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Research

Strategic view on the current role of AI in advancing environmental sustainability: a SWOT analysis

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Abstract
Sustainability has become a critical global concern, focusing on key environmental goals such as achieving net-zero emissions by 2050, reducing waste, and increasing the use of recycled materials in products. These efforts often involve companies striving to minimize their carbon footprints and enhance resource efficiency. Artificial intelligence (AI) has demonstrated significant potential in tackling these sustainability challenges. This study aims to evaluate the various aspects that must be considered when deploying AI for sustainability solutions. Employing a SWOT analysis methodology, we assessed the strengths, weaknesses, opportunities, and threats of 70 research articles associated with AI in this context. The study offers two main contributions. Firstly, it presents a detailed SWOT analysis highlighting recent advancements in AI and its role in promoting sustainability. Key findings include the importance of data availability and quality as critical enablers for AI's effectiveness in sustainable applications, and the necessity of AI explainability to mitigate risks, particularly for smaller companies facing financial constraints in adopting AI. Secondly, the study identifies future research areas, emphasizing the need for appropriate regulations and the evaluation of general-purpose models, such as the latest large language models, in sustainability initiatives. This research contributes to the growing body of knowledge on AI's role in sustainability by providing insights and recommendations for researchers, practitioners, and policymakers, thus paving the way for further exploration at the intersection of AI and sustainable development.

Keywords Artificial intelligence · Sustainability · SWOT analysis

1 Introduction

In recent years, increasing concern about climate change and environmental degradation has highlighted the urgent need for sustainable practices across industries. The urgency of this need has been intensified by political initiatives to mitigate global emissions, such as the Green Deals of the European Union. The goal of the Green Deals is to reduce greenhouse gas emissions and achieve climate neutrality by 2050. Furthermore, the Green Deals have the sub-target of reducing greenhouse gas emissions by at least 55 percent below 1990 levels by 2030 [1].

In the literature, three prominent strategies for achieving the goals can be identified: efficiency, sufficiency, and consistency [2]. While the efficiency strategy focuses on using resources more effectively to reduce waste and increase productivity, the sufficiency strategy emphasizes generally reducing consumption by changing the way of life so that it promotes more sustainable levels of resource use. The consistency strategy, in turn, aims to create a better interaction of nature and technology to create an environmentally friendly circular economy (e.g. according to the cradle-to-cradle

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principle) [3]. Although it is evident that both sufficiency and consistency strategies can offer significant improvements in many cases, more efficient or adapted technological approaches are needed in some areas to be suitable for an environmentally sustainable future in the medium term. For example, in the construction industry, integrating sufficiency principles into office building designs can significantly reduce resource consumption by focusing on frugality and modest use of resources [4]. This is especially relevant for sectors with high baseline emissions, such as agriculture or construction, which, despite their high emissions, can be considered essential for today's and tomorrow's society. In agriculture, implementing integrated nutrient management and sustainable water management practices can enhance crop yields while reducing environmental impacts, demonstrating the need for innovative approaches to achieve sustainability [5].

With recent developments, especially with the emergence of Large Language Models, AI is becoming increasingly important in today's society. Due to this development, the capabilities of AI have improved greatly in recent years, and new ways of using it have emerged. Therefore, it is interesting to assess current advances and limitations for its usage, such as for sustainability. In this sense, AI offers the opportunity to improve the efficiency of sustainability efforts in various sectors. For example, AI methods can be used to improve resource efficiency [6], reduce greenhouse gas emissions [7], and optimize environmental impact assessment [8]. The potential of AI is particularly relevant given the need for increased productivity in many sectors due to the expected increase in the global population [9]. To better understand the potential, this paper will examine how AI can be leveraged to address associated challenges, referring to the mitigation of climate change and ecosystem management.

In dynamically progressing research areas, such as AI for sustainability, the execution of a SWOT analysis—evaluating strengths, weaknesses, opportunities, and threats - serves as a strategic instrument to enhance understanding and delineate future necessities in this domain.

