we are trying to achieve, which is a balanced interaction between the environment, society, and economy such that it can continue indefinitely. A similar concept, sustainable development, on the other hand, is a more dynamic concept that describes the process or approach to achieving sustainability. It was defined in the Brundtland Report in 1987 as follows [26]:

> "Sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs."

This definition also emphasizes the importance of considering the economic, social, and environmental aspects of development in a balanced way to ensure the long-term well-being of present and future generations (Osaki and Kensuke 2013; Ruggerio 2021). To achieve sustainable development, several political initiatives have been established. First, the Millennium Development Goals (MDGs) were announced in 2000 with eight specific goals aimed at addressing major global challenges. These goals were aimed primarily at developing countries, focusing on issues such as extreme poverty, hunger, disease, lack of adequate schooling, and environmental degradation [29]. Each goal had specific targets to be achieved by 2015 and was a product of their time, emphasizing reduction over comprehensive systemic change. In 2015, the United Nations adopted the SDGs as a successor to the MDGs, with a broader agenda and a longer timeline set to 2030. The SDGs comprise 17 goals, significantly expanding the scope of the original MDGs. They incorporate more nuanced challenges of sustainable development, such as economic inequality, innovation, sustainable consumption, peace, and justice, among others (United Nations 2015). One of the critical advances in the SDGs over the MDGs is the shift from a dichotomous view of developed and developing countries to a more inclusive framework. This shift reflects the realization that sustainable development challenges are global and not confined to countries traditionally viewed as "developing." For example:

- Goal 13 (Climate Action) is universally applicable and requires action from all countries, regardless of their economic status, to address climate change effectively.
- Goal 10 (Reduced Inequalities) focuses on reducing inequality within and between countries, acknowledging that inequality is a global issue affecting all nations.

Fig. 2 is a conceptual diagram that illustrates the relationship between the SDGs.

It is structured in concentric layers with the following components:

- **Biosphere:** At the foundation, it is represented as the largest and bottom layer, reflecting its fundamental support role for life and human activity. It specifically highlights SDG 6 (Clean Water and Sanitation), SDG 13 (Climate Action), SDG 14 (Life Below Water) and SDG 15 (Life on Land).
- **Society:** The middle layer, showing that society is built on the biosphere and depends on its health and stability. It encompasses various SDGs related to social aspects: SDG 1 (No Poverty), SDG 2 (Zero Hunger), SDG 3 (Good Health and Well-being), SDG 4 (Quality Education), SDG 5 (Gender Equality), SDG 7 (Affordable and Clean Energy), SDG 11 (Sustainable Cities and Communities) and SDG 16 (Peace, Justice, and Strong Institutions).
- **Economy:** The top layer, indicating that a sustainable economy is supported by a strong society and a healthy biosphere. It includes SDG 8 (Decent Work and Economic Growth), SDG 9 (Industry, Innovation, and Infrastructure), SDG 10 (Reduced Inequality), and SDG 12 (Responsible Consumption and Production).
- SDG 17 (Partnerships for the Goals): Positioned at the top, signifies its role in unifying and facilitating the achievement of all other SDGs through global partnerships.

The figure visualizes the SDGs not as isolated or individual targets, but as interconnected components of a single system. The economy and society are shown to be embedded within the biosphere, highlighting the importance of environmental sustainability as the foundation for social stability and economic prosperity.

We have expanded the scope of the SDGs to incorporate the European Green Deal Goals.

These goals focus on three principles that aim to facilitate the transition to clean energy. These principles encompass ensuring a secure and affordable energy supply throughout the EU, fostering the development of a fully integrated, interconnected, and digitalized EU energy market, and prioritizing energy efficiency. It involves enhancing the energy performance of buildings and cultivating a power sector with a foundational reliance on renewable resources (European Commission 2019).

Several other political initiatives could have been considered alongside the European Green Deal Goals and SDGs but have been excluded for various reasons. The Paris Agreement, while a vital global commitment to reducing carbon emissions, does not provide detailed actionable policies. America's Pledge on Climate Change, focused primarily on the United States, and China's Ecological Civilization,

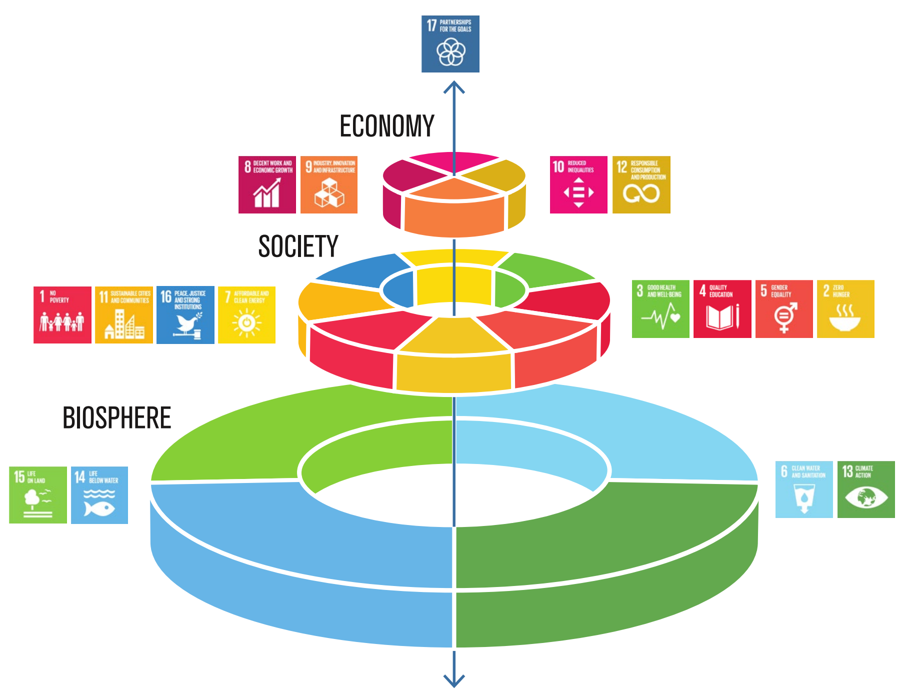


Fig. 2 Stockholm Resilience Center wedding cake representation of the SDGs (Azote for Stockholm Resilience Centre 2016)

centered on national governance, lack the transnational scope and detailed policy frameworks that are key characteristics of the European Green Deal and the SDG. Additionally, the U.S. Green New Deal, though ambitious, remains largely conceptual with significant political obstacles preventing its implementation. In contrast, the European Green Deal aligns well with the SDGs and offers a region-specific, actionable, and already implemented framework, making it a more suitable choice for immediate integration and enrichment of sustainability goals within Europe.

Evaluating each individual SDG and European Green Deal Goal is not practical for our use case since the allocation would result in too few papers for each category, making the analysis less robust. Therefore, we adopted the clustering approach of Vinuesa et al. (2020) and organized the SDGs and the European Green Deal Goals into four clusters, "Economic Growth and Infrastructure", "Social Well-Being and Poverty", "Environment and Climate Action", "Partnerships and Implementation", which is shown in Fig. 3. We identified the clusters by integrating the layers of the wedding cake model with the groupings identified by Vinuesa et al. (2020) which allowed us to align the layers of biosphere, society and economy of the wedding cake model with the environmental, social and economic clusters, while also incorporating a distinct focus on partnerships and implementation. The assignment of SDGs to each cluster was adopted from both sources, while we assigned the European Green Deal goals ourselves based on their similarities to the corresponding clusters. This approach helps to provide a structural overview of the complex and multifaceted goals.

The SDGs and European Green Deal Goals are deeply interrelated and have far-reaching implications across sectors and disciplines. Economic objectives cannot be separated from environmental issues, social objectives require the formation of partnerships, and the effects of environmental actions influence socio-economic areas.

One key area of intersection is the integration of economic, environmental and social goals. Research highlights how the circular economy, the green economy and the bioeconomy converge in their goals to unify the SDGs. Although distinct, these frameworks share common ground in their quest to balance economic growth with ecological prudence and social equity. A comparative analysis reveals that while these concepts operate under different assumptions, they all contribute to a sustainable framework by weaving economic activities with environmental mindfulness and social well-being (D'Amato et al. 2017). System integration is another critical intersection. It is essential to integrate various components of coupled human and natural systems to address global sustainability challenges effectively. This integration

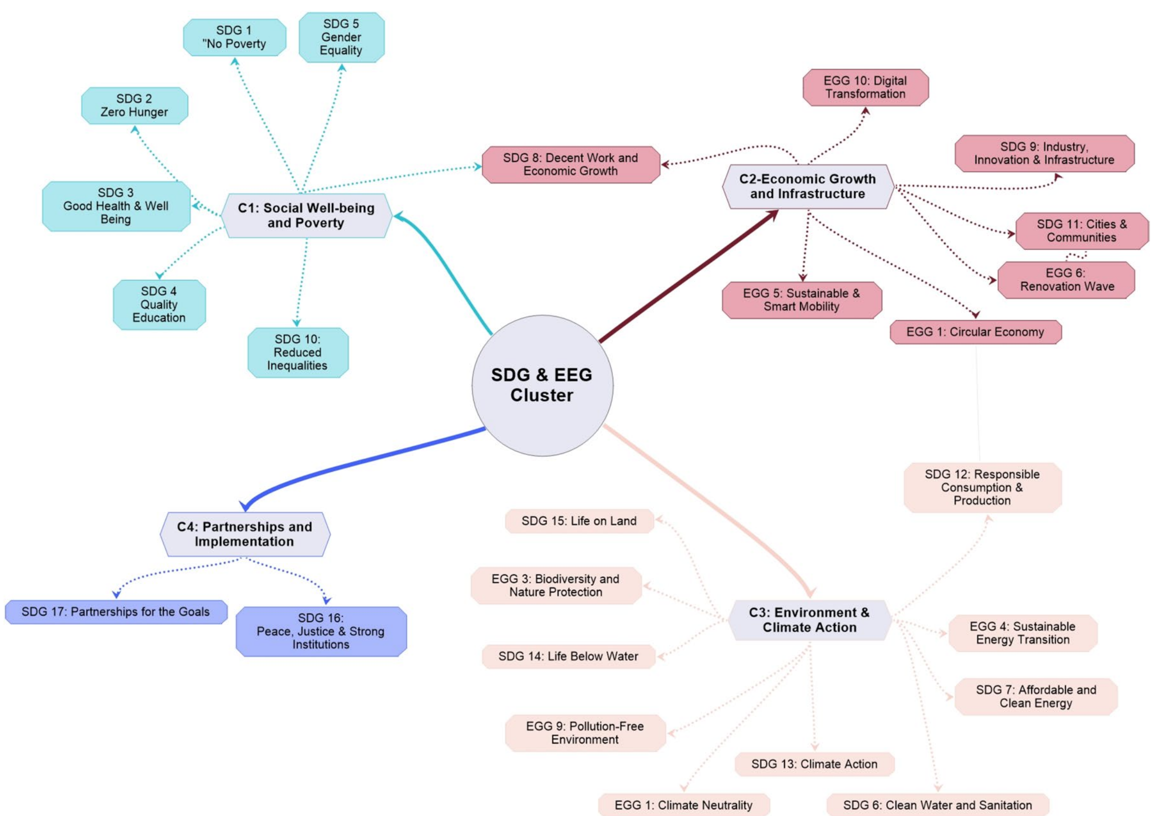


Fig. 3 The 4 Clusters of the SDGs and the European Green Deal Goals

requires holistic approaches that consider socioeconomic and environmental effects simultaneously. Developing effective policies to tackle interconnected issues such as climate change, loss of biodiversity, and resource scarcity showcases how systemic thinking can lead to more effective sustainability strategies (Liu et al. 2015). Analytical and theoretical frameworks also play an important role in understanding the intersections between environmental and social domains. Frameworks such as the capability approach and social capital are used to analyze these interactions. Understanding the environmental-social interface is crucial to holistically address sustainability, as frameworks that consider both social and environmental dimensions can lead to more sustainable outcomes (Lehtonen 2004). Finally, the conceptual representation of sustainability itself can influence how these intersections are understood and acted upon. Some research critiques traditional visual representations of sustainability, advocating for models that depict the dynamic and interconnected nature of sustainability dimensions (Lozano 2008).

As a result, the proposed clustering has to be seen as a highly simplified approach to help understand the application of AI in the wide range of SDGs and European Green Deal goals rather than strict and non-overlapping clusters.

Artificial intelligence

AI encompasses a wide-ranging field with the objective of developing systems capable of performing tasks that traditionally require human intelligence. Such tasks include learning from experience, interpreting natural language, discerning patterns, and decision-making (Kühl et al. 2020; Schoormann et al. 2023).

In discussions of AI, several terms such as ML, Deep Learning (DL), and Statistical Learning are frequently used in a similar context. Although these terms are widely applied across various domains, their exact definitions and usage can vary, often resulting in misunderstandings. Figure 4 illustrates the relationships and terminologies within these fields (Kühl et al. 2020).

ML, a subset of AI, is a computational technique that uses information to improve performance or make accurate predictions (Mohri et al. 2018). It is characterized by its ability to learn from data without being explicitly programmed. ML algorithms are often categorized into supervised learning (SL), unsupervised learning (UL), and reinforcement learning (RL). However, for more nuanced classification, additional variations such as Semi-Supervised Learning, DL, Transfer learning, and Ensemble learning are considered. These provide a more comprehensive and granular differentiation of methods and approaches (Kühl et al. 2020; Mohri et al. 2018).

DL, a subset of ML, uses ANNs with multiple layers. These layers allow the model to learn complex patterns from large amounts of data in hierarchical order. DL has been instrumental in breakthroughs related to classification, speech recognition, NLP, and other tasks such as computer vision (CV) (Mohri et al. 2018; Schoormann et al. 2023).

Building on these advances, the latest trend in AI is the development of even larger and more powerful language models. For example, GPT-3 (4) one of the latest iterations of the Generative Pre-trained Transformer series has 175 (1700) billion parameters, making it one of the largest and most powerful language models to date (Brown et al. 2020). These models are increasingly adept at understanding context, which makes them more useful for a wide range of

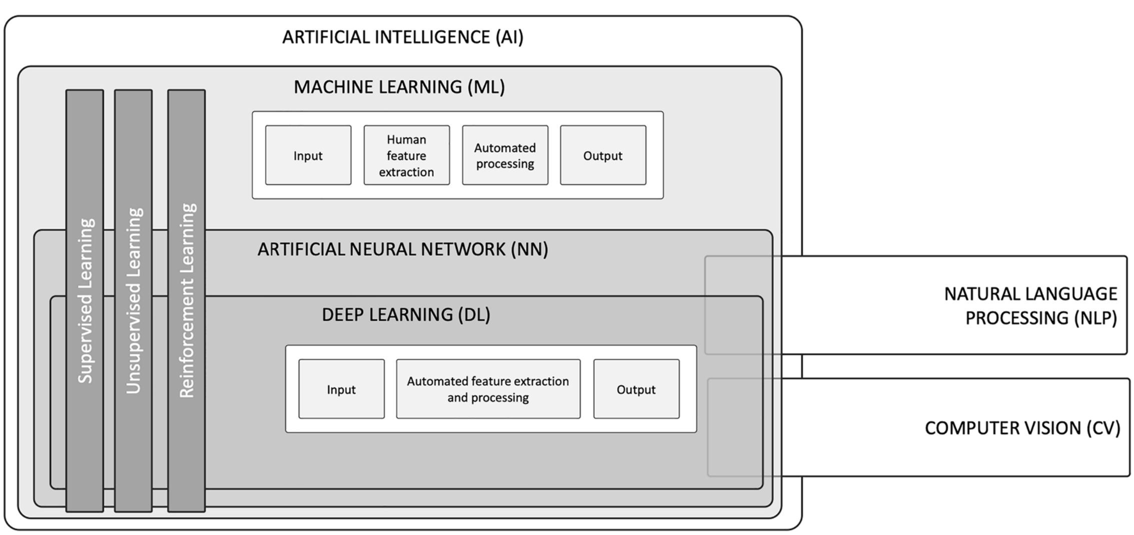


Fig. 4 General terminology for this literature review (Schoormann et al. 2023)

tasks (Ding et al. 2023). This transition from DL to large language models (LLMs) and generative models, in general, illustrates the interconnections and continuous evolution of these fields. In terms of sustainability, LLM and generative AI have several potential applications. For example, they can be used to optimize energy use in data centers or other large-scale operations, reducing their environmental impact (Schwartz et al. 2019). They can also be used to model and predict the effects of climate change, helping policymakers make informed decisions about sustainability measures (Rolnick et al. 2019).

However, it is important to note that these models also have environmental costs. Training large AI models requires a significant amount of computing resources, which in turn requires a lot of energy. This led to concerns about the carbon footprint of AI research and efforts are being made to become more energy efficient (Strubell et al. 2019). In summary, generative AI and LLM represent an exciting frontier in AI research. They have the potential to revolutionize many industries and contribute to sustainability efforts.

Related works

The integration of AI in diverse sectors has garnered significant attention, highlighted by the extensive literature that evaluates its applications and contextual effectiveness. This section will delve into how AI has been utilized within various sustainability domains, reflecting on both the breadth of coverage and potential areas that may require further investigation.

In the realm of environmental and sustainability research, LLMs and NLP have emerged as powerful tools. For example, the pivotal role of AI in the advancement of climate research and sustainability efforts is discussed, advocating a regulated progression of AI technologies to address major social challenges such as climate change. The role of AI in improving research operations, democratizing knowledge access, and aiding comprehensive policy development is emphasized, with a call for proactive regulation over halting technological advances (Larosa et al. 2023).

Furthermore, the literature reveals a substantial focus on the intersection of information systems and AI within sustainability contexts. Studies demonstrate the transformative impact of AI on the sustainable energy sector. A framework for AI-based energy efficiency improvements and the integration of renewable energy into the grid is presented (Schoormann et al. 2023). ML applications are explored to optimize energy production and reduce environmental impact (Ahmad et al. 2021). The applications of AI in renewable energy, including DL tools for energy demand prediction and smart meter analysis, are reviewed (Rangel-Martinez et al. 2021).

AI applications in sustainable food systems are explored, focusing on precision agriculture, supply chain optimization, and reducing food waste. The role of AI in agriculture, particularly in precision farming technologies such as remote sensing, AI-driven irrigation systems, and predictive pest control models, is highlighted (Camaréna 2020). The role of AI in sustainable healthcare is investigated, focusing on diagnostics, patient management, and resource allocation for energy-efficient hospital operations (Vishwakarma et al. 2023). The applications of AI in water and wastewater management, where AI optimizes treatment processes, monitors water quality, and improves resource management efficiency was evaluated (Viet et al. 2022).

Regarding predictive technologies, an extensive review of ANN, Support Vector Machines (SVM), and other time series prediction techniques is provided for building energy optimization (Ahmad et al. 2014). AI-based forecasting models are also compared, including regression methods to optimize building energy consumption (Deb et al. 2017). Different AI models, such as regression models and decision trees, are explored to predict building energy use, highlighting the critical role of accurate forecasting in building energy management (Zhao and Magoulès 2012). Emerging AI methods in structural engineering are also examined, discussing the expanding influence of AI on structural health monitoring, design optimization, and predictive maintenance in construction (Salehi and Burgueño 2018).

Another study evaluates the effectiveness of various ML models in predicting daily streamflow in a semi-arid river using key hydro-meteorological factors such as rainfall, temperature, and solar radiation. The study applies models including bagging ensemble learning, boosting ensemble learning, Gaussian process regression (GPR), and automated machine learning (AutoML). Among these, bagging ensemble learning was the most effective, achieving a correlation coefficient of 0.80 and root-mean-square error (RMSE) of 218 (Kumar et al. 2024).

In the social domain, an article explores the implications of ChatGPT and AI on humanity, science, and education. It debates whether ChatGPT-4 represents a revolutionary advancement in machine science or an epistemological threat. The authors discuss AI's impact on various fields, including education, where it raises concerns over job displacement, ethics, and biases in AI systems. A critical perspective is given on how AI challenges traditional human roles in knowledge production, with questions raised about the potential for AI to exceed human cognitive capacities and whether AI might blur the line between human and ML in the future (Peters et al. 2024). A similar article links generative AI developments with discussions on job displacement and productivity growth. It explores how AI, particularly through computational processes and immersive reality, transforms employment and redefines job roles, offering new perspectives on workforce skills and operational efficiency. AI is presented as a disruptor of traditional labor practices, challenging the idea that human workers alone are essential for productivity. The text emphasizes that AI is not just an automation tool but part of a larger shift that reconfigures managerial roles, workforce demands, and labor market outcomes in a world increasingly driven by ML and autonomous systems (Cramarenco et al. 2023). In addition, an article connects the impact of AI with discussions surrounding the skills and well-being of employees in the global labor market. It examines how AI, particularly through the adoption of new technologies, reshapes employee skills, necessitating up-skilling and re-skilling, and its effect on personal well-being. AI is presented as a key driver of change, challenging traditional role and competency roles, while the need for digital skills is emphasized. The text underscores that AI is not merely a tool, but part of a larger shift that redefines both professional and personal dimensions of work, influencing employee satisfaction, mental health, and overall job security in an increasingly automated global economy (Lazaroiu and Rogalska 2023).

This review adopts a wider approach, including various SDGs to offer a holistic perspective on AI applications in multiple domains. This differs from previous sector-specific reviews, such as those focused on AI and data fusion in environmental monitoring (Holloway and Mengersen 2018), and analyses of pre-2022 algorithms used in this field (Kar et al. 2022). The rapid expansion of AI-driven research, particularly in sustainability, demands continuous updating and reassessment of the literature.

Furthermore, many of the reviews mentioned were published before 2020 and may not adequately reflect the latest advancements such as the transformer architecture and LLMs. Furthermore, the predominant focus on SL and UL in the existing literature overlooks the growing relevance of RL, underscoring a significant gap. Given the fast-paced evolution of the field, addressing these gaps is crucial. This involves identifying key sustainability sectors where AI has been applied and pinpointing overlooked areas that may benefit from AI integration. Furthermore, in light of the rapid advances in AI methodologies, we must consider strategies to remain at the forefront of long-lasting innovations, ensuring that our research remains relevant and impactful in addressing sustainability challenges.

To provide a deeper understanding of this research domain, we conducted a comprehensive and structured review of the literature. This review is based on the following research questions.

- RQ1: What AI methodologies have been implemented to address specific SDGs?
- RQ2: What are the potential future areas of interest in the AI domain for advancing the SDGs?

In addressing RQ1, our goal is to provide a detailed overview of various AI methods utilized for different SDGs. This will help to elucidate how AI contributes to the achievement of specific sustainability goals, clarifying the current landscape of AI applications in sustainability. For RQ2, our aim is to identify future research directions by uncovering potential applications of AI that have not yet been realized in the context of the SDGs. This question is motivated by the identified gaps in the literature, particularly the need to explore the applications of newer AI methodologies such as RL and the latest advancements in AI technologies. Through exploration of these research questions, our aim is to improve the understanding of existing AI techniques used in the context of the SDGs and to pinpoint prospective directions for future research. This will ensure that our work not only reflects the state-of-the-art but also guides future efforts toward more impactful and comprehensive AI applications in sustainability.

Research methodology

Sample, sources, and data

The search included prominent databases such as IEEE Xplore Digital Library, Scopus, Web of Science, ACM Digital Library, and ScienceDirect, using a combination of keywords as depicted in the PRISMA flowchart (Fig. 5). The search period was limited to peer-reviewed academic journals and conference proceedings written in English from the start of 2017 to the end of 2023.

We supplemented our search strategy with a snowball search based on reviews of core literature in this area of interest. This method allowed us to identify and include additional relevant studies that may have been missed in the initial database search or have been published before our cut-off date. The core literature for snowballing was based on reviews by Kar et al. (2022), which analyzed algorithms used before 2022, thus overlapping with our search period. Furthermore, Schoormann et al. (2023) had a focused view on the energy sector, which is a secondary focus of our review, yet many relevant articles were identified.

In the selection phase, a threshold SJR (SCImago Journal Rank) score of 1 was used to ensure the inclusion of journals with a standard level of scientific influence and quality in their academic discipline (González-Pereira et al. 2010). This means that during the initial screening phase, any journal with an SJR score below 1 was excluded from further consideration. However, it is important to note that this SJR threshold was specifically used only in the screening phase to narrow down the pool of potentially relevant journals. For the subsequent snowballing phase, which involves following citation trails to identify additional relevant articles

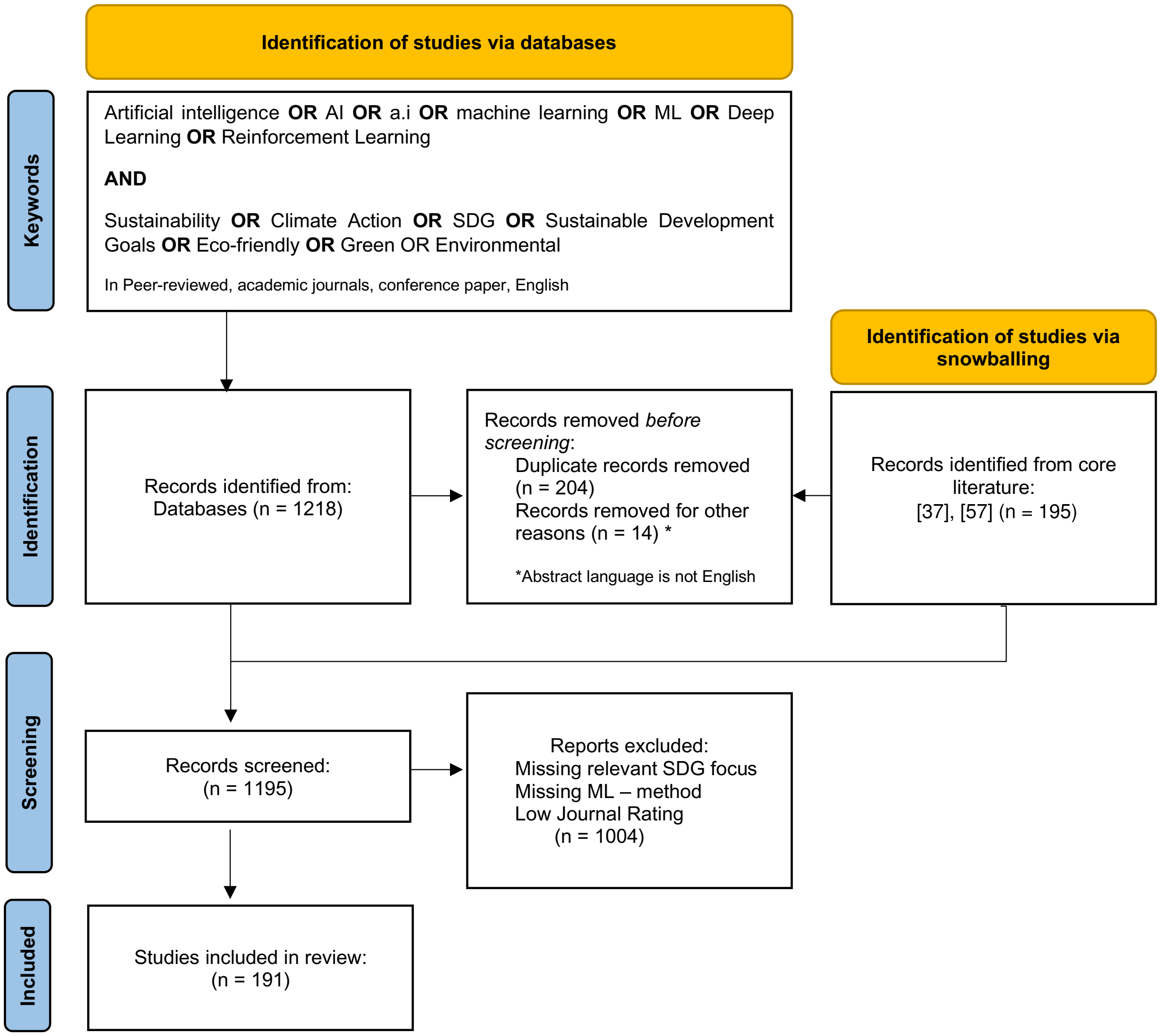


Fig. 5 Adapted PRISMA flow (Page et al. 2021)

regardless of the journal's SJR score, the SJR threshold was not considered. This approach in the snowballing phase allows for the inclusion of potentially valuable studies that could reside in less cited journals, ensuring a comprehensive review of all relevant literature without bias towards journal impact factors.

In our systematic review of the intersection between AI and sustainable development, careful selection of keywords was crucial to accurately capture the relevant literature. The keywords chosen span a broad range of concepts associated with both AI technologies and sustainability issues.

Initially, we identified primary keywords for both domains, including "Sustainability OR SDG OR Sustainable Development Goals" to capture a holistic view of the sustainability domain, and "AI OR artificial intelligence OR a.i. OR Machine Learning OR ML OR Deep Learning" to encompass the range of AI methods used to address various SDGs.

In the second step, we enriched these broad keywords. For AI keywords, we addressed a gap in the literature concerning the identification of RL methods used in the context of the SDGs, as several reviews focused on SL and UL but neglected RL. Therefore, we integrated "Reinforcement Learning" as a separate keyword, while SL and UL are covered more broadly with the general terms.

The sustainability keywords were enriched with environmental sustainability keywords, focusing on climate action: "Climate Action OR Eco-friendly OR Green OR Environmental." Given that sustainability is a very broad concept, not all relevant keywords can be included. Therefore, we limited the addition of keywords in the sustainability domain to a maximum of five keywords to maintain focus and manageability. Furthermore, any keyword that did not achieve a consensus of at least 50% among the authors was excluded.

Our emphasis on environmental keywords is driven by several reasons: First, the foundational role of the biosphere, as illustrated by the Stockholm Resilience Center's wedding cake model, positions environmental sustainability as the basis upon which societal well-being and economic prosperity are built. Second, the European Green Deal emphasizes the urgent need to address environmental issues, particularly climate action, as a critical priority. Third, the literature underscores that significant impacts can be achieved in the environmental domain, highlighting the practical focus on areas where AI can produce tangible and quantifiable benefits (Larosa et al. 2023; Camaréna 2020; Vishwakarma et al. 2023; Viet et al. 2022; Vinuesa et al. 2020).

The keyword selection process is summarized in Table 1.

Data analysis procedure

Following the selection of keywords, we systematically analyzed and evaluated the identified studies, examining their research methods, findings, and contributions to the field with a focus on quantifying potential reductions in resource consumption and greenhouse gas emissions enabled by different AI technologies. This allowed us to synthesize a comprehensive overview of the current state of research in this area.

The data analysis procedure was carried out in the following steps:

1. **Initial Screening:** During the initial screening phase, studies were evaluated based on the inclusion and exclusion criteria summarized in Table 2. The screening process involved reviewing only the titles and abstracts of the studies to determine their relevance. The inclusion criteria ensured that only peer-reviewed academic journals and conference proceedings were considered. Articles had to be written in English and fall within the scope of the SDGs or the European Green Deal. Furthermore, studies needed to have a minimum SJR score of 1. The exclusion criteria filtered out non-peer-reviewed sources, articles without full text, those not within the specified context, or lacking AI methodology.
2. **Detailed Analysis:** For studies considered relevant or for those where the relevance was ambiguous based on the title and abstract, the complete article was examined.

Table 1 Keyword selection process and their specific rationale

Step	Keyword	Rationale for selection
Step 1	Artificial Intelligence, AI, a.i., Machine Learning, ML, Deep Learning	These terms aim to cover a broad spectrum of AI technologies pivotal for addressing SDGs, capturing the variety of methods used in AI-driven sustainability solutions
Step 1	Sustainability, Sustainable Development, SDG	These keywords are selected to encompass both the process ("Sustainable Development") and the goal ("Sustainability") of maintaining global socio-economic growth without depleting natural resources, acknowledging their slightly different connotations in the literature. Additionally, "SDG" emphasizes the global commitment towards these goals
Step 2	Reinforcement Learning	We addressed the gap in the literature concerning the identification of RL methods used in the context of the SDGs, as several reviews focused on SL and UL, but neglected RL. Therefore, we integrated RL as a separate keyword
Step 2	Climate Action, Eco-friendly, Green, Environmental	Focused on the environmental aspects of the SDGs, these terms ensure the inclusion of studies that are involved in ecological preservation and the development of environmentally conscious technologies. "Climate action" aligns directly with SDG 13, targeting climate change mitigation, whereas "Eco-friendly" and "Environmental" broaden the scope of the review to include general environmental stewardship

Table 2 Inclusion and exclusion criteria used for the initial screening and detailed analysis of the review

Inclusion criteria	Exclusion criteria
Peer-reviewed academic journals and conference proceedings	Not open access or paper without full text
Articles published between 2017 and 2023	Neither within the SDG context nor within the European Green Deal context
Articles written in English	Missing AI methodology
	Studies with a SJR score of<1

Each selected study was then analyzed in detail with a focus on:

- Research Methods: The type of AI techniques used, such as ANNs.
- Findings: Key outcomes and results of applying AI technologies in sustainability contexts.
- SDG Cluster: Determining the relevant SDG Cluster for each article.

3. **Synthesis of Results:** The findings from the detailed analysis were synthesized to provide a comprehensive overview of the current research landscape.

Results

The subsequent section outlines the findings of our review. It is important to note that the main focus of this study is the intersection of AI and sustainability. Although a related concept, sustainable AI, is an important sub-stream within this context, it is not the main area of research.

First, we analyzed the studies from a geographical, i.e., continental perspective. Figure 6 illustrates the geographical distribution of the authors who contributed to research on AI applications related to the SDGs. Six continents, Asia, Europe, North America, Africa, Oceania, and South America, are represented by distinct arcs, with the size of each arc corresponding to the proportion of authors from that region.

Asia contributes the highest share of authors at 40%, followed by Europe at 26% and North America at 25%. Fewer contributions come from Africa (5%), Oceania (4%), and South America (1%).

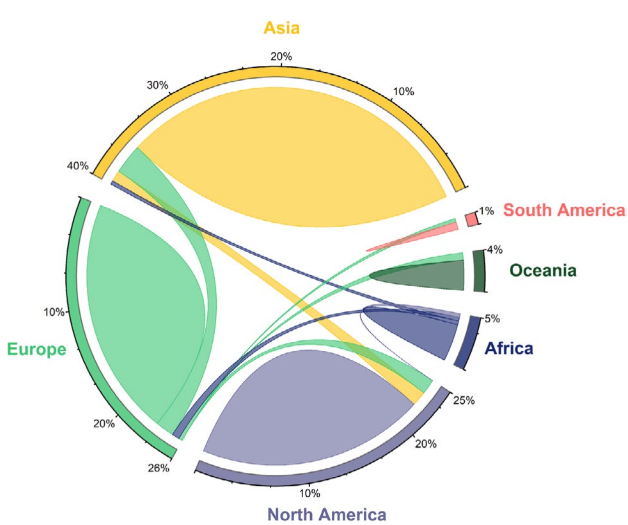


Fig. 6 Geographic distribution of AI-SDG research authors

The chords between continents represent co-authorship and collaboration. Asia shows extensive internal collaboration, with strong links to Europe and North America. Similarly, Europe and North America have robust internal and intercontinental ties, particularly with Asia. In contrast, Africa, Oceania and South America have fewer collaborative connections, primarily linking to Europe and Asia.

In general, the diagram highlights the dominance of Asia, Europe, and North America in AI related SDG research, while also demonstrating that collaborations are generally stronger within the same continent compared to between different continents.

Table 3 was created based on a combination of the results of the consensus-based survey of Vinuesa et al. (2020) and the structural framework outlined by Schoormann et al. (2023). To further refine this structure, we adapted it to our clustering approach, allowing for a more tailored representation of how AI methodologies align with the SDG clusters.

The table categorizes the impact of AI on the SDGs by indicating potential positive and negative effects. Each column of the table corresponds to a different SDG, represented by its respective number. The columns adjacent to each SDG show percentages reflecting the extent of AI's impact: one for positive impacts and another for negative impacts on the targets within that specific SDG. For example, a value of 100% in the positive impact column suggests that AI is perceived capable of benefiting all the targets under that particular SDG. In contrast, an 80% in the Negative Impact column suggests that 80% of the targets could potentially experience negative effects due to AI developments. The percentages in the table depicting the impact of AI on the SDGs are derived from a consensus-based expert elicitation process. This process involved gathering insights from a diverse group of experts, including those with backgrounds in engineering, social sciences, sustainability, and other relevant fields. These experts use a systematic approach to assess the extent to which AI can enable or inhibit the achievement of specific targets within each SDG. Expert elicitation is informed by a comprehensive review of the existing literature and studies that link AI technologies to the targets of the SDGs. Experts evaluate evidence from various sources, including peer-reviewed publications, reports from reputable organizations, and real-world applications of AI. Each piece of evidence is scrutinized for relevance, reliability, and applicability to the targets being assessed (Table 4).

It is important to note that the fourth cluster, which focuses on partnerships and implementation, could benefit the least from the continued emergence of AI because it relies a lot on social interactions and relationships.

If we focus on the methodology rather than the use cases and examine our sampled articles, the results of the review

Table 3 Clustering SDGs and assessing the potential benefit of AI - based on Vinuesa et al. (2020); Schoormann et al. (2023)

SDGs	1 No poverty	2 Zero hunger	3 Good health and well-being	4 Quality education	5 Gender equality	6 Clean water and sanitation	7 Affordable and clean energy	8 Decent work and economic growth	9 Industry, innovation and infrastructure	10 Reduced inequalities	11 Sustainable cities and communities	12 Responsibleconsumption & production	13 Climate action	14 Life below water	15 Life on land	16 Peace, justice and strong institutions	17 Partnerships for the goals
Social well-being and poverty	•	•	•	•	•			•		•							
Economic growth and infrastructure								•	•		•						
Environment & climate action						•	•					•	•	•	•		
Partnerships and implementation																•	•
Positive impact of AI	100%	75%	69%	100%	56%	100%	100%	92%	100%	90%	100%	82%	80%	90%	100%	58%	26%
Negative impact of AI	86%	25%	8%	70%	33%	63%	40%	33%	50%	70%	20%	27%	20%	30%	33%	25%	11%

reveal that SL (65%), followed by UL (18%) and RL (17%) was the primary method used.

Focusing on methodology rather than the use cases highlights the importance of understanding and refining methods themselves within AI-driven sustainability research. This emphasis is crucial because different AI methodologies, such as SL, UL, and RL, bring unique approaches to problem-solving. This focus leads to novel insights and potential solutions, with specific methodologies showing suitability for particular problems, and allows for the improved understanding and optimization of AI models.

This distribution differs from the results of Schoormann et al. (2023), who classified 88% into the Supervised Learning category, but completely neglected RL. A more detailed overview is given in Fig. 7, which highlights the correlation of the ML methods used in the reviewed articles.

Although the primary focus is on environmental and climate issues, as indicated by the keywords biased toward these topics, our analysis adopts a broader perspective by evaluating all four clusters. This inclusive approach is reflected in our consideration of all relevant papers that contribute to the SDGs, regardless of their specific focus.

The majority of the articles reviewed (74%) are found in Cluster 3 "Environment and Climate Action", followed by Cluster 2 "Economic Growth and Infrastructure" (21%), and Cluster 1 "Social well-being and Poverty" (5%). We found no articles for Cluster 4 "Partnerships and Implementations".

The predominant techniques in their respective AI category are ANNs (23%), K-Means Clustering (4%) and Deep Reinforcement Learning (DRL) (5%).

To enhance comprehension of the review, the subsequent subsections will disaggregate the overall picture into subdomains of Supervised, Unsupervised, and RL. Within each subsection, we initially present the distribution of articles according to the clusters and methods used. Subsequently, several examples are elucidated, and a table consolidates the distribution of the articles.

Supervised learning

In Supervised Learning, algorithms are trained using labeled data, with guidance provided by an error function that the algorithm tries to minimize. The primary distinction between neural and non-neural approaches within Supervised Learning lies in the utilization of ANN as the foundational model in the former, while the latter encompasses a broader spectrum of conventional algorithms, including, but not limited to, Decision Trees, SVMs, and Linear Regression (LR) Mohri et al. (2018).