The paper is structured as follows: First, considering that the terms "Artificial Intelligence" and "Sustainability" are widely used and their meanings may vary individually, Section 2 provides a brief explanation of these two key terms. Section 3 describes the research methodology used in this study. Subsequently, there will be an overview of the potential of AI methods in the context of sustainability in the form of a framework inspired by a SWOT analysis. Therefore, Section 4 is divided into four subsections where 4.1 and 4.2 outline the technological strengths and weaknesses of AI methods, respectively. Sections 4.3 and 4.4 will then consider further opportunities as well as a variety of threats potentially preventing or decelerating AIs' use in this context. Section 5 discusses the interdependence of these four areas. Section 6 provides an outlook on future developments in the field. Finally, the paper concludes in Section 7.

2 Terminological foundations and related work

2.1 Artificial intelligence

The definition of AI is still subject to debate, which can be attributed in part to the fact that there is no standard definition of the term intelligence [10]. However, most commonly, AI is understood as human-like intelligence demonstrated by machines instead of humans. This also includes abilities closely related to intelligence, such as learning. However, whether a machine is considered capable of learning or thinking is a subjective assessment itself.

To put it more specifically, AI can be understood as the capability of a machine or computer system to emulate and execute tasks that would generally necessitate human intelligence, such as logical reasoning, learning, and problem-solving [11]. It encompasses the development of systems that can carry out tasks that usually require human intelligence, including learning, reasoning, problem-solving, perception, and language comprehension [12]. The idea of AI has progressed from the initial concepts of robots to contemporary applications in various domains such as healthcare, engineering, and everyday technology [13]. An example of a test to discover the capabilities of AI is called a Turing test or imitation game. This test was introduced by Alan Turing in 1950 [14]. Hence, Turing already illuminated associated concepts, but the invention of AI arguably did not take place until around 1955 by McCarthy [15]. Furthermore, efforts are being made today to subdivide AI or intelligence into further subclasses. One of these attempts provides a breakdown into the four consecutive classes of mechanical, analytical, intuitive, and empathy intelligence [16].

To maintain simplicity and consistency, this paper will use the term AI as a collective reference to various related computational methods. This includes terms such as Machine Learning or Deep Learning, which are considered to be subcategories of AI [17]. With the advent of the Large Language Model (LLM), the term "Artificial General Intelligence" (AGI) has regained prominence [18]. The term's initial appearance can be traced back to 1997, in the context of prospective technologies [19], and later, in relation to powerful AI systems in 2007 [20]. The concept of AGI, which involves systems with "universal characteristics" [21], is also incorporated within the overarching definition of AI in this paper. Note that purely numerical methods are not considered to be part of the class of AI methods, although they can naturally be part of a larger AI application.

2.2 Sustainability

Sustainability is a comprehensive concept that pertains to the capacity to sustain or uphold a process continuously over time. It includes ecological, social, and economic dimensions, ensuring that activities or processes do not exhaust resources or damage ecological and social systems beyond their ability to recover [22]. Thus, sustainability can be viewed as the objective or the ultimate state we aim to achieve, which is a balanced interaction between the environment, society, and economy that can persist indefinitely. A related concept, sustainable development, on the other hand, is a more dynamic concept that describes the process or approach to attaining sustainability [23]. The United Nations definition of Sustainable Development Goals (SDGs) shows how diverse the terms sustainability and sustainable development can be interpreted. The agenda comprises 17 sub-goals that are intended to contribute to the sustainable development. Therefore, it also includes social (e.g. no poverty) and humanitarian (e.g. zero hunger) aspects [24].

Fig. 1 serves as a conceptual illustration of the interconnections among the SDGs.