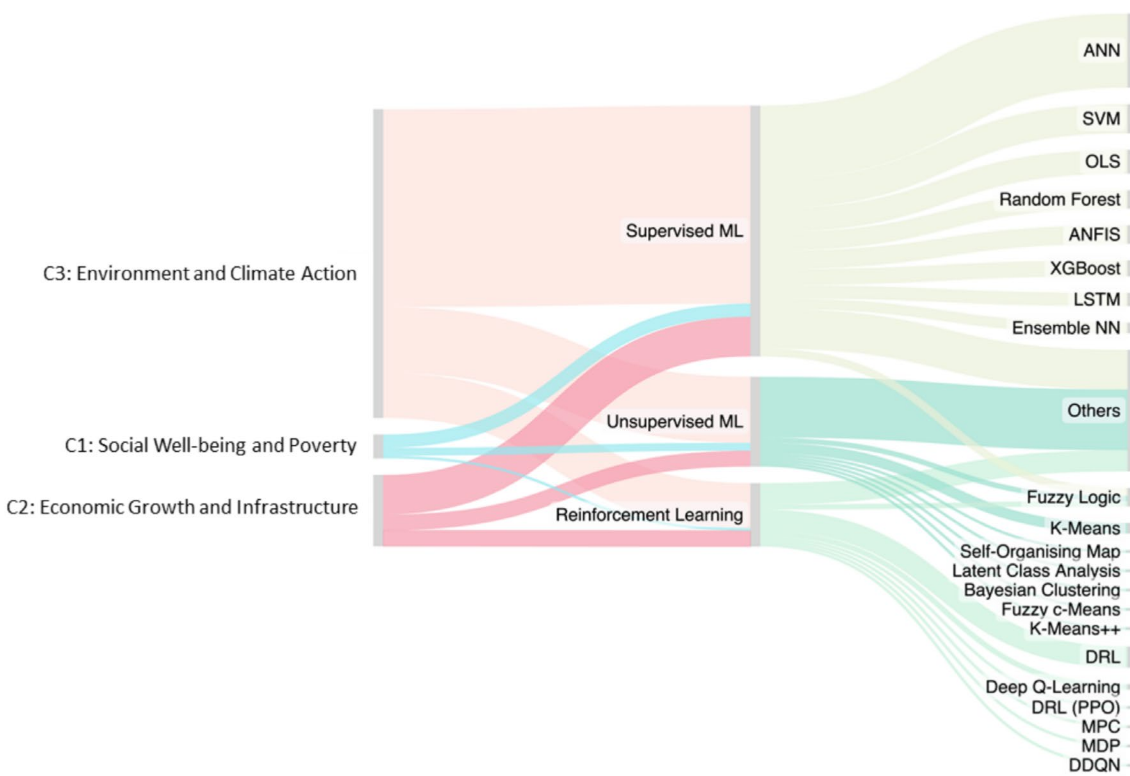


Fig. 7 Correlation of Sustainability Clusters to ML Paradigms and Their Respective Methods (Note: "C4: Partnership and Implementation" is not included in the results due to the insufficient number of studies available to provide a robust analysis for this cluster)

Figure 8 offers a filtered perspective, highlighting the specific algorithms used. A trend towards architectures predicated on neural architectures (e.g., ANNs, Long-Short-Term Memory (LSTMs), Ensemble Learning) is observed, while traditional ML algorithms such as SVMs and Random Forests (RFs) are still present.

Non-Neural We identify that a diverse array of non-neural approaches have been used to address various sustainability issues. For example, LR, RF, and support vector regression have been used to predict electricity and gas consumption in the United States (Kontokosta and Tull 2017). Mirroring this methodology, Gradient Boosting has been used to estimate energy consumption in commercial buildings (Robinson et al. 2017). Several algorithms, including LR, RF, and SVM, have been employed to design a sustainable concrete mix (Naseri et al. 2020), and to evaluate the environmental footprint of returning home (Shinde et al. 2022). Extreme Gradient Boosting (XGBoost) has been implemented in sustainable agriculture (Mohammed et al. 2023). The scarcely used classification and regression tree (CART) algorithm has been applied to determine the feed modes of the lines for the components (Zangaro et al. 2021). The strengths of these methodologies encompass the interpretability of OLS, the ability of RF to decipher complex relationships, and the proficiency of SVM in managing non-linear data (Kontokosta and Tull 2017).

Neural

ANNs are identified as the primary method used, demonstrating their versatility in various sustainability domains. For example, ANN-based models have been used to predict global CO2 emissions (Jena et al. 2021), soot emissions (Jadidi et al. 2020), and NOx emissions from combustion of solid fuels and air in large fluidized circulating bed boilers (Krzywanski et al. 2014; Krzywanski 2022). A Generalized Mapping Regressor (GMR) Neural Network, a Multi-Layer Perceptron (MLP), and a General Regression Neural Network (GRNN) were used to estimate the power curve of a wind farm. The results show that the non-parametric approach achieved satisfactory performance (Marvuglia and Messineo 2012).

LSTM architectures have been shown to be especially effective, outperforming other approaches to predict water and energy requirements for sensor-based agriculture (Mohammed et al. 2023). Recurrent Neural Networks (RNNs) have been widely used in sustainable agriculture (Wongchai et al. 2022).

Fuzzy Neural Networks (FNN) systems are present in various use cases (Elavarasan and Vincent Durai Raj 2021; Ye et al. 2020). Convolutional Neural Networks (CNN) Gao et al. (2021) and LSTM models are used to improve the prediction of energy consumption for green buildings, in order to improve user comfort, safety,

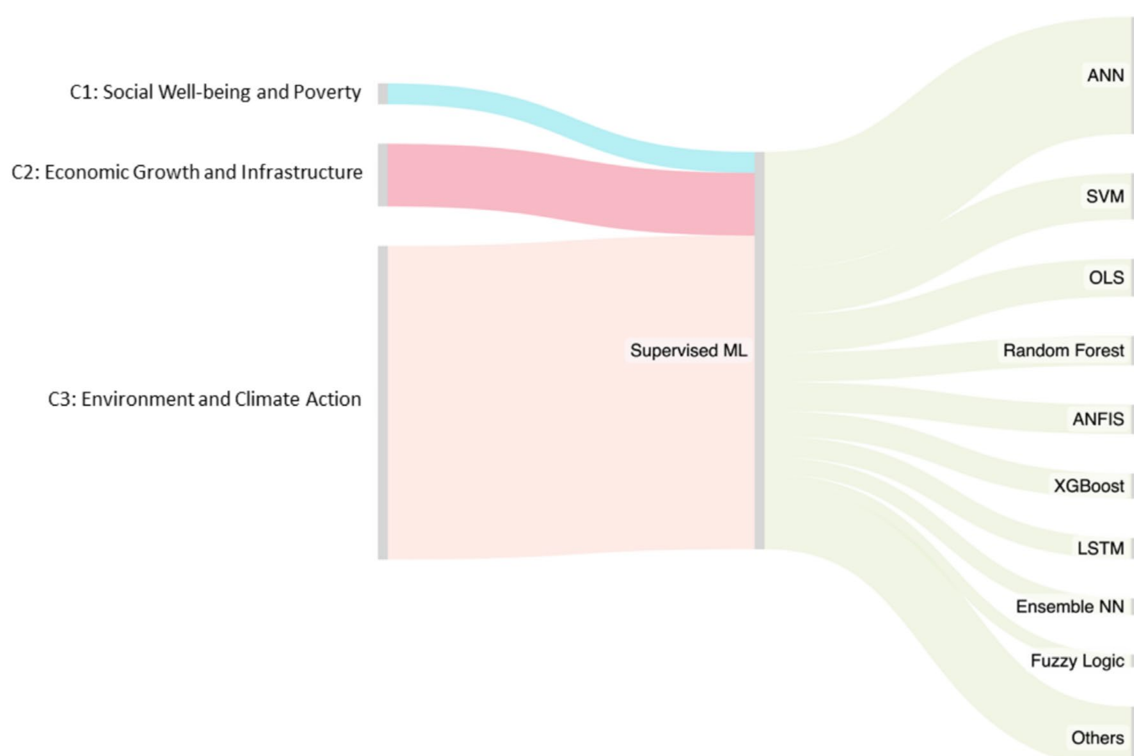


Fig. 8 Correlation of sustainability clusters to supervised learning with its respective methods

Table 4 Overview of articles using supervised learning

SDG Cluster	Algorithm	Paper
C1: Well-being and Poverty	ANN	Jiang et al. (2017), Somers et al. (2021)
	OLS	Jiang et al. (2017)
	XGBoost	Dong et al. (2020)
	Others	Vishwakarma et al. (2023), Damiani et al. (2021), Podder et al. (2021)
C2: Economic Growth and Infrastructure	ANN	Gordan et al. (2021), Wong et al. (2010), Gao et al. (2021), Kassem et al. (2021), Tümer and Akkuş (2018)
		Feng and Zhang (2014), Milačić et al. (2017)
	SVM	Kontokosta and Tull (2017), Kim et al. (2019), Begli et al. (2019)
	OLS	Biller (2019), Aljawder and Al-Karaghouli (2022), Kontokosta and Tull (2017)
	Random Forest	Kontokosta and Tull (2017), Kuenzel et al. (2016), Khalaf (2020)
	XGBoost	Elavarasan and Vincent (2020)
	LSTM	Gao et al. (2021), Sharma et al. (2020), Kocaman and Tümen (2020)
	Fuzzy Logic	Gordan et al. (2021), Li et al. (2020)
	Other	Nemes et al. (2006), López-Vargas et al. (2020)
C3: Environment and Climate Action	ANN	Mohd et al. (2022), Naseri et al. (2020), Krzywanski et al. (2014), Tsang and Jim (2016), Kamali et al. (2021)
		Kaab et al. (2019), Mazzeo et al. (2023), Nabavi-Pelesaraei et al. (2018), Rangel-Martinez et al. (2021), Ye et al. (2020)
		Smith and Wong (2022), Taylan et al. (2021), Nemes et al. (2006), Mohd et al. (2022), Manzoor et al. (2021)
		Marvuglia and Messineo (2012), Wang and Srinivasan (2017), Aniza et al. (2023), Krzywanski (2022), Tsang and Jim (2016)
		Renaud et al. (2023), Asha et al. (2022), Su et al. (2023), Rangel-Martinez et al. (2021), Ferreiro-Cabello et al. (2018)
		Ahmed et al. (2019), Zafar et al. (2022), Darko et al. (2023), Budennyy et al. (2022), Kühl et al. (2020)
		Astobiza et al. (2021), Wolf et al. (2020), Hinton et al. (2018), Dellosa and Palconit (2021), Hinton et al. (2023)
		Rojek et al. (2021), Abdella et al. (2020), Sharma et al. (2020), Jena et al. (2021), Jadidi et al. (2020)
	SVM	Fijani et al. (2019), Lakhouit et al. (2023), Zhao and You (2022), Mohammed et al. (2023), Darko et al. (2023)
		Asrol et al. (2021), Naseri et al. (2020), Huang et al. (2020), Guo et al. (2021)
	OLS	Kontokosta and Tull (2017), Naseri et al. (2020), Ko et al. (2016), Cadenas et al. (2023), Raj and Carvalho (2023)
		Dai et al. (2018), Kulejewski and Rosłon (2023), Rampini and Re Cecconi (2022)
	Random Forest	Abdel-Aty and Haleem (2011), Shinde et al. (2022), Momenitabar et al. (2022), Mohammadi et al. (2022), Albaji et al. (2023)
		Pham et al. (2020), Hai et al. (2023), Naseri et al. (2020)
	ANFIS	Yani et al. (2022), Zayed et al. (2021), Krzywanski (2022), Taylan et al. (2021), Kaab et al. (2019)
		Nabavi-Pelesaraei et al. (2018), Astobiza et al. (2021), Bagheri et al. (2017)
	XGBoost	Momenitabar et al. (2022), Mohammed et al. (2023), Lăzăroiu et al. (2022), Elavarasan and Vincent Durai Raj (2021), Hu and You (2022)
		Robinson et al. (2017)
	LSTM	Riskiawan et al. (2023), Renaud et al. (2023), Mohammed et al. (2023), Xiang et al. (2022), Schürholz et al. (2020)
		Hu and You (2022), Gao et al. (2021)
	Ensemble NN	Momenitabar et al. (2022), Wang and Yao (2023), Wang and Srinivasan (2017), Wongchai et al. (2022), Fijani et al. (2019)
	Fuzzy Logic	Smith and Wong (2022), Yani et al. (2022), Zayed et al. (2021), Heo et al. (2021), Krzywanski (2022)

Table 4 (continued)

SDG Cluster	Algorithm	Paper
		Taylan et al. (2021), Bagheri et al. (2017), Tsang and Jim (2016), Kaab et al. (2019), Elavarasan and Vincent Durai Raj (2021)
		Rezk et al. (2019), Nabavi-Pelesaraei et al. (2018), Ye et al. (2020), Kim (2020), Arashpour (2023)
	Others	Afantitis et al. (2018), Schöning and Richter (2021), Ahmad et al. (2021), Frank (2021), Ahmad et al. (2022)
		Shi et al. (2022), Tsolakis et al. (2022), Marvuglia and Messineo (2012), Yani et al. (2022), Pham et al. (2020)
		Miller et al. (2020), Chen et al. (2022), Nishant et al. (2020), Sætra (2021), Karthiban and Raj (2020)
		Kar et al. (2019), Zangaro et al. (2021)

monitoring, and energy efficiency, resulting in a reduced energy consumption ratio of 15.7% (Xiang et al. 2022; Riskiawan et al. 2023; Gao et al. 2021).

Diverse DL models such as CNN-LSTM, Transformer, and Temporal Fusion Transformer (TFT) have been examined to monitor urban environmental noise in smart cities (Renaud et al. 2023). Transformers exhibit the ability to capture long-range dependencies and facilitate parallel computation, while TFT amalgamates the advantages of Transformers and Temporal Fusion models to address temporal dependencies, offer better interpretability, and manage diverse time series features, rendering it for smart city applications. Ensemble methods for waste management, together with CNNs and other neural-based methodologies, have been used for tasks such as visual pollution classification (Ahmed et al. 2019), further exemplifying the adaptability and efficacy of these approaches.

The prominence of ANNs aligns with the findings of various other studies. Specifically in the realm of environmental sustainability, with a focus on clean water and wastewater treatment, ANNs emerge as the leading AI technique (Aniza et al. 2023; Kamali et al. 2021). In research on renewable energy systems, ANNs, Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and Genetic Algorithms (GA) have been identified as the main methods for tasks related to energy management, maintenance, and control (Zayed et al. 2021; Bagheri et al. 2017; Dellosa and Palconit 2021). The superior performance of ANNs in terms of computational efficiency, accuracy, and generalization capacity compared to other methods has also been underscored (Dellosa and Palconit 2021). Furthermore, in the domain of green buildings, ANN and fuzzy logic are the most common techniques, accounting for more than 50% of applications (Smith and Wong 2022).

Unsupervised learning

UL employs algorithms that distinguish patterns and structures from unlabeled data, functioning without a predefined target outcome. This section delves into the usage of UL within the sphere of sustainability, showcasing methodologies from selected articles, and emphasizing their contributions and findings (Fig. 9).

K-means is acknowledged as the primary technique in UL in all sustainability clusters. For example, in the domain of sustainable agriculture, K-Means clustering was used to classify the size of nanoparticles in aqueous matrices (Bi et al. 2014). However, it is worth noting that other methods such as Bayesian Clustering, Latent Class Analysis, K-Means++ and Fuzzy C-Means also play significant roles, with their usage being fairly widespread. K-Means++, an enhancement of the k-means clustering algorithm, has been implemented for environmental monitoring in agriculture. This variation aims to refine the preliminary selection of cluster centroids through a more intelligent initialization step (Dooyum Uyeh et al. 2022).

In addition, there is a substantial emphasis on various specialized methodologies tailored to specific use cases. For example, a specialized unsupervised method that integrates a self-organizing map and Ward clustering has been used for investigating carbon footprints of cities in Australia. This approach facilitates the identification of lifestyle archetypes based on expenditure data and socioeconomic attributes, providing insights into household consumption patterns compared to the extensively used K-Means clustering, by incorporating additional attributes and discerning distinct lifestyle archetypes (Froemelt and Wiedmann 2020).

In contrast to findings that identified Linear Discriminant Analysis (LDA), K-Means, Stacked Autoencoders, and Principal Component Analysis (PCA) as the predominant UL techniques in the sustainability domain, ranked in

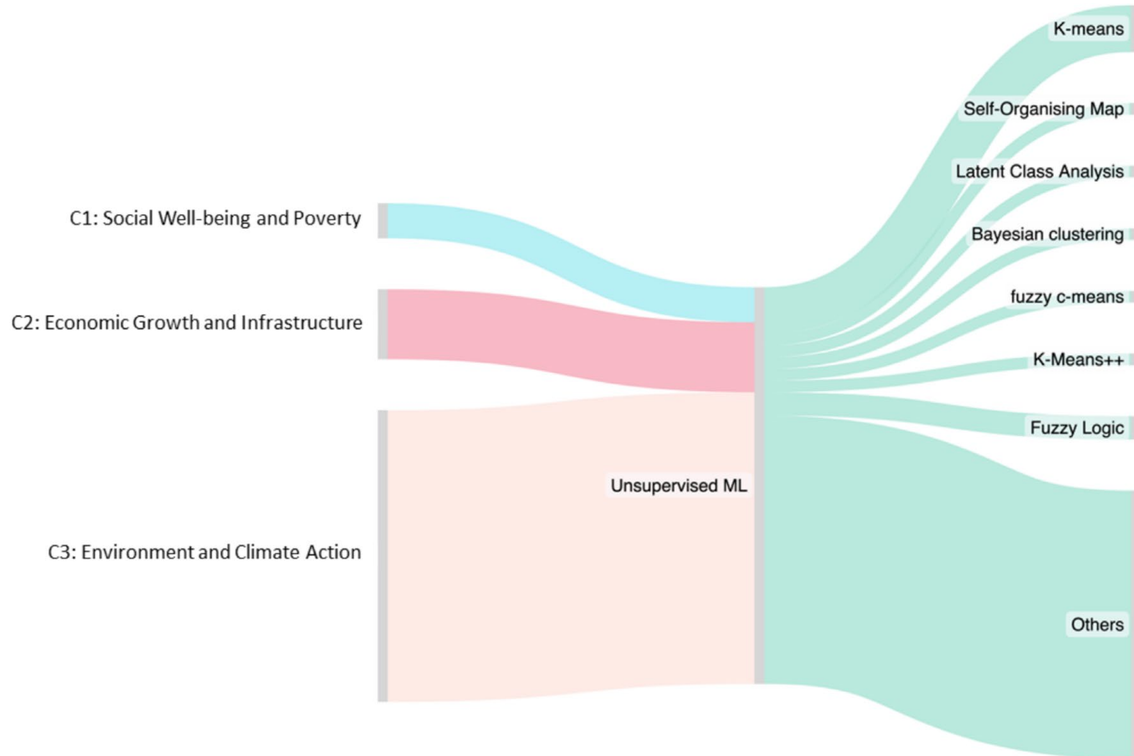


Fig. 9 Mapping of sustainability clusters to UL with its respective methods

descending order of prevalence (Schoormann et al. 2023), our review did not find LDA, Autoencoders, or PCA to be widespread (Table 5).

Table 5 Overview of articles using UL

SDG cluster	Algorithm	Paper
C1: Well-being and Poverty	Others	Mani (2022), Vishwakarma et al. (2023), Abu et al. (2020)
C2: Economic Growth and Infrastructure	K-Means	Tabianan et al. (2022), Facendola et al. (2023), Ran et al. (2021), Chen et al. (2019)
	Latent Class Analysis	Grymshi et al. (2022)
	fuzzy c-means	Parlina et al. (2021)
	Others	Liakos et al. (2018), Biller (2019), Qureshi et al. (2020), Pal and Hsieh (2021), Choi et al. (2021)
		Aziz et al. (2021), Rai and Dwivedi (2020), Li et al. (2020)
C3: Environment and Climate Action	K-Means	Bi et al. (2014), Ko et al. (2016), Abdella et al. (2020), Zhao and You (2022), Tazay (2020)
	Self-Organising Map	Froemelt and Wiedmann (2020), Wu et al. (2022)
	Latent Class Analysis	Ko et al. (2016)
	Bayesian Clustering	Ko et al. (2016), Hossain and Muromachi (2012)
	fuzzy c-means	Heo et al. (2021)
	K-Means++	Dooyum Uyeh et al. (2022), Cadenas et al. (2023)
	Others	Pedroso et al. (2010), Debrah et al. (2022), Khalaf (2020), Huang et al. (2022), Paulvannan Kanmani et al. (2020)
		Gace et al. (2021), Donti and Kolter (2021), De Clercq et al. (2018), Feng et al. (2018)

Reinforcement learning

RL is a type of ML in which an agent learns how to behave in an environment by performing certain actions and observing the results. In the context of AI and sustainability, this section examines how RL has been used, focusing on key papers and their distinctive approaches. The emergence of the RL algorithm has been mentioned for sustainable agriculture (Liakos et al. 2018), water-related SDGs (Mehmood et al. 2020; Viet et al. 2022; Hernández-del-Olmo et al. 2016), general impact on sustainability (Kar et al. 2022) (it is claimed that 45% of the articles focus on RL approaches), construction industry (Rampini and Re Cecconi 2022) but mainly with a focus on use cases and not the methodology used. The sampled studies present different RL methods used to tackle sustainability problems, each bringing unique benefits compared to traditional ML approaches (Fig. 10).

Our review identifies DRL as the main technique. In particular, deep Q-learning, a specific algorithm within the DRL framework, emerges as a prominent method used in various sustainability domains.

Q-Learning was used to recognize and model distinct phases within the life cycle of a system, allowing for adaptive decision-making at each phase, particularly in optimizing resource allocation and system management (Liu et al. 2022).

Deep Q Network (DQN), on the other hand, extends Q-Learning by using Deep Neural Networks to approximate the Q function. It was used, for example, to design an autonomous and data-driven energy management system for plug-in hybrid electric vehicles, resulting in energy savings of 16.3% compared to conventional strategies (Qi et al. 2019). Another study used the same DQN approach to optimize the environmental impact of green data centers (Zhou et al. 2021).

DRL has been applied to complex nonlinear World-Earth System models used to analyze the dynamics of biophysical, socio-economic, and socio-cultural interactions. This approach aims to identify sustainable pathways, particularly in mitigating anthropogenic climate change, while respecting both planetary and socio-economic limits. DRL is highlighted as having the potential to inform global governance policies for a safe and sustainable future (Strnad et al. 2019). Specifically in the area of DRL, Proximal Policy Optimization (PPO) has been investigated to identify sustainable pavement management strategies that result in a possible reduction in the expected impact of global warming by 16% compared to traditional practices. The results underscore the potential of DRL to create environmentally sustainable strategies with fewer training iterations, which could result in energy savings (Kazemeini and Swei 2023).

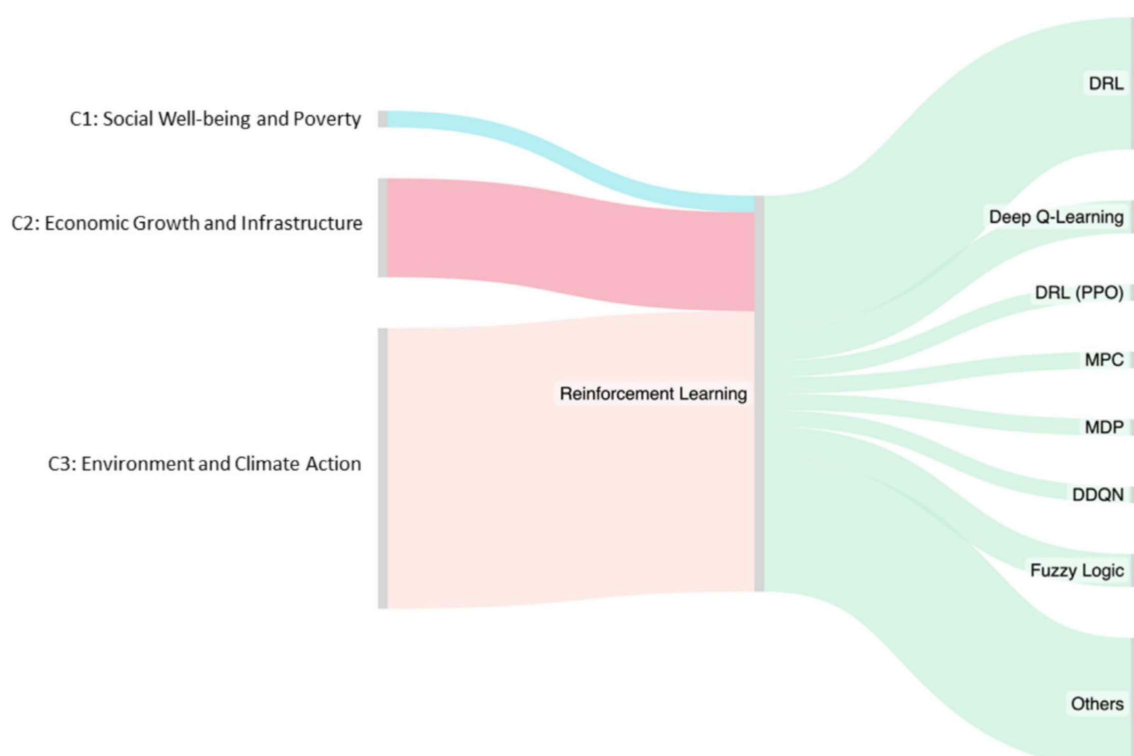


Fig. 10 Mapping of sustainability clusters to RL with its respective methods

A DRL optimization framework (DRLOF) using an Advantage Actor-Critic (A2C) agent with two different architectures, separate-A2CN and shared-A2CN, has been proposed for the electric power sector. This approach resulted in a 1.97% increase in power generation and a 1.59% reduction in NOx emissions, demonstrating the potential of DRL to improve performance while ensuring sustainability (Adams et al. 2021). Similarly, Reinforced Extreme Gradient Boosting, a combination of RL and Gradient Boosting methods, has been introduced in agricultural applications, applying RL at each node during the Decision Tree construction process to effectively utilize samples and improve performance (Elavarasan and Vincent 2020) (Table 6).

Discussion

Table 7 summarizes our key finding, the AI methodologies identified, the corresponding SDGs, their applications in sustainability, and the reasons for their use.

The methodologies are categorized into SL, UL, and RL. SL techniques such as ANNs, LSTMs, CNNs, and SVMs are used for tasks such as energy management, emission forecasting, and energy consumption prediction due to their high accuracy and ability to handle complex data. UL methods, including K-Means Clustering and SOMs, are effective for pattern recognition and environmental monitoring. RL approaches, such as DQN and PPO, are used to manage complex systems and improve energy management strategies. In addition, Ensemble Learning methods are utilized for waste management and pollution classification, leveraging multiple models to improve prediction accuracy and robustness.

Data from Fig. 1 highlighted the growing trend in academic publications at the intersection of AI and SDGs. Between 2000 and 2014, research on the role of AI in sustainability was limited, with annual publication counts ranging from 706 to 2,760, reflecting the early development of AI technologies and their minimal application in sustainability-related fields. From 2015 onward, there was a marked increase in research activity, with publication counts increasing to 3,580 in 2015. This shift aligns with the adoption of the 2030 Agenda for Sustainable Development and the formalization of the 17 SDGs, driving interest in how AI could contribute to global goals. Simultaneously, advancements in machine learning, data analytics, and automation increased the potential of AI to address challenges such as climate change, poverty, and healthcare. The upward trend accelerated after 2017, with publications nearly doubling from 7,390 in 2017 to 16,100 in 2019. This surge reflects the growing recognition of AI as a transformative tool to achieve the SDGs, supported by developments in deep learning, computational power, and data availability. Starting in 2020, the publication counts exhibited exponential growth, reaching 31,600 in 2023. This rapid increase is driven by the global urgency to meet the 2030 SDG targets, the influence of the COVID-19 pandemic on AI-driven crisis management, increased funding and policy support for AI research, and the critical role of AI in the fight against climate change.

The uneven geographical distribution of AI-SDG research, as shown in Fig. 1, could be explained by several key factors. Asia, Europe, and North America lead in

Table 6 Overview of articles using RL

SDG Cluster	Algorithm	Paper
C1: Well-being and Poverty	Others	Damoah et al. (2021)
C2: Economic Growth and Infrastructure	DRL	Khakurel et al. (2018), Selukar et al. (2022) Strnad et al. (2019)
	Deep Q-Learning	Scott-Fordsmand and Amorim (2023)
	MPC	Mani (2022)
	DDQN	Li et al. (2022)
	Others	Kuenzel et al. (2016)
C3: Environment and Climate Action	DRL	Rampini and Re Cecconi (2022), Suanpang et al. (2022), Strnad et al. (2019), Sloane and Zakrzewski (2022), Lundberg and Lee (2017)
		Oke et al. (2021), Muhammad and Hossain (2021), Popper et al. (2021)
	Deep Q-Learning	Qi et al. (2019), Pérez-Pons et al. (2021), Walk et al. (2023), Kuutti et al. (2021), Zhou et al. (2021)
	DRL (PPO)	Kazemeini and Swei (2023), Toorajipour et al. (2021)
	MPC	Li et al. (2021)
	MDP	Lekan et al. (2022), Raj and Carvalho (2023)
	DDQN	Kuutti et al. (2021)
	Others	Kar et al. (2022), Xiang et al. (2021), Hinton et al. (2018), Binas et al. (2019), Perera and Kamalaruban (2021)
		Liu et al. (2022), Adams et al. (2021), Elavarasan and Vincent (2020)

Table 7 Summary of AI methodologies, their applications, the corresponding SDG, reasons for usage, and corresponding SDGs in sustainability

Category	AI methodology	Corresponding SDGs	Applications in sustainability	Reasons for usage
SL	ANNs	7, 11, 13	Energy management, emission forecasting, pollutant classification	Short computation time, increased accuracy, generalization capabilities
SL	RNN, LSTM	2, 6, 7	Predicting water and energy requirements, sensor-based agriculture	Effective in processing and predicting temporal data with complex sequences with long-range dependencies
SL	CNNs	7, 11	Energy consumption prediction, urban environmental noise monitoring	Effective in handling spatial data and enhancing prediction accuracy
SL	FNNs, ANFIS	7, 13	Energy management, pollution control	Improves precision of predictions by combining fuzzy logic with neural networks
SL	SVMs	9, 11	Predicting energy consumption, designing sustainable concrete mixes	Effective in handling non-linear data and providing accurate predictions
SL	RF, XGBoost	2, 7, 12	Sustainable agriculture, predicting electricity and gas consumption, evaluating environmental footprints	High performance in prediction tasks due to the ability to decipher complex relationships and handle large datasets with different types of data
UL	K-Means	11, 13, 15	Pattern recognition, environmental monitoring	Simplicity and efficacy in detecting patterns and structures in data
UL	SOMs	11, 13, 15	Environmental monitoring, pattern detection	Effective in clustering and visualizing high-dimensional data
RL	DQN, PPO	7, 9	Design Energy management systems, identify sustainable pavement strategies	DRL can continuously learn and adapt from real-time data interactions, making it particularly effective in environments where conditions change frequently
Other	Ensemble Learning Methods	11, 12, 13	Waste management, pollution classification	Combines multiple models to improve prediction accuracy and robustness
Other	GA	7, 12	Optimization in sustainable energy and resource management	Effective in optimization tasks due to its ability to explore a wide solution space

AI-SDG publications due to their advanced economic and technological infrastructure, which supports high levels of research and development. These regions also have access to significant funding, cutting-edge AI tools, and strong academic-industry partnerships, enabling large-scale collaborations and a steady output of research. In contrast, regions like Africa, Oceania, and South America contribute less to AI-SDG research due to limited financial resources, fewer educational opportunities in AI, and restricted access to necessary computational infrastructure and datasets. Furthermore, researchers in these regions may prioritize local, immediate issues over AI-driven solutions due to practical constraints. This disparity highlights the need for increased collaboration and support to enhance AI research capabilities in underrepresented regions.

RQ1: What AI methodologies have been implemented to address specific SDGs

The review of the literature presented indicates a broad spectrum of ML algorithms applied within the realm of AI aimed at fostering the SDGs. The methodologies implemented span across supervised learning techniques, encompassing LR, Random Forest (RF), and SVM, to more complex DL strategies, which include a variety of neural networks such as ANNs, LSTM networks, and CNNs. Additionally, the use of RL approaches like DQL and PPO, as well as UL algorithms such as K-means and SOMs, further illustrates the extensive methodological array leveraged in this field.

ANNs, DRL, and K-Means clustering are notably predominant. ANNs are extensively used for various applications such as energy management, emission forecasting, and pollutant classification, attributed to their shorter computation time, increased accuracy, and generalization capabilities. DRL methods, exemplified by Deep Q-Network and Proximal Policy Optimization, are effective in energy management and sustainable pavement strategies, providing unique benefits over conventional ML techniques. K-Means clustering is a favored choice for pattern recognition due to its simplicity and efficacy.

With regard to SL, the diversity of applications in various domains, including agriculture, energy management, and environmental monitoring, is remarkable, showcasing the adaptability of these algorithms. However, an unbalanced distribution of algorithms is evident, with certain specialized methods being heavily favored for specific domains.

For example, ANN is frequently used in environmental applications, whereas XGBoost dominates in the agriculture and energy sectors. This concentration may reflect domain-specific preferences or data requirements, but it limits exploration of alternative methods. Furthermore, the results indicate that algorithms such as ANN, XGBoost, and similar approaches often seem to outperform other methods such as SVMs in terms of accuracy, efficiency, and scalability, as highlighted by several studies (Darko et al. 2023; Naseri et al. 2020; Smith and Wong 2022; Wang and Srinivasan 2017; Ye et al. 2020). However, a more thorough and nuanced analysis should be performed to assess the generalizability of these results, ensuring that potential biases toward popular algorithms do not overshadow other promising approaches.

Our analysis revealed certain discrepancies compared to the findings of Schoormann et al. (2023), who identified a different distribution of commonly used methods. This variation could likely be attributed to the inclusion of RL, reviewing more recent articles, and using a broader sample of articles in our review.

We align with the observations of Kar et al. (2022), who also noted a skewed distribution of ML methods in the sustainability literature, identifying a comparable set of prevalent algorithms (ANN, SVM, CNN, etc.). This alignment underscores that despite variations in keywords, databases, and search parameters, the results of different reviews consistently indicate a trend towards the use of ANNs and, as highlighted by Kar et al. (2022).

Among neural architectures, LSTMs, Ensemble Networks, and various types of ANN are prominently adopted, especially in applications such as the prediction of emissions and power management of renewable energy systems. Although its widespread use could attest to its effectiveness, deeper investigation may be needed to determine whether other architectures may have been underexplored and could potentially yield comparable, or even superior, results. In this sense, hybrid or two-stage approaches, exemplified by the method proposed by Abdella et al. (2020), present innovative and insightful perspectives that need further exploration and consideration.

RQ2: What are the potential future areas of interest in the AI domain for advancing the SDGs?

The reviewed studies highlight various ML methods, such as ANNs, K-Means clustering, and DRL, being applied in the field of sustainability. These technologies suggest opportunities for further research and application, offering significant advances in how we approach environmental and sustainability challenges. For example, replacing traditional LSTM models with Transformer-based models can enhance the processing of complex sequences Brown et al. (2020) and maintain precise long-range dependency between outputs and inputs Zhou et al. (2021). In addition, transformer models are designed to compute more rapidly than traditional LSTMs by facilitating parallel processing Vaswani et al. (2017). As for RL, there seems to be interest in applying both non-neural RL methods, such as Q-Learning and DRL, especially DQN and PPO. Although these studies demonstrate the promising applications of RL in sustainability, there are other state-of-the-art RL methods that could potentially contribute to this field. These include, but are not limited to, other model-based methods such as Soft Actor-Critic (SAC), which uses off-policy learning and entropy regularization to achieve stable and efficient learning (Haarnoja et al. 2018), and Twin Delayed Deep Deterministic Policy Gradient (TD3), which addresses the overestimation bias in Q-learning (Woo et al. 2020). These could potentially make significant contributions to the sustainability domain due to their unique characteristics, especially when dealing with complex systems and scenarios. Therefore, further exploration of these approaches in sustainability contexts would be desirable. In addition, H-DQN incorporates hierarchical structures in decision making (Kulkarni et al. 2016), which can be advantageous in managing complex persistent systems with different levels of granularity. Finally, model-based RL, which creates a model of the environment for simulation and learning, can also be an effective approach when environmental interactions are expensive or limited and were not used in the reviewed literature (Atkeson and Santamaria 1997). Furthermore, it is essential to acknowledge the emergence of innovative trends in AI. This includes the development of generative AI technologies, such as LLMs and foundation models. Models such as open-source LLAMA2 (Touvron et al. 2023) exemplify this advance, possessing the ability to generate human-like text and analyze large datasets relevant to climate and sustainability (Brown et al. 2020). These models have the potential to analyze climate data, craft reports, and even propose viable climate interventions, potentially contributing to the often overlooked cluster of "Partnerships and Implementation". Foundation models, pre-trained on extensive data and fine-tuned for specific tasks, could facilitate the creation of more accurate and efficient models for predicting climate trends and analyzing the environmental repercussions of different policies. Furthermore, recent advances in LLMs highlight the potential of hybrid learning approaches, which combine unsupervised, supervised, and RL techniques. These integrative approaches are relatively novel in the field and offer substantial benefits despite their complexity and cost. For example, a study highlights that such models can adapt to multiple environments, significantly improving their utility in diverse applications (Mutti et al. 2021). Furthermore, it was shown that unsupervised pre-training in RL enables agents to quickly adapt to various downstream tasks (Zeng et al. 2022), indicating potential benefits for applications in the sustainability sector, where adaptability to new and evolving conditions is crucial. Such synergistic models could potentially revolutionize applications within the sustainability sector. In the short term, the use of LLMs for roles such as educational aids and analytical tools shows promise, as evidenced in sectors such as medical education (Kung et al. 2023; Gilson et al. 2023). In the medium term, AI's potential to generate innovative content for scenario planning and impact assessments could be pivotal (Goodfellow et al. 2014).

Besides these developments, the incorporation of AutoML into AI-driven decision-making processes can further enhance the efficiency and effectiveness of environmental and sustainability-focused systems. AutoML, by automating key stages of the ML pipeline, including data pre-processing, feature selection, and model tuning, significantly reduces the need for human expertise and enables the rapid deployment of optimized models across various applications. For example, an AutoML framework was implemented to oversee complex energy systems aiming to achieve net zero carbon emissions. By automating the use of AI models to optimize energy use and grid operations, this framework proved successful in a multicampus microgrid setting, resulting in notable improvements in energy efficiency and emission reductions (Moraliyage et al. 2023). Likewise, another AutoML-based system was capable of diagnosing faults in intricate energy systems. This particular framework used 42 input parameters to predict failures with an accuracy of 99.23% (Krzywanski et al. 2024). Another research highlights the application of AutoML and big data optimization to enhance the design and operational strategies of adsorption cooling and desalination systems. This study introduced an innovative concept of fluidized bed adsorption to enhance system performance, achieving improved cooling capacity and desalination efficiency through optimized setups (Krzywanski et al. 2024). In addition, an AI-driven system was developed for a 660 MWe supercritical coal power plant, integrating environmental conditions and operational parameters such as boiler efficiency, turbine heat rate, and flue gas temperature into models such as ANN, SVM, and AutoML. This framework improved strategic-level performance, achieving a 3.12% point increase in thermal efficiency, equivalent to a reduction of 288.2 kilotons of annual emissions of CO2, SO2, CH4, N2O and Hg (Ashraf et al. 2021). An AI-based framework applied to fluidized bed adsorption systems also effectively predicted heat and mass transfer processes, enabling the optimization of low-grade thermal energy conversion. The system used silica gel with aluminum and carbon nanotube additives, which demonstrated a maximum water vapor uptake of 1.654 g/g and a convective heat transfer coefficient of 1212.62 W/m^2K. These findings underscore the significant potential for improving energy efficiency in adsorption cooling and desalination applications through AI-driven predictive models (Krzywanski et al. 2023).