The diagram is organized into concentric layers with the following elements:

1. **Biosphere:** Forming the base, it is depicted as the largest and lowest layer, emphasizing its essential role in supporting life and human activities. It specifically includes SDG 6 (Clean Water and Sanitation), SDG 13 (Climate Action), SDG 14 (Life Below Water) and SDG 15 (Life on Land).
2. **Society:** The middle layer, indicating that society is built on the biosphere and relies on its health and stability. Covers various SDGs related to social dimensions: 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).
3. **Economy:** The topmost layer, suggesting that a sustainable economy is underpinned by a robust 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).
4. **SDG 17 (Partnerships for the Goals):** Placed at the apex, it symbolizes its role in uniting and facilitating the achievement of all other SDGs through global partnerships.

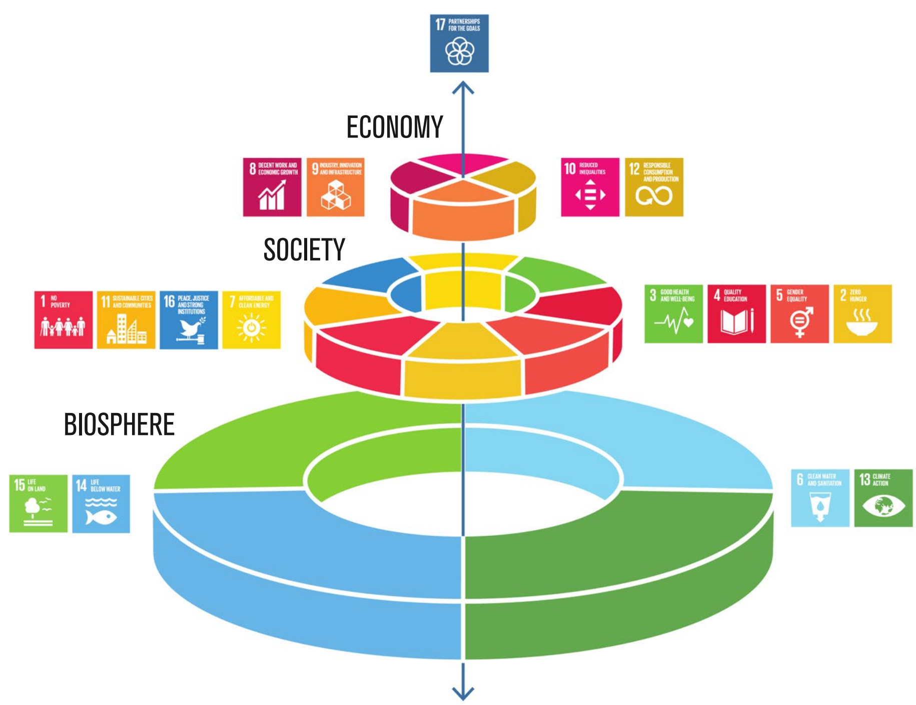


Fig. 1 Stockholm Resilience Center's wedding cake model of the SDGs [25]

The figure portrays the SDGs not as separate or individual goals, but as interconnected parts of a unified system. The economy and society are depicted as embedded within the biosphere, underscoring the importance of environmental sustainability as the foundation for social stability and economic prosperity. Although these elements cannot be distinctly separated, the term sustainability in this work will primarily refer to the foundational sphere, i.e., the environmental aspects, as suggested by the title. Topics such as mitigating climate change by reducing greenhouse gas emissions and using natural resources more sustainably will be discussed. However, this paper will also occasionally address economic aspects, as these will significantly influence the adoption of new, more environmentally sustainable technologies.