Furthermore, the future implementation of AI for sustainability must be embedded within a well-developed innovation ecosystem to effectively manage and scale these technologies to maximize impact. This ecosystem could involve regulatory frameworks, research and development (R&D) infrastructures, financial support mechanisms, industry-academia collaborations, and active stakeholder participation. This ecosystem ensures that AI technologies are not only developed, but also deployed in ways that align with the SDGs. Regulatory frameworks are crucial for providing guidelines and standards that ensure that AI applications adhere to ethical principles and sustainability goals. This includes addressing data privacy, bias in AI algorithms, and the digital divide, as highlighted in the domain of personalized e-learning systems (Tripathi et al. 2024). Robust R&D infrastructures facilitate the continuous improvement and adaptation of AI technologies. For example, the integration of AI in ecosystem management to model complex ecological interactions and predict changes (Coccia et al. 2023) requires ongoing research to refine AI models and simulations. Financial support mechanisms, including public funding and private investment, drive innovation and ensure the scalability of successful AI applications. Optimization of renewable energy systems through AI, which improves efficiency and reliability (Raman et al. 2024), exemplifies the need for substantial financial support to support large-scale deployment. Industry-academia collaborations can spur innovative solutions by combining practical insights with cutting-edge research. The role of AI in urban planning, which optimizes land use, transportation systems, and infrastructure development (Regona et al. 2024), benefits significantly from such collaborations to address urban challenges effectively. Active stakeholder participation, including local communities, policymakers, and environmental organizations, is essential to align AI solutions with societal needs and values, ensuring broader acceptance and effective implementation. This involvement is crucial in areas such as agriculture, where AI-driven precision farming techniques help optimize yields and reduce waste (Coccia 2017). By framing AI's role in sustainability within the problem-driven innovation framework and situating it within a comprehensive innovation ecosystem, it becomes clear that AI is not just a tool but a transformative force driving targeted solutions to pressing environmental challenges. This approach underscores the importance of leveraging advanced technologies such as AI within a supportive ecosystem to create sustainable and resilient systems, aligning technological advances with ecological and social well-being.

Long-term outlook

Looking further ahead, envisioning LLMs and other AI technologies in roles such as "Guidance Counselors" and "Creative Assistants" at both individual and government levels could significantly aid in sustainable practices and informed decision making.

By 2050, AI's capacity for predictive modeling and real-time data analysis will enable governments to anticipate environmental shifts and make proactive adjustments to policies addressing climate change, biodiversity loss, and sustainable agriculture. In addition, AI could help citizens and businesses adopt greener practices by offering personalized guidance on reducing carbon footprints, optimizing energy use, and promoting sustainable consumption. As AI becomes more sophisticated, it will play a critical role in the integration of the SDGs with long-term climate action strategies, accelerating progress toward achieving net zero emissions and promoting social equity.

In addition, the growing interactions and applicability of AI technologies in fields such as healthcare, agriculture, energy, and transportation will significantly influence and change human behavior. For example, as AI systems offer more efficient solutions and personalized recommendations, individuals and organizations will increasingly adopt sustainable behaviors by default, integrating eco-friendly practices into daily routines. The ability of AI to connect and adapt strategies in multiple sectors will promote systemic changes in how societies address sustainability challenges, leading to greater synergy between different industries and a more holistic approach to environmental and social governance.

With advances in AI ethics and transparency, future AI systems will also incorporate ethical frameworks to ensure fairness, accountability, and sustainability in decision-making processes. This will be crucial in addressing the potential risks of AI, such as environmental costs and data privacy concerns. In general, the long-term integration of AI in various sectors promises to be a key driver in shaping sustainable behaviors and a resilient future by 2050.

Challenges and recommendations

As the exploration of these innovative methods and applications continues, it will be essential to address ethical considerations, challenges, and risks in AI application. DeepMind emphasizes the critical need for comprehensive evaluations of AI models, specifically designed to ensure alignment with human values and goals. These evaluations should also assess the hazardous capabilities of these systems to enhance risk management processes and prevent potential misuse or accidents (Shevlane et al. 2023). This call for caution is especially urgent given that existing AI models have already shown the ability to produce potentially harmful and unintended results, such as biased decision making or hallucination in real-world applications (Ganguli et al. 2022).

Sustainability, with its broad scope and strategic importance, faces similar challenges, necessitating risk assessment for AI models deployed in sustainability enhancement. A 2022 survey revealed that 36 % of AI researchers and stakeholders expressed concern about AI systems that could cause catastrophic events in this century, comparable to or exceeding a nuclear war (Michael et al. 2022), highlighting the social and environmental implications of extreme AI risks. AI technologies raise several ethical concerns that must be addressed to ensure that they contribute positively to sustainability goals. Ethical considerations include the potential for AI to infringe privacy through data misuse, perpetuate biases if not properly managed, and influence public policy in ways that may not align with public interest. Furthermore, the risk of automation bias, where an undue reliance on AI could overshadow human judgment, could lead to overlooking critical insights or alternative solutions (Shevlane et al. 2023). Furthermore, the significant resources required to train large AI models pose environmental and economic challenges, as energy consumption and hardware requirements can be substantial, potentially offset by the environmental benefits these models aim to achieve (Ganguli et al. 2022).

The referred challenges emphasize the importance of Explainable AI (XAI) and AI ethics. XAI refers to methodologies that aim to make AI solutions understandable by human experts, while AI ethics aims to ensure that the application and impact of AI are in line with ethical norms and values. As AI systems are increasingly integrated into society, the design and operation of these systems with respect to human rights, fairness, transparency, and accountability is essential. Sophisticated strategies in XAI and transparent AI ethics are invaluable, possessing the capability to address identified weaknesses and risks (Brasse et al. 2023). For example, these strategies could quickly detect manipulation or bias, mitigate legal risks by offering rationales for AI-driven decisions, and improve the traceability of results to address social concerns. Therefore, various companies, including Google [243] and IBM IBM (2023), are advancing the comprehensibility of their AI systems through XAI platforms.

Ethical, educational, and security considerations in the application of AI for environmental research

In the context of the increasing application of AI in environmental fields, several critical considerations should be addressed regarding the general applicability, sustainability, and ethical aspects of AI. The questions raised here are pertinent not only to the technicalities of AI deployment but also to broader issues of data safety, accessibility, and regulation, especially with respect to nonexpert users.

Non-experts' readiness for AI implementation in environmental fields

One of the main challenges for non-experts, such as workers in the environmental sectors, lies in the steep learning curve associated with the implementation and use of AI technologies. AI, especially in terms of large-scale data analysis, requires technical knowledge of algorithms, ML models, and data science principles. Although there is growing interest in the use of AI to improve decision making and optimize workflows, the ability of these workers to implement, store, and manage AI-driven metadata, software, and databases remains limited.

To bridge this gap, automation tools such as AutoML and LLMs have emerged as solutions, as they significantly lower the technical requirements for AI implementation. AutoML automates the process of selecting, tuning, and deploying machine learning models, enabling non-experts to leverage AI without extensive knowledge of the underlying algorithms. Similarly, LLMs simplify complex data analysis and decision-making tasks through natural language processing, allowing workers to interact with AI systems in a more intuitive manner.

Furthermore, it is essential that educational institutions adjust environmental courses by incorporating data science and AI subjects. These courses do not need to be highly technical but should focus on teaching the fundamental concepts of AI and data science. The primary goal is to ensure that future workers understand the underlying principles well enough to evaluate and interpret the outputs of automation tools such as AutoML and LLMs. This foundational knowledge will allow workers to make informed decisions when using AI-driven technologies, ensuring that they can benefit from these tools while maintaining data integrity and ethical standards.

AI-processed data security in the Era of quantum computing

Currently, modern classical informatics technologies provide a relatively secure environment for storing and processing AI-generated metadata. However, the emergence of quantum computing represents a potential threat to existing encryption standards. AI-supported decryption algorithms powered by quantum computing could, in theory, crack encryption that is considered safe today.

Data scientists and cybersecurity experts are aware of the potential risks quantum computing poses, especially with regard to the decryption of sensitive environmental or biomedical data. There is growing concern that once quantum computers become mainstream, encryption methods such as RSA (Rivest–Shamir–Adleman), which is based on the difficulty of factoring large numbers, and ECC (Elliptic Curve Cryptography), which provides efficient encryption with shorter key lengths, could be rendered obsolete. This raises the urgent need to develop quantum-safe encryption technologies to protect AI-processed data from unauthorized access by malicious actors in the future. Governments, research institutions, and private organizations must collaborate in the development and implementation of post-quantum cryptographic techniques to ensure data remain secure in the coming era of quantum computing.

Ethical considerations and data privacy in the context of FAIR and GDPR

The FAIR (Findable, Accessible, Interoperable, Reusable) principles promote transparency and accessibility in data sharing, especially in scientific research. However, the implementation of FAIR protocols introduces ethical concerns related to data ownership, privacy, and governance. Although open source databases facilitate global collaboration, the identity and accountability of data administrators or owners can become problematic. Open data presents challenges in protecting personal or sensitive information, particularly when stored in privately owned cloud systems.

The General Data Protection Regulation (GDPR) of the EU sets high standards for the protection of personal data, and the recently proposed EU AI Act further underscores the need for strict regulation of AI-driven data processing. These regulations require that data be handled responsibly, with strict privacy protocols in place. One of the key challenges lies in extending similar protections outside Europe, especially in countries where regulations around personal data and AI use are less stringent.

There is a need for international frameworks or agreements to ensure uniformity in data protection laws. Cloud storage services provided by private companies, such as Amazon Web Services or Google Cloud, play a pivotal role in hosting large datasets, but the question of regulatory oversight remains critical. Governments around the world may need to regulate the use of personal and research data in clouds more effectively to ensure data integrity is maintained. In this context, globally recognized ethical standards for AI usage, similar to the GDPR, would be beneficial, especially in fields such as environmental research, where data could have public health implications.

The future of AI and data regulation

Looking ahead, the regulation of AI and data safety is expected to become more stringent, especially outside Europe. Countries around the world are likely to introduce their own versions of AI regulations, following the precedent set by the European Commission. These regulations would focus not only on privacy and data security, but also on ethical AI development, ensuring that AI technologies do not lead to bias or harm, particularly in fields as sensitive as environmental and biomedical research.

Governments must work collaboratively to create a unified global framework for AI governance, one that balances openness, innovation, and ethical responsibility. In regions with weaker regulatory structures, pressure from global organizations and international standards bodies can drive stronger protections for data privacy and security.

Limitations and future work

This work is not without limitations. One primary constraint is the literature review process. Due to the vast amount of literature available, many filters were applied to condense the material to a manageable size. This may have led to the exclusion of some relevant studies that may have overlooked certain aspects or innovations in the field.

It is important to note that the selection of keywords, while comprehensive, inherently introduces a bias towards certain topics and methodologies within the field of AI and sustainability. The focus on specific terms may limit the breadth of research captured, potentially excluding studies that utilize different terminologies or explore less conventional intersections of AI and sustainable development. This bias represents a significant limitation of the study, as it could affect the generalizability and applicability of the findings across the entire spectrum of sustainability research. Acknowledging this limitation is crucial for interpreting the results within the appropriate context and for guiding future research to explore beyond the boundaries set by the initial keyword selection.

An additional limitation of this review is the reliance on the SJR threshold of 1 during the selection phase to ensure the inclusion of journals with a standard level of scientific influence. Although this approach was intended to maintain academic rigor, it may have inadvertently excluded newer emerging journals that are impactful in terms of citations but have not yet reached a high SJR score. Future studies should use tools such as AMSTAR, BIBOT, CASP, and other systematic review quality assessment tools, which would have provided a more balanced assessment of journal quality.

Another limitation is the fast-paced development in AI. The field of AI evolves rapidly, and new breakthroughs or methodologies could emerge shortly after the publication of this work. As such, some of the discussions and conclusions might become outdated or less relevant in light of new developments.

Furthermore, reporting on the effectiveness of different ML methods in addressing sustainability problems should be encouraged. To address these shortcomings, we strongly recommend incorporating a systematic effectiveness analysis in future research. Such an analysis could involve:

- **Comparative Studies:** Implement controlled experiments or comparative studies that measure the performance of popular methods against underexplored ones. This could reveal untapped potential in less conventional AI architectures that might be better suited for specific SDGs.
- **Impact Metrics:** Develop and apply clear and relevant metrics to quantify the impact of different AI methods on sustainability targets. This goes beyond the simple accuracy or loss metrics commonly used in ML and should be directly related to environmental, social, and economic benefits.
- **Longitudinal Studies:** Conduct longitudinal studies to assess the sustainability of AI implementations over time. Sustainability challenges often require long-term solutions, and the effectiveness of AI applications should be evaluated on the basis of their durability and adaptability to changing conditions.
- **Contextual Analysis:** Include contextual analysis to understand the environments in which AI methods are implemented. The effectiveness of AI technologies can vary significantly based on local socioeconomic, cultural, and environmental factors.
- **Stakeholder Feedback:** Engage with stakeholders, including local communities, policymakers, and industry experts, to gather feedback on the practical impacts of AI technologies. This real-world insight can help refine effectiveness analyses and ensure that they are grounded in actual user experiences and needs.

This analysis is beneficial for several reasons: It verifies the effectiveness of AI methods beyond their popularity or theoretical capabilities, identifies best practices for specific sustainability challenges, and ensures optimal resource allocation.

In conclusion, while this work provides valuable insight and a solid foundation for understanding the role of AI in sustainability, it should be viewed as a snapshot in time, with the recognition that the field is continuously evolving. Stakeholders should be informed about the latest advancements in AI to fully capitalize on its potential for sustainability.

Conclusion

This work has implications for a variety of stakeholders, from researchers and policy makers to industry leaders.

The deployment of AI is essential to address the multifaceted challenges of sustainable development. AI was shown to improve the ability to optimize resource use and improve energy efficiency in various use cases, which contributes to the achievement of the SDGs. However, the utilization of AI is not without challenges; it requires rigorous consideration of ethical implications and potential risks. For example, the considerable energy demands of training extensive AI models and the inherent biases within AI algorithms necessitate a careful and responsible approach to AI implementation to ensure it does not exacerbate existing social and environmental issues. The key challenges from our perspective are summarized in Table 8.

AI researchers are encouraged to continuously explore innovative applications of AI across various sustainability domains, thus broadening the scope of the impact of AI. The interdisciplinary collaboration between AI experts and sustainability professionals is vital to ensure that AI solutions are effectively aligned with real-world sustainability challenges and are developed considering diverse perspectives, particularly those of communities most affected by these challenges. Furthermore, there is a pressing need for AI researchers to prioritize the development of ethical AI by focusing on creating energy efficient algorithms, improving transparency, and ensuring fairness in automated decisions. Furthermore, given the rapid evolution of AI technologies, researchers must remain agile and receptive to new knowledge and methodologies, ensuring that their work is current and relevant. This dual focus on innovation and responsibility is essential for harnessing AI's potential to foster sustainable development while mitigating its risks.

For researchers, the insights and methodologies presented offer a foundation for further exploration of the applications of AI in sustainability. This can inspire new research directions and foster interdisciplinary collaborations. Moreover, engaging with AI can help sustainability researchers address complex problems that require the analysis of large datasets, or where traditional analytical methods fall short. The predictive power of AI can be harnessed to foresee environmental trends and their socio-economic impacts, facilitating proactive rather than reactive strategies. This integration also calls for an ethical approach to research, where sustainability researchers must consider the implications of data privacy, the fairness of AI algorithms, and the overall transparency of AI-driven decisions. Collaborations with AI ethicists and social scientists could help address these aspects, ensuring that AI solutions are developed and deployed responsibly and inclusively. Lastly, this new paradigm highlights the necessity for capacity building in AI skills among sustainability researchers to enable them to use advanced AI tools effectively. Training programs and workshops, interdisciplinary research groups, and collaborative projects can be instrumental in building these capacities, thus ensuring that the sustainability research community is well equipped to use AI in their work effectively. This approach not only enriches the research landscape, but also ensures that technological advancements are leveraged towards achieving a sustainable future.

Policymakers, especially within the EU, can derive benefits from our study. By understanding the potential applications of AI in sustainability, policymakers can identify strategic areas for research funding and policy development that align with the objectives of the EU Green Deal and the SDGs. The application of AI has been shown to improve efficiency and precision in resource management and energy use, policymakers can devise strategies that align well with the goals of the EU Green Deal and the SDGs. For example, AI's ability to optimize energy grids or predict energy demand can facilitate the transition to renewable energy sources, a key objective of the Green Deal.

The recommendations for different stakeholders are summarized in Table 9.

Furthermore, while our focus has been largely on energy, the implications of AI in agriculture and water management also suggest pathways for policy strategies. AI technologies can aid in the development of precision agriculture practices that minimize waste and maximize productivity, or in water management systems that predict and mitigate risks related to water scarcity and quality. The industry sector can also benefit. Businesses can take advantage of these insights to adopt more sustainable practices, integrate AI into their operations to improve efficiency, and innovate in product development. This not only aids in meeting sustainability goals, but also opens up new market opportunities and competitive advantages in an increasingly eco-conscious global marketplace.

We hope that our findings will assist researchers, policymakers, and practitioners in obtaining a comprehensive

Table 8 Key AI challenges

Challenge	Description
Ethical concerns	The impact of AI on privacy, bias, and public policy requires careful ethical consideration
Automation bias	There is a risk that overreliance on AI could lead to the neglect of valuable human insights
Resource intensity	The environmental cost of training extensive AI models involves substantial energy and computational resources

Table 9 Recommendations for various stakeholders in AI development

Stakeholder	Recommendations
Researchers	Researchers should adhere to the principle of **Transparency**, by, for example, fostering XAI technologiesand clearly communicating the sustainability impacts, such as energy use and environmental impacts of AI technologies. Furthermore, exploration of ML techniques should also emphasize **Equity**, ensuring benefits across all societal segments, and **Collaboration**, involving diverse teams to address sustainability challenges comprehensively
Policymakers	Policymakers play a crucial role by creating policies that promote **Transparency** and **Accountability**, ensuring that AI systems are understandable and their impacts are managed. They should develop clear guidelines on decision-making processes. Regulations should also promote **Equity** in AI applications, ensuring accessibility and non-reinforcement of societal biases
Industry Practitioners	For industry practitioners, the implementation of AI should go beyond mere efficiency gains to promote sustainability-driven approaches, where AI helps to achieve broader environmental goals such as reducing waste, lowering energy consumption, and optimizing supply chains for minimal environmental impact

overview and deeper comprehension of the application of AI to advance the SDGs and stimulate future research in this field.

Funding Open Access funding enabled and organized by Projekt DEAL. Open Access funding enabled and organized by Projekt DEAL.

Data availability Not applicable.

Declarations

Conflict of interest The authors declare no Conflict of interest.

Ethical approval Not applicable.