2.3 Related work

This paper builds on the 2021 SWOT analysis to use AI to achieve all the SDGs conducted by Palomares et al. [26], as well as the 2020 SWOT analysis by Nishant et al. [27]. These SWOT analysis have highlighted the emphasis on synergies between AI and digital technologies, along with the critical role of high-quality data, despite computational challenges. Similarly, a detailed exposition on the practical application of AI in domains such as smart water management and AI-enhanced agriculture has been provided, advocating for strategic collaboration to optimize benefits and attenuate risks [28]. Currently, there is an emphasis on adopting a regulatory approach to overcome potential obstructions resulting from the practices of tech firms [29]. For supply chains, a more recent study [30] was conducted that emphasized the need to incorporate AI into supply chains to integrate sustainability dimensions. A more general study [31] was conducted that provides a review of the application of artificial intelligence towards sustainable development goals in various industries, focusing on popular models and suggesting future research avenues. A comprehensive exploration of the multifaceted influence of AI on the SDGs has been presented, drawing attention to the ability to amplify and hinder targets depending on the application, to underscore the need for stringent regulations to increase the positive repercussions of AI and reduce its adverse effects [24]. Another research evaluates current frameworks for measuring AI's impacts regarding sustainability. The authors argue that current models do not adequately capture the sustainability implications of AI, often resulting in the non-disclosure of potential adverse effects [32].

In contrast to the existing literature, this study aims to focus on environmental sustainability, evaluating the current characteristics of AI's latest developments and its potential influence on the promotion or deterioration of sustainable development. Unlike conventional review papers, this study uses a SWOT analysis to assess the role of AI from a more strategic point of view. Given that the most recent SWOT analysis dates back to 2021, and considering the dynamic nature of AI, it is expected that examining current developments will provide numerous new insights. In addition, strategies that could help improve strengths and opportunities or mitigate some of the weaknesses and threats will be addressed.

3 Research methodology

SWOT analysis first evaluates the internal factors *Strengths* and *Weaknesses*, followed by an evaluation of the external factors of *Opportunities* and *Threats* [33]. This tool, which originated in the business management sphere [34] primarily for strategic planning, has seen extensive use in a diverse range of disciplines [35]. For example, SWOT analyzes have been conducted to investigate construction waste management in Shenzhen, China, highlighting the urgent need for strategic improvement [35], the digitalization of workflows using machine learning in the oil and gas industry, emphasizing the importance of strategic focus and collaboration [36], and the implications of the AI tool ChatGPT, for education, revealing both the immense potential and the accompanying risks of AI in educational settings [37].

The research methodology used consists mainly of four parts, as shown in Fig. 2.

First, a deductive analysis [38] was performed, sourcing relevant literature from the field of applied AI to improve sustainability, including, for example, case studies or secondary analyses. The notable characteristics and results were extracted from the compiled literature, with an emphasis on recurrent terms. The subsequent SWOT analysis of these key attributes allowed categorization of the insights. The study culminated with the generation of recommendations to increase the use of AI in the context of sustainability. Therefore, identified SWOTs are evaluated with regard to the common guideline 'maximizing strengths and opportunities, transforming weaknesses into strengths, and minimizing threats' [39, 40].

The refinement of the methodology had an iterative nature that became evident during the SWOT analysis and recommendation formation stages, as new insights required a further review of the literature in the field.

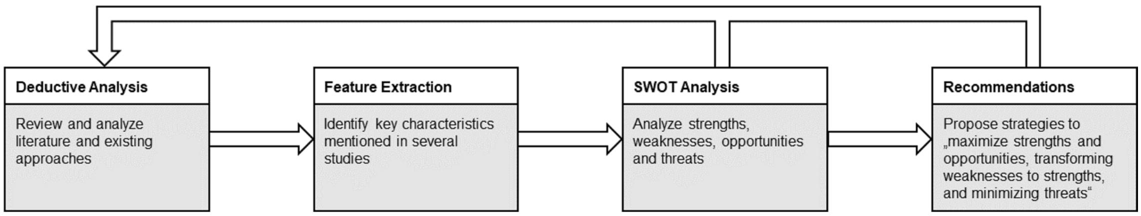


Fig. 2 Methodological approach

4 SWOT analysis

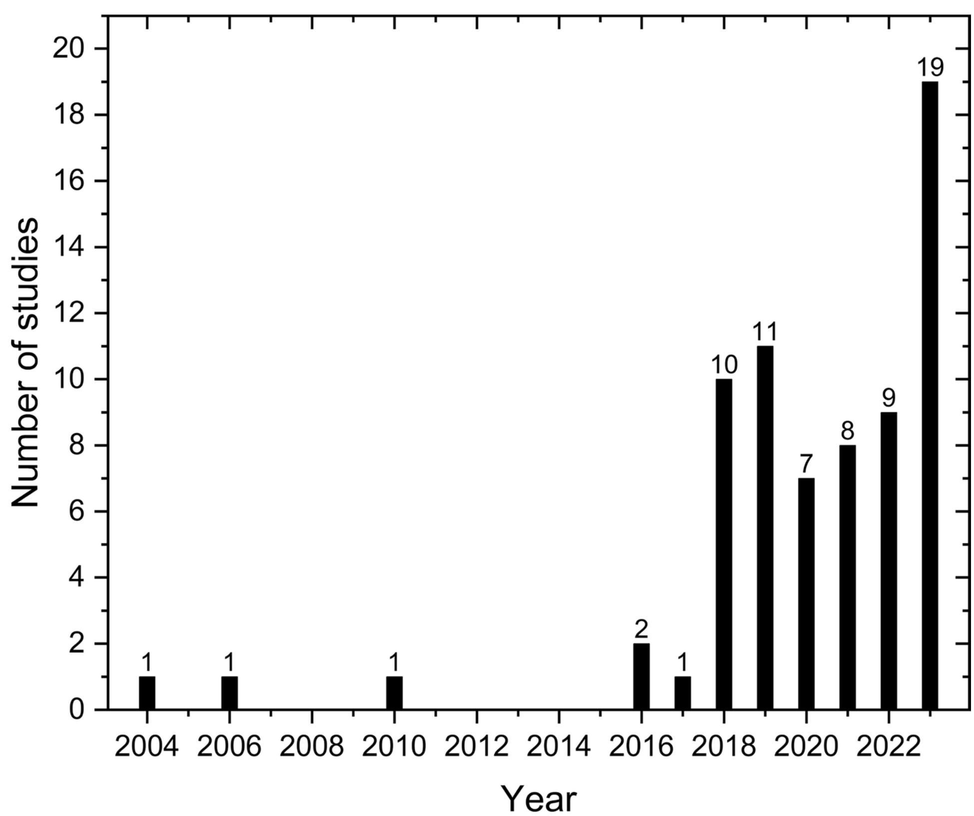
In evaluating the contemporary role of AI in the development of sustainability efforts, our review methodology prioritized research and literature published in the last 5 years, that is, after 2018 to reflect the most recent developments in the field. However, certain foundational works were also considered due to their enduring relevance and validity in the current context. Figure 3 presents a histogram representation of the distribution of publication year associated with the studies included in the SWOT analysis.

Throughout each section of the SWOT analysis, a figure will highlight the three key aspects that should be considered when implementing AI methods for sustainability. Given the dynamic and unpredictable nature of AI advancements, some speculative elements are unavoidable in SWOT analysis. However, this work will concentrate on the immediate and foreseeable aspects.

4.1 Strengths

Based on the understanding and delimitation provided in Sect. 2, this paper identified three main strengths of AI with regard to its use for sustainability.

Fig. 3 Distribution of publishing years of the papers incorporated within the SWOT analysis



The first strength is the possibility of learning solutions purely from data, and in many cases, only relying on very little knowledge about the underlying process. This means that detailed knowledge of the natural sequence of the process to be depicted (relationship between input and output) is not necessarily required to train an AI model. While numerical methods usually try to represent or approximate this process mathematically, AI methods normally "do not care" how the actual process works (e.g. physically), as long as a sufficient amount of data to learn is available and a model structure appropriate for the complexity of the process is chosen. Especially for new and therefore potentially under-researched questions, this can offer a great advantage compared to numerical methods. This is illustrated, for example, by a study of fluid mechanics that highlights implications for sustainability by using machine learning, particularly in relation to energy efficiency and environmental impact [41]. Closely connected is AI's ability to efficiently process very large amounts of data. Therefore, AI can often find solutions to problems of unusually high complexity. AI can exploit the full information density of input data, enabling solutions to complex problems that appeared previously unsolvable without human intelligence. An example of this strength is autonomous driving. On the one hand, the problem is very complex and requires a large amount of data as a decision-making basis. On the other hand, since decisions must be made in real time, it is crucial to quickly process the large amount of sensor and image data and filter relevant information according to the situation [42].