References

Abdel-Aty M, Haleem K (2011) Analyzing angle crashes at unsignalized intersections using machine learning techniques. Accident Analysis & Prevention 43(1):461–470. https://doi.org/10.1016/j.aap.2010.10.002

Abdella GM, Kucukvar M, Onat NC, Al-Yafay HM, Bulak ME (2020) Sustainability assessment and modeling based on supervised machine learning techniques: The case for food consumption. Journal of Cleaner Production 251, 119661 https://doi.org/10.1016/j.jclepro.2019.119661

Abu A, Hamdan R, Sani N (2020) Ensemble learning for multidimensional poverty classification. Sains Malaysiana 49(2):447–459. https://doi.org/10.17576/jsm-2020-4902-24

Adams D, Oh D-H, Kim D-W, Lee C-H, Oh M (2021) Deep reinforcement learning optimization framework for a power generation plant considering performance and environmental issues. Journal of Cleaner Production 291, https://doi.org/10.1016/j.jclepro.2021.125915

Afantitis A, Melagraki G, Tsoumanis A, Valsami-Jones E, Lynch I (2018) A nanoinformatics decision support tool for the virtual screening of gold nanoparticle cellular association using protein corona fingerprints. Nanotoxicology 12(10):1148–1165. https://doi.org/10.1080/17435390.2018.1504998

Ahmad AS, Hassan MY, Abdullah MP, Rahman HA, Hussin F, Abdullah H, Saidur R (2014) A review on applications of ann and svm for building electrical energy consumption forecasting. Renew Sustain Energy Rev 33:102–109. https://doi.org/10.1016/j.rser.2014.01.069

Ahmad T, Madonski R, Zhang D, Huang C, Mujeeb A (2022) Data-driven probabilistic machine learning in sustainable smart energy/smart energy systems: Key developments, challenges, and future research opportunities in the context of smart grid paradigm. Renewable & Sustainable Energy Reviews 160, https://doi.org/10.1016/j.rser.2022.112128

Ahmad T, Zhang D, Huang C, Zhang H, Dai N, Song Y, Chen H (2021) Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. Journal of Cleaner Production 289, https://doi.org/10.1016/j.jclepro.2021.125834

Ahmed N, Islam MN, Tuba AS, Mahdy MRC, Sujauddin M (2019) Solving visual pollution with deep learning: A new nexus in environmental management. Journal of Environmental Management 248, https://doi.org/10.1016/j.jenvman.2019.07.024

Albaji AO, Rashid RBA, Abdul Hamid SZ (2023) Investigation on Machine Learning Approaches for Environmental Noise Classifications. Journal of Electrical & Computer Engineering, 1–26 https://doi.org/10.1155/2023/3615137

Aljawder A, Al-Karaghouli W (2022) The adoption of technology management principles and artificial intelligence for a sustainable lean construction industry in the case of Bahrain. Journal of Decision Systems, 1–30 https://doi.org/10.1080/12460125.2022.2075529

Aniza R, Chen W-H, Pétrissans A, Hoang AT, Ashokkumar V, Pétrissans M (2023) A review of biowaste remediation and valorization for environmental sustainability: Artificial intelligence approach. Environmental Pollution 324, https://doi.org/10.1016/j.envpol.2023.121363

Arashpour, M (2023) AI explainability framework for environmental management research. Journal of Environmental Management 342, https://doi.org/10.1016/j.jenvman.2023.118149

Asha P, Natrayan L, Geetha BT, Beulah JR, Sumathy R, Varalakshmi G, Neelakandan S (2022) IoT enabled environmental toxicology for air pollution monitoring using AI techniques. Environmental Research 205, https://doi.org/10.1016/j.envres.2021.112574

Ashraf WM, Uddin GM, Arafat SM, Krzywanski J, Xiaonan W (2021) Strategic-level performance enhancement of a 660 mwe supercritical power plant and emissions reduction by ai approach. Energy Conversion and Management 250, 114913 https://doi.org/10.1016/j.enconman.2021.114913

Asrol M, Papilo P, Gunawan FE (2021) Support vector machine with k-fold validation to improve the industry's sustainability performance classification. Procedia Computer Science 179:854–862. https://doi.org/10.1016/j.procs.2021.01.074

Astobiza AM, Toboso M, Aparicio M, López D (2021) AI Ethics for Sustainable Development Goals. IEEE Technol Soc Mag 40(2):66–71. https://doi.org/10.1109/MTS.2021.3056294

Atkeson CG, Santamaria JC (1997) A comparison of direct and model-based reinforcement learning. Proceedings of International Conference on Robotics and Automation 4:3557–3564. https://doi.org/10.1109/ROBOT.1997.606886

Aziz NA, Adnan NAA, Wahab DA, Azman AH (2021) Component design optimisation based on artificial intelligence in support of additive manufacturing repair and restoration: Current status and future outlook for remanufacturing. Journal of Cleaner Production 296, 126401 https://doi.org/10.1016/j.jclepro.2021.126401 . Accessed 2023-05-24

Azote for Stockholm Resilience Centre, Stockholm University: The SDGs wedding cake (2016). https://www.stockholmresilience.org/research/research-news/2016-06-14-the-sdgs-wedding-cake.html Accessed 2023-10-16

Bagheri M, Bazvand A, Ehteshami M (2017) Application of artificial intelligence for the management of landfill leachate penetration into groundwater, and assessment of its environmental impacts. J Clean Prod 149:784–796. https://doi.org/10.1016/j.jclepro.2017.02.157

Begli M, Derakhshan F, Karimipour H (2019) A layered intrusion detection system for critical infrastructure using machine learning. In: 2019 IEEE 7th International Conference on Smart Energy Grid Engineering (SEGE), pp. 120– 124 . https://doi.org/10.1109/SEGE.2019.8859950

Bi X, Lee S, Ranville JF, Sattigeri P, Spanias A, Herckes P, Westerhoff P (2014) Quantitative resolution of nanoparticle sizes using single particle inductively coupled plasma mass spectrometry with the K-means clustering algorithm. J Anal At Spectrom 29(9):1630–1639. https://doi.org/10.1039/C4JA00109E. (**Accessed 2023-05-15**)

Biller S (2019) The operational butterfly effect: How IoT data + AI help deliver on the promise of 4IR. In: 2019 IEEE 15th International Conference on Automation Science and Engineering (CASE), pp. 1– 6. https://doi.org/10.1109/COASE.2019.8843176

Binas J, Luginbuehl L, Bengio Y (2019) Reinforcement learning for sustainable agriculture. In: ICML 2019 Workshop Climate Change: How Can AI Help . https://api.semanticscholar.org/CorpusID:197862923

Brasse J, Broder HR, Förster M, Klier M, Sigler I (2023) Explainable artificial intelligence in information systems: A review of the status quo and future research directions. Electron Mark 33(1):26. https://doi.org/10.1007/s12525-023-00644-5

Brown, T.B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D.M., Wu, J., Winter, C., Hesse, C., Chen, M., Sigler, E., Litwin, M., Gray, S., Chess, B., Clark, J., Berner, C., McCandlish, S., Radford, A., Sutskever, I., Amodei, D (2020) Language Models are Few-Shot Learners. arXiv . https://doi.org/10.48550/arXiv.2005.14165

Brown B, Hanson M, Liverman D, Merideth R (1987) Global sustainability: Toward definition. Environ Manage 11:713–719. https://doi.org/10.1007/BF01867238

Budennyy SA, Lazarev VD, Zakharenko NN, Korovin AN, Plosskaya OA, Dimitrov DV, Akhripkin VS, Pavlov IV, Oseledets IV, Barsola IS, Egorov IV, Kosterina AA, Zhukov LE (2022) eco2AI: Carbon Emissions Tracking of Machine Learning Models as the First Step Towards Sustainable AI. Dokl Math 106(1):118–128. https://doi.org/10.1134/S1064562422060230

Cadenas JM, Garrido MC, Martínez-España R (2023) A Methodology Based on Machine Learning and Soft Computing to Design More Sustainable Agriculture Systems. Sensors (14248220) 23(6), 3038 https://doi.org/10.3390/s23063038

Camaréna, S (2020) Artificial intelligence in the design of the transitions to sustainable food systems. Journal of Cleaner Production 271, https://doi.org/10.1016/j.jclepro.2020.122574

Chen Y, Zhang Z, Liang T (2019) Assessing urban travel patterns: An analysis of traffic analysis zone-based mobility patterns. Sustainability 11(19):5452. https://doi.org/10.3390/su11195452

Chen H, Zhang C, Yu H, Wang Z, Duncan I, Zhou X, Liu X, Wang Y, Yang S (2022) Application of machine learning to evaluating and remediating models for energy and environmental engineering. Applied Energy 320, https://doi.org/10.1016/j.apenergy.2022.119286

Choi S-W, Lee E-B, Kim J-H (2021) The Engineering Machine-Learning Automation Platform (EMAP): A Big-Data-Driven AI Tool for Contractors' Sustainable Management Solutions for Plant Projects. Sustainability 13(18):10384. https://doi.org/10.3390/su131810384. (. **Number: 18 Publisher: Multidisciplinary Digital Publishing Institute. Accessed 2023-05-25**)

Coccia M (2017) Sources of technological innovation: Radical and incremental innovation problem-driven to support competitive advantage of firms. Technology Analysis & Strategic Management 29(9):1048–1061. https://doi.org/10.1080/09537325.2016.1268682

Coccia M (2024) Converging artificial intelligence and quantum technologies: Accelerated growth effects in technological evolution. Technologies 12(5):66. https://doi.org/10.3390/technologies12050066

Coccia M, Ghazinoori S, Roshani S (2023) Evolutionary Pathways of Ecosystem Literature in Organization and Management Studies. PREPRINT (Version 1) available at Research Square https://doi.org/10.21203/rs.3.rs-2499460/v1

Cramarenco RE, Burcă-Voicu MI, Dabija DC (2023) The impact of artificial intelligence (ai) on employees' skills and well-being in global labor markets: A systematic review. Oeconomia Copernicana 14(3):731–767. https://doi.org/10.24136/oc.2023.022

Dai S, Niu D, Han Y (2018) Forecasting of energy-related co2 emissions in china based on gm (1, 1) and least squares support vector machine optimized by modified shuffled frog leaping algorithm for sustainability. Sustainability 10(4):958. https://doi.org/10.3390/su10040958

D'Amato D, Droste N, Allen B, Kettunen M, Lähtinen K, Korhonen J, Leskinen P, Matthies BD, Toppinen A (2017) Green, circular, bio economy: A comparative analysis of sustainability avenues. J Clean Prod 168:716–734. https://doi.org/10.1016/J.JCLEPRO.2017.09.053

Damiani, G., Nurchis, M., Sapienza, M., Jevtic, M (2021)Artificial Intelligence and Urban health: a step forward to the achievement of SDGs. European Journal of Public Health 31, 280–280 https://doi.org/10.1093/eurpub/ckab164.731

Damoah IS, Ayakwah A, Tingbani I (2021) Artificial intelligence (AI)-enhanced medical drones in the healthcare supply chain (HSC) for sustainability development: A case study. J Clean Prod 328:129598. https://doi.org/10.1016/j.jclepro.2021.129598

D'Amore G, Di Vaio A, Balsalobre-Lorente D, Boccia F (2022) Artificial Intelligence in the Water-Energy-Food Model: A Holistic

Approach towards Sustainable Development Goals. Sustainability 14(2):867. https://doi.org/10.3390/su14020867
Darko A, Glushakova I, Boateng EB, Chan APC (2023) Using Machine Learning to Improve Cost and Duration Prediction Accuracy in Green Building Projects. Journal of Construction Engineering & Management 149(8):1–21. https://doi.org/10.1061/jcemd4.coeng-13101
De Clercq D, Smith K, Chou B, Gonzalez A, Kothapalle R, Li C, Dong X, Liu S, Wen Z (2018) Identification of urban drinking water supply patterns across 627 cities in china based on supervised and unsupervised statistical learning. J Environ Manage 223:658–667. https://doi.org/10.1016/j.jenvman.2018.06.073
Deb C, Zhang F, Yang J, Lee SE, Shah KW (2017) A review on time series forecasting techniques for building energy consumption. Renew Sustain Energy Rev 74:902–924. https://doi.org/10.1016/j.rser.2017.02.085
Debrah C, Chan APC, Darko A (2022) Artificial intelligence in green building. Autom Constr 137:104192. https://doi.org/10.1016/j.autcon.2022.104192
Dellosa JT, Palconit EC (2021) Artificial Intelligence (AI) in Renewable Energy Systems: A Condensed Review of its Applications and Techniques. In: 2021 IEEE International Conference on Environment and Electrical Engineering and 2021 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I &CPS Europe), pp. 1– 6 . https://doi.org/10.1109/EEEIC/ICPSEurope51590.2021.9584587
Ding J, Ma S, Dong L, Zhang X, Huang S, Wang W, Zheng N, Wei F (2023) Longnet: Scaling transformers to 1,000,000,000 tokens. arXiv https://doi.org/10.48550/arxiv.2307.02486 2307.02486
Dong W, Huang Y, Lehane B, Ma G (2020) Xgboost algorithm-based prediction of concrete electrical resistivity for structural health monitoring. Autom Constr 114:103155. https://doi.org/10.1016/j.autcon.2020.103155
Donti PL, Kolter JZ (2021) Machine Learning for Sustainable Energy Systems. Annual Review of Environment & Resources 46:719–747. https://doi.org/10.1146/annurev-environ-020220-061831
Dooyum Uyeh D, Akinsoji A, Asem-Hiablie S, Itoro Bassey B, Osinuga A, Mallipeddi R, Amaizu M, Ha Y, Park T (2022) An online machine learning-based sensors clustering system for efficient and cost-effective environmental monitoring in controlled environment agriculture. Computers & Electronics in Agriculture 199, https://doi.org/10.1016/j.compag.2022.107139
Elavarasan D, Vincent DR (2020) Reinforced XGBoost machine learning model for sustainable intelligent agrarian applications. Journal of Intelligent & Fuzzy Systems 39(5):7605–7620. https://doi.org/10.3233/JIFS-200862
Elavarasan D, Vincent Durai Raj, P.M. (2021) Fuzzy deep learning-based crop yield prediction model for sustainable agronomical frameworks. Neural Computing & Applications 33(20):13205–13224. https://doi.org/10.1007/s00521-021-05950-7. (**Publisher: Springer Nature**)
European Commission: The European Green Deal (2019). https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en Accessed 2024-04-30
Facendola R, Ottomano Palmisano G, De Boni A, Acciani C, Roma R (2023) Profiling citizens on perception of key factors of food security: An application of k-means cluster analysis. Sustainability 15(13):9915. https://doi.org/10.3390/su15139915
Feng L, Zhang J (2014) Application of artificial neural networks in tendency forecasting of economic growth. Econ Model 40:76–80. https://doi.org/10.1016/j.econmod.2014.03.024
Feng C, Cui M, Hodge B-M, Lu S, Hamann HF, Zhang J (2018) Unsupervised clustering-based short-term solar forecasting. IEEE Transactions on Sustainable Energy 10(4):2174–2185. https://doi.org/10.1109/TSTE.2018.2881531
Ferreiro-Cabello J, Fraile-Garcia E, Pison Ascacibar E, Martinez-de-Pison FJ (2018) Metamodel-based design optimization of structural one-way slabs based on deep learning neural networks to reduce environmental impact. Eng Struct 155:91–101. https://doi.org/10.1016/j.engstruct.2017.11.005
Fijani E, Barzegar R, Deo R, Tziritis E, Skordas K (2019) Design and implementation of a hybrid model based on two-layer decomposition method coupled with extreme learning machines to support real-time environmental monitoring of water quality parameters. Science of the Total Environment 648, 839– 853 https://doi.org/10.1016/j.scitotenv.2018.08.221
Fox MP, MacLehose RF, Lash TL (2022) Applying quantitative bias analysis to epidemiologic data. Springer. https://doi.org/10.1007/978-3-030-82673-4
Frank B (2021) Artificial intelligence-enabled environmental sustainability of products: Marketing benefits and their variation by consumer, location, and product types. Journal of Cleaner Production 285, https://doi.org/10.1016/j.jclepro.2020.125242
Froemelt A, Wiedmann T (2020) A two-stage clustering approach to investigate lifestyle carbon footprints in two Australian cities. Environ Res Lett 15(10):104096. https://doi.org/10.1088/1748-9326/abb502
Gace I, Pevec D, Vdovic H, Babic J, Podobnik V (2021) Driving style categorisation based on unsupervised learning: a step towards sustainable transportation. In: 2021 6th International Conference on Smart and Sustainable Technologies (SpliTech), pp. 1– 6 . https://doi.org/10.23919/splitech52315.2021.9566371
Ganguli, D., Hernandez, D., Lovitt, L., Askell, A., Bai, Y., Chen, A., Conerly, T., Dassarma, N., Drain, D., Elhage, N., et al(2022) Predictability and surprise in large generative models. In: 2022 ACM Conference on Fairness, Accountability, and Transparency, pp. 1747– 1764 https://doi.org/10.1145/3531146.353322
Gao L, Liu T, Cao T, Hwang Y, Radermacher R (2021) Comparing deep learning models for multi energy vectors prediction on multiple types of building. Applied Energy 301, 117486 https://doi.org/10.1016/j.apenergy.2021.117486
Gilson A, Safranek CW, Huang T, Socrates V, Chi L, Taylor RA, Chartash D et al (2023) How does chatgpt perform on the united states medical licensing examination? the implications of large language models for medical education and knowledge assessment. JMIR Medical Education 9(1):45312. https://doi.org/10.2196/45312
González-Pereira B, Guerrero-Bote VP, Anegón FM (2010) A new approach to the metric of journals' scientific prestige: The sjr indicator. J. Informetrics 4:379–391. https://doi.org/10.1016/J.JOI.2010.03.002
Goodfellow I, Pouget-Abadie J, Mirza M, Xu B, Warde-Farley D, Ozair S, Courville A, Bengio Y (2014) Generative Adversarial Nets. In: Advances in Neural Information Processing Systems, vol. 27 . https://doi.org/10.1145/3422622
Google(Ed.): Explainable AI (2023). https://cloud.google.com/explainable-ai Accessed 2023-07-24
Gordan M, Ghaedi K, Ismail Z, Benisi H, Hashim H, Ghayeb HH (2021) From Conventional to Sustainable SHM: Implementation of Artificial Intelligence in The Department of Civil Engineering, University of Malaya. In: 2021 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET), pp. 1– 6 . https://doi.org/10.1109/IICAIET51634.2021.9573713
Grymshi D, Crespo-Cebada E, Elghannam A, Mesías FJ, Díaz-Caro C (2022) Understanding consumer attitudes towards ecolabeled food products: A latent class analysis regarding their purchasing motivations. Agribusiness 38(1):93–107. https://doi.org/10.1002/agr.21714
Guo Y, Fu Y, Hao F, Zhang X, Wu W, Jin X, Bryant CR, Senthilnath J (2021) Integrated phenology and climate in rice yields prediction

using machine learning methods. Ecol Ind 120:106935. https://doi.org/10.1016/j.ecolind.2020.106935

Haarnoja T, Zhou A, Hartikainen K, Tucker G, Ha S, Tan J, Kumar V, Zhu H, Gupta A, Abbeel P, et al (2018) Soft actor-critic algorithms and applications. arXiv https://doi.org/10.48550/arXiv.1812.05905

Hai T, Zhou J, Almojil SF, Almohana AI, Alali AF, Mehrez S, Mohamed A, Sharma K, Mohammed AG, Almoalimi KT (2023) Deep learning optimization and techno-environmental analysis of a solar-driven multigeneration system for producing sustainable hydrogen and electricity: A case study of SanFrancisco. Int J Hydrogen Energy 48(6):2055–2074. https://doi.org/10.1016/j.ijhydene.2022.09.301

Halkos G, Gkampoura E-C (2021) Where do we stand on the 17 sustainable development goals? an overview on progress. Economic Analysis and Policy 70, 94– 122 https://doi.org/10.1016/j.eap.2021.02.001

Heo, S., Nam, K., Tariq, S., Lim, J.Y., Park, J., Yoo, C (2021) A hybrid machine learning-based multi-objective supervisory control strategy of a full-scale wastewater treatment for cost-effective and sustainable operation under varying influent conditions. Journal of Cleaner Production 291, https://doi.org/10.1016/j.jclepro.2021.125853

Hernández-del-Olmo F, Gaudioso E, Dormido R, Duro N (2016) Energy and Environmental Efficiency for the N-Ammonia Removal Process in Wastewater Treatment Plants by Means of Reinforcement Learning. Energies (19961073) 9(9), 755 https://doi.org/10.3390/en9090755

Hinton GE, Frosst NMW, Aghdam SSR (2023) Capsule Neural Networks. US20230027069A1, January . https://patents.google.com/patent/US20230027069A1/en

Hinton GE, Sabour S, Frosst N (2018) Matrix capsules with em routing. In: International Conference on Learning Representations . https://openreview.net/forum?id=HJWLfGWRb

Holloway J, Mengersen K (2018) Statistical Machine Learning Methods and Remote Sensing for Sustainable Development Goals: A Review. Remote Sensing 10(9):1365. https://doi.org/10.3390/rs10091365

Hong Z, Xiao K (2024) Digital economy structuring for sustainable development: the role of blockchain and artificial intelligence in improving supply chain and reducing negative environmental impacts. Sci Rep 14(1):3912. https://doi.org/10.1038/s41598-024-53760-3

Hossain M, Muromachi Y (2012) A Bayesian network based framework for real-time crash prediction on the basic freeway segments of urban expressways. Accident Analysis & Prevention 45:373–381. https://doi.org/10.1016/j.aap.2011.08.004

Huang S, Zheng X, Ma L, Wang H, Huang Q, Leng G, Meng E, Guo Y (2020) Quantitative contribution of climate change and human activities to vegetation cover variations based on ga-svm model. J Hydrol 584:124687. https://doi.org/10.1016/j.jhydrol.2020.124687

Huang L, Pena B, Liu Y, Anderlini E (2022) Machine learning in sustainable ship design and operation: A review. Ocean Eng 266:112907. https://doi.org/10.1016/j.oceaneng.2022.112907

Hu G, You F (2022) Renewable energy-powered semi-closed greenhouse for sustainable crop production using model predictive control and machine learning for energy management. Renewable & Sustainable Energy Reviews 168, https://doi.org/10.1016/j.rser.2022.112790

IBM(Ed.): IBM Watson OpenScale - Overview. (2023). https://www.ibm.com/docs/en/cloud-paks/cp-data/3.5.0?topic=services-watson-openscale Accessed 2023-07-24

Jadidi M, Kostic S, Zimmer L, Dworkin SB (2020) An Artificial Neural Network for the Low-Cost Prediction of Soot Emissions. Energies 13(18):4787. https://doi.org/10.3390/en13184787

Jauhiainen JS (2024) The metaverse: Innovations and generative ai. International Journal of Innovation Studies 8(3):262–272. https://doi.org/10.1016/j.ijis.2024.04.004