A more abstract but potentially relevant strength of AI methods may be its ability to improve the simulation of highly complex systems relevant to the topic of sustainability. For example, it is argued that this could benefit effective monitoring of natural resources or, more generally, contribute to knowledge in the field of climate science [8]. More specifically, deep learning models can help to acquire new insights from the rapidly increasing amount of geospatial data, and thus better assess the evolution of various environmental processes. AI methods have already been implemented for weather forecasting and focused physical modeling, and can now be applied to increasingly holistic use cases [43].

As a third strength of AI methods, the possibility to separate the training and application process of a given AI method was identified, for example, demonstrated in the field of medical logistics [44], medical imaging [45], and the detection of precancerous cervical lesion [46]. While training and application often have an iterative approach in certain machine learning methods, such as reinforcement learning, the process of fitting the model structure by the data and generating the output for a given input data set can be decoupled in the majority of machine learning techniques. This makes it possible to run through the time-consuming training process in advance and then provide comparatively efficient decisions afterward.

A specific area where AI can be seen as a great sustainability enabler is agriculture [8]. Due to the expected growth in the world population [9] and the massive demand for ammonia in the agricultural sector, it can be considered a very relevant economic field with regard to sustainability.

Two concrete applications involving AI in this context are precision farming [47] and real-time control of the application of fertilizers and herbicides [48]. For precision agriculture, AI algorithms could help support the growing process and significantly increase crop yields by managing controllable parameters such as irrigation or fertilization [49].

Furthermore, AI can optimize resource use through advanced algorithms and predictive analytics, reducing natural resource and energy consumption [50]. Furthermore, AI optimizes transportation systems by reducing traffic congestion and emissions, thereby improving urban mobility and contributing to the development of smart cities [51].

AI can be used in biodiversity conservation through advanced data analysis and monitoring techniques. For example, AI algorithms can process large volumes of data from remote sensors, camera traps, and satellite imagery to monitor wildlife populations and track changes in ecosystems. Machine learning models can identify species, count individuals, and detect patterns that indicate environmental changes or threats, such as poaching or habitat destruction. This enables conservationists to make informed decisions and implement timely interventions to protect endangered species and preserve biodiversity [52]. In the realm of renewable energy, AI assists in strategic planning and optimization of energy production and distribution by analyzing weather patterns, historical data on energy consumption, and geographic information. This allows AI systems to predict energy demand and optimize the placement and operation of renewable energy sources such as solar panels and wind turbines. Machine learning models can forecast energy output based on weather conditions, enhancing the integration of renewable energy into the grid, and ensuring a stable energy supply. In addition, AI optimizes maintenance schedules and predicts equipment failures, reducing downtime and improving the efficiency of renewable energy systems [53].

As another example, it is highlighted that AI could provide helpful insights in pollution management [54]. Therefore, the potential to minimize greenhouse gas emissions and groundwater contamination is taken into account through intelligent management of landfill waste disposal [55]. Furthermore, the transport sector is also known to produce a large amount of climate-damaging emissions. In addition, it is indicated that these could be reduced even more by using autonomous vehicles [7]. Explicitly, the reduction in emissions could be achieved by a fuel consumption-reducing style of driving, as well as by reducing traffic congestion. In addition, it should be mentioned that this could have a positive and scalable effect for commercial transport, especially (e.g., supply chain) [56]. The mentioned problems seem rather difficult to solve with alternative methods, as they require AI's strengths of being able to compute large amounts of data. Furthermore, other areas such as the chemical industry [57], as well as manufacturing processes [58], are considered to have the ability to improve environmental sustainability by using AI, as many others.

In conclusion, the three key internal strengths of AI methods for sustainable development are their *speed*, their ability to solve highly *complex* problems, and the possibility of *separating* training and application processes, which are presented in Fig. 4.

4.2 Weaknesses

One of the most prominent challenges in the application of AI methods is the concern of explainability of the AI method implemented [59]. The reason for the appearance of this problem is the perceived lack of understanding or representation of how recommendations or estimates resulting from AI methods are computed. Therefore, decision makers may be reluctant to implement the recommendations of AI methods, despite their potential high quality.

Another weakness of AI methods in terms of sustainability is the high power consumption that many of the methods cause. The energy consumption for developing and operating AI systems can negate some of the benefits of sustainability [51]. Above all, training large models, and thus in most cases particularly powerful models, causes significant computational effort and requires a considerable amount of energy [24]. This is demonstrated by training (GPU) an NLP model (Natural Language Processing), which was estimated to cause around 300 tons of C02 emissions [60]. However, it should be noted that the environmental impact greatly depends on the mix of electricity. Even if sufficient sustainable energy is available in the long term, this will be an important consideration at least in the short to medium term, especially as the total electricity demand is expected to increase in many industrialized countries as they switch from fossil fuels to more sustainable solutions (e.g. heating buildings, transportation).

Furthermore, the vulnerability of AI methods to systemic risks [8] should be highlighted. These include, for example, algorithmic bias and allocative harms. It is indicated that the results of complex AI methods can be strongly distorted by data bias [61].

In many AI applications, particularly those involving deep learning, the models function as "black boxes," meaning their decision-making processes are not transparent. For example, Holzinger et al. [62] highlight that while deep learning models can achieve high performance, their internal representations are often too complex for humans to understand, making it difficult to interpret why a model made a particular decision [62]. One major challenge is that most AI models are designed to optimize performance metrics such as accuracy, often at the expense of interpretability. This trade-off makes it difficult to provide explanations that are accurate and understandable in specific contexts, such as environmental sustainability, where stakeholders need to see how different environmental factors interact and contribute to the model outputs [63].

Data biases are especially relevant, for example, in the healthcare sector, where numerous studies must be performed from which data can be derived. However, even with careful implementation, biases such as "information bias, selection bias, and uncontrolled confounding" [64] cannot be avoided there. As data sets increase in size, this issue is likely to become even more pronounced, underlining the need to understand data bias or even data bias mitigation strategies.

Fig. 4 Overview of key strengths of AI methods for sustainability

Strengths	
Speed	Faster computation leads to a reduction in: energy consumtion, cooling materials and other resources.
Complexity	New use cases can be addressed, which can handle previously unsolvolable problems due to high complexity of the data.
Seperability	By frontloading the high computational training effort, AI facilitates fast decision-making, opening up opportunities for application in new areas.

Furthermore, phenomena that are underrepresented in the data set often cannot be mapped with sufficient precision by the methods applied to the data [65]. This could lead to overestimation of historical risks and underestimated new risk phenomena [66], which can lead to issues regarding regime changes, for example. The reliance of AI models on historical data can also lead to inaccurate prediction of future scenarios, leading to potential inaccuracies in applications [50]. These occur often unexpectedly in ecological systems [67].

Another problem is that some solutions may become impractical for certain classes of companies because these companies are subject to special conditions for which a sufficient data basis cannot be ensured or for which separate optimization is not economically reasonable [68]. Furthermore, the integration of AI into sustainability efforts is hampered by barriers such as data privacy concerns and high implementation costs, which need to be addressed to realize its full potential [69].

In summary, the three internal weaknesses of AI methods for sustainable development are their lack of *explainability*, their high *energy use*, and their potential *data bias*, as presented in Fig. 5.