Jena PR, Managi S, Majhi B (2021) Forecasting the CO2 Emissions at the Global Level: A Multilayer Artificial Neural Network Modelling. Energies 14(19):6336. https://doi.org/10.3390/en14196336

Jiang F, Jiang Y, Zhi H, Dong Y, Li H, Ma S, Wang Y, Dong Q, Shen H, Wang Y (2017) Artificial intelligence in healthcare: past, present and future. Stroke and Vascular Neurology **2**(4) https://doi.org/10.1136/svn-2017-000101

Kaab A, Sharifi M, Mobli H, Nabavi-Pelesaraei A, Chau, K.-w, (2019) Combined life cycle assessment and artificial intelligence for prediction of output energy and environmental impacts of sugarcane production. Science of the Total Environment 664:1005–1019. https://doi.org/10.1016/j.scitotenv.2019.02.004

Kamali M, Appels L, Yu X, Aminabhavi TM, Dewil R (2021) Artificial intelligence as a sustainable tool in wastewater treatment using membrane bioreactors. Chemical Engineering Journal 417. https://doi.org/10.1016/j.cej.2020.128070

Kar AK, Ilavarasan V, Gupta MP, Janssen M, Kothari R (2019) Moving beyond Smart Cities: Digital Nations for Social Innovation & Sustainability. Inf Syst Front 21(3):495–501. https://doi.org/10.1007/s10796-019-09930-0

Kar A, Choudhary S, Singh V (2022) How can artificial intelligence impact sustainability: A systematic literature review:. Journal of Cleaner Production 376, 134120 https://doi.org/10.1016/j.jclepro.2022.134120

Karthiban K, Raj JS (2020) An efficient green computing fair resource allocation in cloud computing using modified deep reinforcement learning algorithm. Soft Computing - A Fusion of Foundations, Methodologies & Applications 24(19):14933–14942. https://doi.org/10.1007/s00500-020-04846-3

Kassem M, Mahamedi E, Rogage K, Duffy K, Huntingdon J (2021) Measuring and benchmarking the productivity of excavators in infrastructure projects: A deep neural network approach. Autom Constr 124:103532. https://doi.org/10.1016/j.autcon.2020.103532

Kazemeini A, Swei O (2023) Identifying environmentally sustainable pavement management strategies via deep reinforcement learning. Journal of Cleaner Production 390, https://doi.org/10.1016/j.jclepro.2023.136124

Khakurel J, Penzenstadler B, Porras J, Knutas A, Zhang W (2018) The Rise of Artificial Intelligence under the Lens of Sustainability. Technologies 6(4):100. https://doi.org/10.3390/technologies6040100

Khalaf SA (2020) Review Articles - Management Impacts of Desalination Seawater and Marine Environment. In: 2020 Second International Sustainability and Resilience Conference: Technology and Innovation in Building Designs, pp. 1– 5 . https://doi.org/10.1109/IEEECONF51154.2020.9320001

Kim J (2020) Visual Analytics for Operation-Level Construction Monitoring and Documentation: State-of-the-Art Technologies, Research Challenges, and Future Directions. Frontiers in Built Environment **6**[SPACE]https://doi.org/10.3389/fbuil.2020.575738

Kim C, Costello FJ, Lee KC (2019) Integrating qualitative comparative analysis and support vector machine methods to reduce passengers' resistance to biometric e-gates for sustainable airport operations. Sustainability 11(19):5349. https://doi.org/10.3390/su11195349

Ko Y-A, Mukherjee B, Smith JA, Kardia SLR, Allison M, Diez Roux AV (2016) Classification and Clustering Methods for Multiple Environmental Factors in Gene-Environment Interaction: Application to the Multi-Ethnic Study of Atherosclerosis. Epidemiology 27(6), 870 https://doi.org/10.1097/EDE.0000000000000548

Kocaman B, Tümen V (2020) Detection of electricity theft using data processing and lstm method in distribution systems. Sādhanā 45(1):286. https://doi.org/10.1007/s12046-020-01512
Kontokosta CE, Tull C (2017) A data-driven predictive model of city-scale energy use in buildings. Appl Energy 197:303–317. https://doi.org/10.1016/j.apenergy.2017.04.005
Krzywanski J (2022) Advanced AI Applications in Energy and Environmental Engineering Systems. Energies 15(15):5621. https://doi.org/10.3390/en15155621
Krzywanski J, Sztekler K, Skrobek D, Grabowska K, Ashraf WM, Sosnowski M, Ishfaq K, Nowak W, Mika L (2024) Automl-based predictive framework for predictive analysis in adsorption cooling and desalination systems. Energy Science & Engineering 12(5):1969–1986. https://doi.org/10.1002/ese3.1725
Krzywanski J, Blaszczuk A, Czakiert T, Rajczyk R, Nowak W (2014) Artificial intelligence treatment of NOx emissions from CFBC in air and oxy-fuel conditions. Proceedings of the 11th International Conference on Fluidized Bed Technology (CFB-11) https://doi.org/10.1061/(ASCE)EY.1943-7897.0000280
Krzywanski J, Skrobek D, Sosnowski M, Ashraf WM, Grabowska K, Zylka A, Kulakowska A, Nowak W, Sztekler K, Shahzad MW (2024) Towards enhanced heat and mass exchange in adsorption systems: The role of automl and fluidized bed innovations. International Communications in Heat and Mass Transfer 152, 107262 https://doi.org/10.1016/j.icheatmasstransfer.2024.107262
Krzywanski J, Skrobek D, Zylka A, Grabowska K, Kulakowska A, Sosnowski M, Nowak W, Blanco-Marigorta AM (2023) Heat and mass transfer prediction in fluidized beds of cooling and desalination systems by ai approach. Applied Thermal Engineering 225, 120200 https://doi.org/10.1016/j.applthermaleng.2023.120200
Kuenzel R, Teizer J, Mueller M, Blickle A (2016) SmartSite: Intelligent and autonomous environments, machinery, and processes to realize smart road construction projects. Autom Constr 71:21–33. https://doi.org/10.1016/j.autcon.2016.03.012
Kühl N, Goutier M, Hirt R, Satzger G (2020) Machine Learning in Artificial Intelligence: Towards a Common Understanding. arXiv . https://doi.org/10.48550/arXiv.2004.04686
Kulejewski J, Rosłon J (2023) Optimization of Ecological and Economic Aspects of the Construction Schedule with the Use of Metaheuristic Algorithms and Artificial Intelligence. Sustainability 15, 890 https://doi.org/10.3390/su15010890
Kulkarni TD, Narasimhan K, Saeedi A, Tenenbaum J (2016) Hierarchical deep reinforcement learning: Integrating temporal abstraction and intrinsic motivation. Advances in neural information processing systems **29**[SPACE]https://doi.org/10.48550/arXiv.1604.06057
Kumar A, Singh RP, Dubey SK, Gaurav K (2022) Streamflow of the betwa river under the combined effect of lu-lc and climate change. Agriculture 12(12):2005. https://doi.org/10.3390/agriculture12122005
Kumar A, Singh A, Gaurav K (2023) Assessing the synergic effect of land use and climate change on the upper betwa river catchment in central india under present, past, and future climate scenarios. Environ Dev Sustain 25(6):5163–5184. https://doi.org/10.1007/s10668-022-02260-3
Kumar A, Gaurav K, Singh A, Yaseen ZM (2024) Assessment of machine learning models to predict daily streamflow in a semiarid river catchment. Neural Computing and Applications, 1–20 https://doi.org/10.1007/s00521-024-09748-1
Kung TH, Cheatham M, Medenilla A, Sillos C, De Leon L, Elepaño C, Madriaga M, Aggabao R, Diaz-Candido G, Maningo J, et al (2023) Performance of chatgpt on usmle: Potential for ai-assisted medical education using large language models. PLoS digital health **2**(2) https://doi.org/10.1371/journal.pdig.0000198
Kuutti S, Bowden R, Jin Y, Barber P, Fallah S (2021) A Survey of Deep Learning Applications to Autonomous Vehicle Control. IEEE Trans Intell Transp Syst 22(2):712–733. https://doi.org/10.1109/TITS.2019.2962338
Lakhouit A, Shaban M, Alatawi A, Abbas SYH, Asiri E, Al Juhni T, Elsawy M (2023) Machine-learning approaches in geo-environmental engineering: Exploring smart solid waste management. Journal of Environmental Management 330, https://doi.org/10.1016/j.jenvman.2022.117174
Larosa F, Hoyas S, García-Martínez J, Conejero JA, Fuso Nerini F, Vinuesa R (2023) Halting generative ai advancements may slow down progress in climate research. Nat Clim Chang 13(6):497–499. https://doi.org/10.1038/s41558-023-01686-5
Lazaroiu G, Rogalska E (2023) How generative artificial intelligence technologies shape partial job displacement and labor productivity growth. Oeconomia Copernicana 14(3):703–706. https://doi.org/10.24136/oc.2023.020
Lăzăroiu G, Androniceanu A, Grecu I, Grecu G, Neguriță O (2022) Artificial intelligence-based decision-making algorithms, Internet of Things sensing networks, and sustainable cyber-physical management systems in big data-driven cognitive manufacturing. Oeconomia Copernicana 13(4), 1047– 1080 https://doi.org/10.24136/oc.2022.030
Lehtonen M (2004) The environmental-social interface of sustainable development: capabilities, social capital, institutions. Ecol Econ 49:199–214. https://doi.org/10.1016/J.ECOLECON.2004.03.019
Lekan A, Aigbavboa C, Babatunde O, Olabosipo F, Christiana A (2022) Disruptive technological innovations in construction field and fourth industrial revolution intervention in the achievement of the sustainable development goal 9. Int J Constr Manag 22(14):2647–2658. https://doi.org/10.1080/15623599.2020.1819522
Li J, Chen W-H, Xu Q, Shah N, Kohler JC, Mackey TK (2020) Detection of self-reported experiences with corruption on twitter using unsupervised machine learning. Social Sciences & Humanities Open 2(1):100060. https://doi.org/10.1016/j.ssaho.2020.100060
Li H, Liu Y, Yang J (2021) A novel fcs-mpc method of multi-level apf is proposed to improve the power quality in renewable energy generation connected to the grid. Sustainability 13(8):4094. https://doi.org/10.3390/su13084094
Li Y, Shi J, Jiang W, Zhang W, Lyu Y (2022) Autonomous maneuver decision-making for a ucav in short-range aerial combat based on an ms-ddqn algorithm. Defence Technology 18(9):1697–1714. https://doi.org/10.1016/j.dt.2021.09.014
Liakos KG, Busato P, Moshou D, Pearson S, Bochtis D (2018) Machine Learning in Agriculture: A Review. Sensors 18(8):2674. https://doi.org/10.3390/s18082674. (**Number: 8 Publisher: Multidisciplinary Digital Publishing Institute. Accessed 2023-05-16**)
Liu Y, Yang M, Guo Z (2022) Reinforcement learning based optimal decision making towards product lifecycle sustainability. Int J Comput Integr Manuf 35(10/11):1269–1296. https://doi.org/10.1080/0951192X.2022.2025623
Liu J, Mooney H, Hull V, Davis S, Gaskell J, Hertel T, Lubchenco J, Seto K, Gleick P, Kremen C, Li S (2015) Systems integration for global sustainability. Science **347**[SPACE]https://doi.org/10.1126/science.1258832
Li X, Xu H, Shen H, Hsu W-L, Yu P-Y (2020) Smart City Governance: Artificial Intelligence and Internet of Things. In: 2020 IEEE 2nd Eurasia Conference on Biomedical Engineering, Healthcare and Sustainability (ECBIOS), pp. 60– 63. https://doi.org/10.1109/ECBIOS50299.2020.9203748
López-Vargas A, Fuentes M, Vivar M (2020) Challenges and Opportunities of the Internet of Things for Global Development to Achieve the United Nations Sustainable Development Goals.

IEEE Access 8:37202–37213. https://doi.org/10.1109/ACCESS.2020.2975472

Lozano, R(2008) Envisioning sustainability three-dimensionally. Journal of Cleaner Production 16, 1838– 1846 https://doi.org/10.1016/J.JCLEPRO.2008.02.008

Lundberg S, Lee S-I (2017) A Unified Approach to Interpreting Model Predictions. arXiv . https://doi.org/10.48550/arXiv.1705.07874

Mani GS (2022) Applying Artificial Intelligence for accelerating pace of achieving SD Goal 4 in India: A viewpoint. In: 2022 IEEE 7th International Conference for Convergence in Technology (I2CT), pp. 1– 7 . https://doi.org/10.1109/I2CT54291.2022.9825371

Manzoor B, Othman I, Durdyev S, Ismail S, Wahab MH (2021) Influence of Artificial Intelligence in Civil Engineering toward Sustainable Development-A Systematic Literature Review. Applied System Innovation. https://doi.org/10.3390/asi4030052

Marvuglia A, Messineo A (2012) Monitoring of wind farms' power curves using machine learning techniques. Appl Energy 98:574–583. https://doi.org/10.1016/j.apenergy.2012.04.037

Mazzeo D, Matera N, Peri G, Scaccianoce G (2023) Forecasting green roofs' potential in improving building thermal performance and mitigating urban heat island in the Mediterranean area: An artificial intelligence-based approach. Applied Thermal Engineering 222, https://doi.org/10.1016/j.applthermaleng.2022.119879

Mehmood, H., Liao, D., Mahadeo, K (2020) A Review of Artificial Intelligence Applications to Achieve Water-related Sustainable Development Goals. In: 2020 IEEE / ITU International Conference on Artificial Intelligence For Good (AI4G), pp. 135– 141. https://doi.org/10.1109/AI4G50087.2020.9311018

Michael J, Holtzman A, Parrish A, Mueller A, Wang A, Chen A, Madaan D, Nangia N, Pang RY, Phang J., et al (2022) What do nlp researchers believe? results of the nlp community metasurvey. arXiv https://doi.org/10.48550/arXiv.2208.12852

Milačić L, Jović S, Vujović T, Miljković J (2017) Application of artificial neural network with extreme learning machine for economic growth estimation. Physica A 465:285–288. https://doi.org/10.1016/j.physa.2016.08.040

Miller L, Bolton M, Boulton J, Mintrom M, Nicholson A, Rüdiger C, Skinner R, Raven R, Webb GI (2020) AI for monitoring the Sustainable Development Goals and supporting and promoting action and policy development. 2020 IEEE / ITU International Conference on Artificial Intelligence for Good (AI4G), 180–185 https://doi.org/10.1109/AI4G50087.2020.9311014

Mohammadi M, Naghibi SA, Motevalli A, Hashemi H (2022) Human-induced arsenic pollution modeling in surface waters - An integrated approach using machine learning algorithms and environmental factors. Journal of Environmental Management 305, https://doi.org/10.1016/j.jenvman.2021.114347

Mohammed M, Hamdoun H, Sagheer A (2023) Toward Sustainable Farming: Implementing Artificial Intelligence to Predict Optimum Water and Energy Requirements for Sensor-Based Micro Irrigation Systems Powered by Solar PV. Agronomy 13(4):1081. https://doi.org/10.3390/agronomy13041081

Mohd, Alqadhi S, Mallick J, Ben Kahla N, Anh Le H, Singh C, Hang H (2022) Artificial Neural Networks for Sustainable Development of the Construction Industry. Sustainability 14:14738. https://doi.org/10.3390/su142214738

Mohri M, Rostamizadeh A, Talwalkar A (2018) Foundations of Machine Learning. . https://lccn.loc.gov/2018022812 Accessed 2023-05-16

Momenitabar M, Dehdari Ebrahimi Z, Ghasemi P (2022) Designing a sustainable bioethanol supply chain network: A combination of machine learning and meta-heuristic algorithms. Industrial Crops & Products 189, https://doi.org/10.1016/j.indcrop.2022.115848

Moraliyage H, Haputhanthri D, Samarajeewa C, Mills N, De Silva D, Manic M, Jennings A (2023) Automated machine learning in critical energy infrastructure for net zero carbon emissions. In: 2023 IEEE 32nd International Symposium on Industrial Electronics (ISIE), pp. 1– 7 . https://doi.org/10.1109/ISIE51358.2023.10227985

Muhammad G, Hossain MS (2021) Deep-reinforcement-learning-based sustainable energy distribution for wireless communication. IEEE Wirel Commun 28(6):42–48. https://doi.org/10.1109/MWC.015.2100177

Mutti M, Mancassola M, Restelli M (2021) Unsupervised reinforcement learning in multiple environments. Proceedings of the 36th AAAI Conference on Artificial Intelligence 36(7):7850–7858. https://doi.org/10.1609/aaai.v36i7.20754

Nabavi-Pelesaraei A, Rafiee S, Mohtasebi SS, Hosseinzadeh-Bandbafha H, Chau, K.-w, (2018) Integration of artificial intelligence methods and life cycle assessment to predict energy output and environmental impacts of paddy production. Science of the Total Environment 631:1279–1294. https://doi.org/10.1016/j.scitotenv.2018.03.088

Naseri H, Jahanbakhsh H, Hosseini P, Moghadas Nejad F (2020) Designing sustainable concrete mixture by developing a new machine learning technique. J Clean Prod 258:120578. https://doi.org/10.1016/j.jclepro.2020.120578

Naveenkumar R, Iyyappan J, Pravin R, Kadry S, Han J, Sindhu R, Awasthi MK, Rokhum SL, Baskar G (2023) A strategic review on sustainable approaches in municipal solid waste management and energy recovery: Role of artificial intelligence, economic stability and life cycle assessment. Bioresource Technology 379, https://doi.org/10.1016/j.biortech.2023.129044

Nemes A, Rawls W, Pachepsky Y (2006) Use of the Nonparametric Nearest Neighbor Approach to Estimate Soil Hydraulic Properties. Soil Science Society of America Journal **70**[SPACE]https://doi.org/10.2136/sssaj2005.0128

Nishant R, Kennedy M, Corbett J (2020) Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. International Journal of Information Management 53, https://doi.org/10.1016/j.ijinfomgt.2020.102104

Oke A, Aigbavboa C, Stephen S, Thwala W (2021). Artificial intelligence for sustainable construction. In: Sustainable Construction in the Era of the Fourth Industrial Revolution, pp. 11– 20 https://doi.org/10.1201/9781003179849-2

Osaki M, Kensuke F (2013) Sustainability Science: A Multidisciplinary Approach. United Nations . https://doi.org/10.18356/6ababf78-en

Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, Shamseer L, Tetzlaff JM, Akl EA, Brennan SE et al (2021) The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. British Medical Journal Publishing Group. https://doi.org/10.1136/bmj.n71

Pal A, Hsieh S-H (2021) Deep-learning-based visual data analytics for smart construction management. Autom Constr 131:103892. https://doi.org/10.1016/j.autcon.2021.103892. (**Accessed 2023-05-25**)

Parlina A, Ramli K, Murfi H (2021) Exposing emerging trends in smart sustainable city research using deep autoencoders-based fuzzy c-means. Sustainability 13(5):2876. https://doi.org/10.3390/su13052876

Paulvannan Kanmani A, Obringer R, Rachunok B, Nateghi R (2020) Assessing global environmental sustainability via an unsupervised clustering framework. Sustainability 12(2):563. https://doi.org/10.3390/su12020563

Pedroso M, Taylor J, Tisseyre B, Charnomordic B, Guillaume S (2010) A segmentation algorithm for the delineation of agricultural management zones. Comput Electron Agric 70(1):199–208. https://doi.org/10.1016/j.compag.2009.10.007

Perera A, Kamalaruban P (2021) Applications of reinforcement learning in energy systems. Renew Sustain Energy Rev 137:110618

Pérez-Pons ME, Alonso RS, García O, Marreiros G, Corchado JM (2021) Deep Q-Learning and Preference Based Multi-Agent System for Sustainable Agricultural Market. Sensors (14248220) 21(16), 5276– 5276 https://doi.org/10.3390/s21165276

Peters MA, Jackson L, Papastephanou M, Jandrić P, Lazaroiu G, Evers CW, Cope B, Kalantzis M, Araya D, Tesar M et al (2024) Ai and the future of humanity: Chatgpt-4, philosophy and education-critical responses. Educ Philos Theory 56(9):828–862. https://doi.org/10.1080/00131857.2023.2213437

Pham A-D, Ngo N-T, Ha Truong TT, Huynh N-T, Truong N-S (2020) Predicting energy consumption in multiple buildings using machine learning for improving energy efficiency and sustainability. Journal of Cleaner Production 260, https://doi.org/10.1016/j.jclepro.2020.121082

Pham Q-V, Fang F, Ha VN, Piran MJ, Le M, Le LB, Hwang W-J, Ding Z (2020) A Survey of Multi-Access Edge Computing in 5G and Beyond: Fundamentals, Technology Integration, and State-of-the-Art. IEEE Access 8:116974–117017. https://doi.org/10.1109/ACCESS.2020.3001277

Podder KK, Tabassum S, Khan LE, Salam KMA, Maruf RI, Ahmed A (2021) Design of a sign language transformer to enable the participation of persons with disabilities in remote healthcare systems for ensuring universal healthcare coverage. In: 2021 IEEE Technology & Engineering Management Conference-Europe (TEMSCON-EUR), pp. 1– 6 . https://doi.org/10.1109/TEMSCON-EUR52034.2021.9488605

Popper J, Motsch W, David A, Petzsche T, Ruskowski M (2021) Utilizing multi-agent deep reinforcement learning for flexible job shop scheduling under sustainable viewpoints. In: 2021 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME), pp. 1– 6 . https://doi.org/10.1109/ICECCME52200.2021.9590925

Qi X, Luo Y, Wu G, Boriboonsomsin K, Barth M (2019) Deep reinforcement learning enabled self-learning control for energy efficient driving. Transportation Research Part C: Emerging Technologies 99, 67– 81 https://doi.org/10.1016/j.trc.2018.12.018

Qureshi AH, Alaloul WS, Manzoor B, Musarat MA, Saad S, Ammad S (2020) Implications of Machine Learning Integrated Technologies for Construction Progress Detection Under Industry 4.0 (IR 4.0). In: 2020 Second International Sustainability and Resilience Conference: Technology and Innovation in Building Designs(51154), pp. 1– 6 . https://doi.org/10.1109/IEEECONF51154.2020.9319974

Rai AK, Dwivedi RK (2020) Fraud detection in credit card data using unsupervised machine learning based scheme. In: 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), pp. 421– 426 . https://doi.org/10.1109/icesc48915.2020.9155615

Raj VHA, Carvalho C (2023) A Perspective on the Application of Artificial Intelligence in Sustainable Agriculture with Special Reference to Precision Agriculture. SDMIMD Journal of Management 14:1–15. https://doi.org/10.18311/sdmimd/2023/33006

Raman R, Pattnaik D, Lathabai HH, Govindan K, Nedungadi P (2024) Green and sustainable ai research: an integrated thematic and topic modeling analysis. Journal of Big Data 11(1):55. https://doi.org/10.1186/s40537-024-00920-x

Rampini L, Re Cecconi F (2022) Artificial intelligence in construction asset management: a review of present status, challenges and future opportunities. Journal of Information Technology in Construction 27:884–913. https://doi.org/10.36680/j.itcon.2022.043

Ran X, Zhou X, Lei M, Tepsan W, Deng W (2021) A novel k-means clustering algorithm with a noise algorithm for capturing urban hotspots. Appl Sci 11(23):11202. https://doi.org/10.3390/app112311202

Rangel-Martinez D, Nigam KDP, Ricardez-Sandoval LA (2021) Machine learning on sustainable energy: A review and outlook on renewable energy systems, catalysis, smart grid and energy storage. Chemical Engineering Research & Design: Transactions of the Institution of Chemical Engineers Part A 174, 414– 441 https://doi.org/10.1016/j.cherd.2021.08.013

Regona M, Yigitcanlar T, Hon C, Teo M (2024) Artificial intelligence and sustainable development goals: Systematic literature review of the construction industry. Sustain Cities Soc 108:105499. https://doi.org/10.1016/j.scs.2024.105499

Renaud J, Karam R, Salomon M, Couturier R (2023) Deep learning and gradient boosting for urban environmental noise monitoring in smart cities. Expert Systems with Applications 218, https://doi.org/10.1016/j.eswa.2023.119568

Rezk H, Nassef AM, Inayat A, Sayed ET, Shahbaz M, Olabi AG (2019)Improving the environmental impact of palm kernel shell through maximizing its production of hydrogen and syngas using advanced artificial intelligence. Science of the Total Environment 658, 1150– 1160 https://doi.org/10.1016/j.scitotenv.2018.12.284

Riskiawan HY, Gupta N, Setyohadi DPS, Anwar S, Kurniasari AA, Hariono B, Firmansyah MH, Yogiswara Y, Mansur ABF, Basori AH (2023) Artificial Intelligence Enabled Smart Monitoring and Controlling of IoT-Green House. Arabian Journal for Science & Engineering (Springer Science & Business Media B.V.), 1–19 https://doi.org/10.1007/s13369-023-07887-6

Robinson C, Dilkina B, Hubbs J, Zhang W, Guhathakurta S, Brown MA, Pendyala RM (2017) Machine learning approaches for estimating commercial building energy consumption. Appl Energy 208:889–904. https://doi.org/10.1016/j.apenergy.2017.09.060

Rojek I, Mikołajewski D, Macko M, Szczepański Z, Dostatni E (2021) Optimization of extrusion-based 3d printing process using neural networks for sustainable development. Materials 14(11):2737. https://doi.org/10.3390/ma14112737

Rolnick, D., Donti, P.L., Kaack, L.H., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A.S., Milojevic-Dupont, N., Jaques, N., Waldman-Brown, A., Luccioni, A., Maharaj, T., Sherwin, E.D., Mukkavilli, S.K., Kording, K.P., Gomes, C., Ng, A.Y., Hassabis, D., Platt, J.C., Creutzig, F., Chayes, J., Bengio, Y (2019) Tackling Climate Change with Machine Learning. arXiv . https://doi.org/10.48550/arXiv.1906.05433

Ruggerio, C (2021) Sustainability and sustainable development: A review of principles and definitions. The Science of the total environment 786, 147481 https://doi.org/10.1016/j.scitotenv.2021.147481

Sætra HS (2021) A Framework for Evaluating and Disclosing the ESG Related Impacts of AI with the SDGs. Sustainability 13(15):8503. https://doi.org/10.3390/su13158503

Salehi H, Burgueño R (2018) Emerging artificial intelligence methods in structural engineering. Eng Struct 171:170–189. https://doi.org/10.1016/j.engstruct.2018.05.084

Schöning J, Richter ML (2021) AI-Based Crop Rotation for Sustainable Agriculture Worldwide. In: 2021 IEEE Global Humanitarian Technology Conference (GHTC), pp. 142– 146 . https://doi.org/10.1109/GHTC53159.2021.9612460

Schoormann T, Strobel G, Möller F, Petrik D, Zschech P (2023) Artificial Intelligence for Sustainability-A Systematic Review of Information Systems Literature. Commun Assoc Inf Syst 52:199–237. https://doi.org/10.17705/1CAIS.05209

Schürholz D, Kubler S, Zaslavsky A (2020) Artificial intelligence-enabled context-aware air quality prediction for smart cities. Journal of Cleaner Production 271:121941. https://doi.org/10.1016/j.jclepro.2020.121941

Schwartz R, Dodge J, Smith NA, Etzioni O (2019) Green AI. arXiv (2019). https://doi.org/10.48550/arXiv.1907.10597

Scott-Fordsmand JJ, Amorim MJB (2023) Using Machine Learning to make nanomaterials sustainable. Science of the Total

Environment 859, https://doi.org/10.1016/j.scitotenv.2022.160303
Selukar M, Jain P, Kumar T (2022) Inventory control of multiple perishable goods using deep reinforcement learning for sustainable environment. Sustainable Energy Technol Assess 52:102038. https://doi.org/10.1016/j.seta.2022.102038
Sharma R, Kamble SS, Gunasekaran A, Kumar V, Kumar A (2020) A systematic literature review on machine learning applications for sustainable agriculture supply chain performance. Computers & Operations Research 119, https://doi.org/10.1016/j.cor.2020.104926
Sharma S, Rai S, Krishnan NC (2020) Wheat crop yield prediction using deep lstm model. arXiv https://doi.org/10.48550/arXiv.2011.01498
Shevlane T, Farquhar S, Garfinkel B, Phuong M, Whittlestone J, Leung J, Kokotajlo D, Marchal N, Anderljung M, Kolt N, et al (2023) Model evaluation for extreme risks. arXiv https://doi.org/10.48550/arXiv.2305.15324
Shi C, Feng X, Jin Z (2022) Sustainable development of China's smart energy industry based on artificial intelligence and low-carbon economy. Energy Science & Engineering 10(1):243–252. https://doi.org/10.1002/ese3.856
Shinde R, Froemelt A, Kim A, Hellweg S (2022) A novel machine-learning approach for evaluating rebounds-associated environmental footprint of households and application to cooperative housing. J Environ Manage 304:114205. https://doi.org/10.1016/j.jenvman.2021.114205
Sloane M, Zakrzewski J (2022) German AI Start-Ups and "AI Ethics": Using A Social Practice Lens for Assessing and Implementing Socio-Technical Innovation. In: Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency. FAccT '22, pp. 935– 947 . https://doi.org/10.1145/3531146.3533156
Smith C, Wong A (2022) Advancements in Artificial Intelligence-Based Decision Support Systems for Improving Construction Project Sustainability: A Systematic Literature Review. Informatics 9, 43 https://doi.org/10.3390/informatics9020043
Somers MJ, Birnbaum D, Casal J (2021) Supervisor support, control over work methods and employee well-being: New insights into nonlinearity from artificial neural networks. The International Journal of Human Resource Management 32(7), 1620– 1642 https://doi.org/10.1080/09585192.2018.1540442
Strnad FM, Barfuss W, Donges JF, Heitzig J (2019) Deep reinforcement learning in World-Earth system models to discover sustainable management strategies. Chaos 29(12):1–16. https://doi.org/10.5194/egusphere-egu2020-11263
Strubell, E., Ganesh, A., McCallum, A(2019) Energy and Policy Considerations for Deep Learning in NLP. In: Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pp. 3645– 3650. Association for Computational Linguistics, Florence, Italy . https://doi.org/10.18653/v1/P19-1355
Suanpang P, Jamjuntr P, Jermsittiparsert K, Kaewyong P (2022) Autonomous Energy Management by Applying Deep Q-Learning to Enhance Sustainability in Smart Tourism Cities. Energies (19961073) 15(5), 1906 https://doi.org/10.3390/en15051906
Suryanarayana KS, Prasad Kandi VS, Pavani G, Rao AS, Rout S, Krishna TSR (2024) Artificial intelligence enhanced digital learning for the sustainability of education management system. Journal of High Technology Management Research 35(2):100495. https://doi.org/10.1016/j.hitech.2024.100495
Su Z, Xing L, Ali HE, Alkhalifah T, Alturise F, Khadimallah MA, Assilzadeh H (2023) Latest insights on separation and storage of carbon compounds in buildings towards sustainable environment: Recent innovations, challenges, future perspectives and application of machine learning. Chemosphere 329, https://doi.org/10.1016/j.chemosphere.2023.138573
Tabianan K, Velu S, Ravi V (2022) K-means clustering approach for intelligent customer segmentation using customer purchase behavior data. Sustainability 14(12):7243. https://doi.org/10.3390/su14127243
Taylan O, Alkabaa AS, Alamoudi M, Basahel A, Balubaid M, Andejany M, Alidrisi H (2021) Air Quality Modeling for Sustainable Clean Environment Using ANFIS and Machine Learning Approaches. Atmosphere 12(6):713–713. https://doi.org/10.21203/rs.3.rs-282971/v1
Tazay AF (2020) A Comparison of Techno-economic Analysis of a Hybrid Renewable Energy Supply Options for Grid-connected Buildings : Case Study. In: 2020 Second International Sustainability and Resilience Conference: Technology and Innovation in Building Designs(51154), pp. 1– 7 . https://doi.org/10.1109/IEEECONF51154.2020.9319929
Toorajipour R, Sohrabpour V, Nazarpour A, Oghazi P, Fischl M (2021) Artificial intelligence in supply chain management: A systematic literature review. J Bus Res 122:502–517. https://doi.org/10.1016/j.jbusres.2020.09.009
Touvron H, Martin L, Stone K, Albert P, Almahairi A, Babaei Y, Bashlykov N, Batra S, Bhargava P, Bhosale S, et al (2023) Llama 2: Open foundation and fine-tuned chat models . https://doi.org/10.48550/arXiv.2307.09288
Tripathi S, Bachmann N, Brunner M, Rizk Z, Jodlbauer H (2024) Assessing the current landscape of ai and sustainability literature: identifying key trends, addressing gaps and challenges. Journal of Big Data 11(1):65. https://doi.org/10.1186/s40537-024-00912-x
Tsang SW, Jim CY (2016) Applying artificial intelligence modeling to optimize green roof irrigation. Energy & Buildings 127:360–369. https://doi.org/10.1016/j.enbuild.2016.06.005
Tsolakis N, Zissis D, Papaefthimiou S, Korfiatis N (2022) Towards AI driven environmental sustainability: an application of automated logistics in container port terminals. Int J Prod Res 60(14):4508–4528. https://doi.org/10.1080/00207543.2021.1914355
Tümer AE, Akkuş A (2018) Forecasting gross domestic product per capita using artificial neural networks with non-economical parameters. Physica A 512:468–473
United Nations: Millennium Development Goals. https://www.un.org/millenniumgoals/ Accessed 2024-04-30
United Nations: Our Common Future: From One Earth to One World - A/42/427 Annex, Overview - UN Documents: Gathering a body of global agreements. http://www.un-documents.net/ocf-ov.htm Accessed 2023-08-15
United Nations: The UN Sustainable Development Goals (2015). http://www.un.org/sustainabledevelopment/summit/ Accessed 2023-07-20
Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gomez AN, Kaiser Ł, Polosukhin I (2017) Attention is all you need **30**[SPACE]https://doi.org/10.48550/arXiv.1706.03762
Viet ND, Jang D, Yoon Y, Jang A (2022) Enhancement of membrane system performance using artificial intelligence technologies for sustainable water and wastewater treatment: A critical review. Critical Reviews in Environmental Science & Technology 52(20):3689–3719. https://doi.org/10.1080/10643389.2021.1940031
Vinuesa R, Azizpour H, Leite I, Balaam M, Dignum V, Domisch S, Felländer A, Langhans SD, Tegmark M, Fuso Nerini F(2020) The role of artificial intelligence in achieving the Sustainable Development Goals. Nature Communications 11, 233 https://doi.org/10.1038/s41467-019-14108-y
Vishwakarma LP, Singh RK, Mishra R, Kumari A (2023) Application of artificial intelligence for resilient and sustainable healthcare system: systematic literature review and future research

directions. International Journal of Production Research, 1–23 https://doi.org/10.1080/00207543.2023.2188101
Walk J, Kühl N, Saidani M, Schatte J (2023) Artificial intelligence for sustainability: Facilitating sustainable smart product-service systems with computer vision. Journal of Cleaner Production **402**[SPACE]https://doi.org/10.1016/j.jclepro.2023.136748
Wang HS-H, Yao Y (2023) Machine learning for sustainable development and applications of biomass and biomass-derived carbonaceous materials in water and agricultural systems: A review. Resources, Conservation & Recycling 190, https://doi.org/10.1016/j.resconrec.2022.106847
Wang Z, Srinivasan RS (2017) A review of artificial intelligence based building energy use prediction: Contrasting the capabilities of single and ensemble prediction models. Renew Sustain Energy Rev 75:796–808. https://doi.org/10.1016/j.rser.2016.10.079
Wolf T, Debut L, Sanh V, Chaumond J, Delangue C, Moi A, Cistac P, Rault T, Louf R, Funtowicz M, Davison J, Shleifer S, Platen P, Ma C, Jernite Y, Plu J, Xu C, Le Scao T, Gugger S, Drame M, Lhoest Q, Rush A (2020) Transformers: State-of-the-Art Natural Language Processing. In: Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pp. 38– 45. https://doi.org/10.18653/v1/2020.emnlp-demos.6
Wong SL, Wan KKW, Lam TNT (2010) Artificial neural networks for energy analysis of office buildings with daylighting. Appl Energy 87(2):551–557. https://doi.org/10.1016/j.apenergy.2009.06.028
Wongchai A, Jenjeti Dr, Priyadarsini AI, Deb N, Bhardwaj A, Tomar P (2022) Farm monitoring and disease prediction by classification based on deep learning architectures in sustainable agriculture. Ecological Modelling 474, https://doi.org/10.1016/j.ecolmodel.2022.110167
Wongchai A, Shukla SK, Ahmed MA, Sakthi U, Jagdish M, kumar R(2022) Artificial intelligence - enabled soft sensor and internet of things for sustainable agriculture using ensemble deep learning architecture. Computers & Electrical Engineering 102, https://doi.org/10.1016/j.compeleceng.2022.108128
Woo JH, Wu L, Park J-B, Roh JH (2020) Real-time optimal power flow using twin delayed deep deterministic policy gradient algorithm. IEEE Access 8:213611–213618. https://doi.org/10.1109/ACCESS.2020.3041007
Wu X, Zhou Q, Mu L, Hu X (2022) Machine learning in the identification, prediction and exploration of environmental toxicology: Challenges and perspectives. Journal of Hazardous Materials 438, https://doi.org/10.1016/j.jhazmat.2022.129487
Xiang Y, Chen Y, Xu J, Chen Z (2022) Research on sustainability evaluation of green building engineering based on artificial intelligence and energy consumption. Energy Rep 8:11378–11391. https://doi.org/10.1016/j.egyr.2022.08.266
Xiang X, Li Q, Khan S, Khalaf OI (2021) Urban water resource management for sustainable environment planning using artificial intelligence techniques. Environmental Impact Assessment Review 86, https://doi.org/10.1016/j.eiar.2020.106515
Yani M, Machfud Asrol M, Hambali E, Papilo P, Mursidah S, Marimin M (2022) An Adaptive Fuzzy Multi-Criteria Model for Sustainability Assessment of Sugarcane Agroindustry Supply Chain. IEEE Access 10:5497–5517. https://doi.org/10.1109/ACCESS.2022.3140519
Ye Z, Yang J, Zhong N, Tu X, Jia J, Wang J (2020) Tackling environmental challenges in pollution controls using artificial intelligence: A review. Science of the Total Environment 699, https://doi.org/10.1016/j.scitotenv.2019.134279
Zafar MH, Khan NM, Mansoor M, Khan UA (2022) Towards green energy for sustainable development: Machine learning based MPPT approach for thermoelectric generator. Journal of Cleaner Production 351, https://doi.org/10.1016/j.jclepro.2022.131591
Zangaro F, Minner S, Battini D (2021) A supervised machine learning approach for the optimisation of the assembly line feeding mode selection. Int J Prod Res 59(16):4881–4902. https://doi.org/10.1080/00207543.2020.1851793
Zayed ME, Zhao J, Li W, Elsheikh AH, Elaziz MA (2021) A hybrid adaptive neuro-fuzzy inference system integrated with equilibrium optimizer algorithm for predicting the energetic performance of solar dish collector. Energy 235:121289. https://doi.org/10.1016/j.energy.2021.121289
Zeng K, Zhang Q, Chen B, Liang B, Yang J (2022) Apd: Learning diverse behaviors for reinforcement learning through unsupervised active pre-training. IEEE Robotics and Automation Letters 7, 12251– 12258 https://doi.org/10.1109/LRA.2022.3214057
Zhao H-X, Magoulès F (2012) A review on the prediction of building energy consumption. Renew Sustain Energy Rev 16(6):3586–3592. https://doi.org/10.1016/j.rser.2012.02.049
Zhao N, You F (2022) Sustainable power systems operations under renewable energy induced disjunctive uncertainties via machine learning-based robust optimization. Renewable & Sustainable Energy Reviews **161**[SPACE]https://doi.org/10.1016/j.rser.2022.112428
Zhou X, Wang R, Wen Y, Tan R (2021) Joint IT-Facility Optimization for Green Data Centers via Deep Reinforcement Learning. IEEE Network 35(6):255–262. https://doi.org/10.1109/mnet.011.2100101
Zhou H, Zhang S, Peng J, Zhang S, Li J, Xiong H, Zhang W (2021) Informer: Beyond efficient transformer for long sequence time-series forecasting. Proceedings of the AAAI Conference on Artificial Intelligence 35:11106–11115. https://doi.org/10.1609/aaai.v35i12.17325

Authors and Affiliations

Lucas Greif[1] · Fabian Röckel[1] · Andreas Kimmig[1] · Jivka Ovtcharova[1]

✉ Lucas Greif
Lucas.Greif@kit.edu

[1] Institute for Information Management in Engineering, Karlsruhe Institute of Technology, 76133 Karlsruhe, Germany