4.3 Opportunities

As considered in the Strengths section, there are numerous applications involving AI methods that could help improve sustainability. Most of the efforts presented have the goal of limiting the consequences of climate change by decelerating its progress (e.g., by lowering greenhouse gas emissions). However, depending on the success of the overall effort to mitigate problems caused by climate change, there are likely to be a number of unpleasant early, medium and possibly long-term consequences. Some authors see this as another opportunity to use AI methods. For example, AI-powered systems are argued to enable more effective and accurate monitoring of the ecosystem [8]. For example, AI can improve climate change mitigation by advancing weather forecasting, enhancing disaster resilience, and optimizing renewable energy systems [70].

Improvements in this area could subsequently help predict associated effects more accurately and take appropriate precautions (e.g. to protect society, the ecosystem, or infrastructure). The expected permanent increase in extreme weather events is an example of one of these unpleasant effects. AI methods are well suited to assess weather conditions more accurately than conventional methods and to indicate threatening weather conditions earlier [43]. For example, AI methods can be used to predict the course and emergence of wildfires. These methods enable a more accurate prediction, helping to protect forests at risk, which are considered a key asset for a sustainable future [71].

Additionally, AI's application in education for sustainable development can promote knowledge and skills necessary for building a sustainable world, further supporting global sustainability initiatives [72].

Another opportunity is aligning AI with the SDG goals by making the appropriate governance decisions to promote its use for positive purposes [8]. Like any other technology, AI has no natural inclination to bring about "good", but can be an enabler for many different purposes. Therefore, meaningful governance for the use of AI could be a great enabler of positive design. Governance frameworks that emphasize ethical and socially responsible AI can significantly reduce the environmental impact of computing systems. These frameworks ensure that AI applications promote sustainability by addressing issues related to bias, privacy, and job displacement [73].

Quantum AI represents a frontier opportunity in sustainable energy, combining quantum computing with AI to optimize energy production and reduce environmental impact. This approach can improve the efficiency of renewable energy systems by providing advanced predictive analytics and real-time optimization capabilities, which are crucial for managing complex energy networks and maximizing renewable energy output [74].

Fig. 5 Overview of key weaknesses of AI methods for sustainability

Weaknesses	
Explainability	The lack in transparency of AI methods can hinder their adoption.
Energy Use	While AI methods often consume less energy than numerical methods, the development of new applications could potentially lead to an overall increase in total energy consumption.
Data Bias	AI methods rely on large datasets, which often contain biases. These biases can result in imbalanced outcomes, potentially affecting social, economic, and environmental aspects disproportionately.

AI presents opportunities for developing sustainable computing practices, such as energy-efficient data centers and smart grids. Green AI aims to create environmentally friendly AI systems that reduce the ecological footprint of various sectors. Applications include optimizing energy consumption in buildings, improving crop yields, optimizing public transportation, and managing waste. These innovations can lead to significant reductions in greenhouse gas emissions and conservation of natural resources [75].

In addition, AI has the potential to accelerate scientific fields that themselves contribute to improving environmental sustainability. For example, AI could help advance materials science [76] (for example, by contributing to the development of more sustainable building materials). For example, a conditional variational autoencoder (cVAE) has been developed, which is capable of generating UV–Vis spectra from an image of the material, providing an accelerated method for material characterization [77, 78].

Similarly, AI could help to gain new insights into chemistry [79], for example, AI can predict reactions and synthesis [80]. AI could improve sustainability by accelerating the pace and reducing the cost of scientific discoveries, thus stimulating an increase in research productivity [81].

Therefore, the three external opportunities that can facilitate the use of AI methods for sustainable development are their ability to *mitigate the consequences of climate change*, an appropriate *governance*, and their potential *scientific value*, as presented in Fig. 6.

4.4 Threats

As great as AI's potential for improvement may be, there is a considerable number of threats to an even faster and widespread adoption. Arguably, it is as important to discuss these as it is to outline the opportunities, since it helps to encourage novel solutions and social openness towards the use of AI in the long term.

One of the most significant threats to the increased adoption of AI methods for sustainability is implied by the technical nature of these methods, namely cybersecurity, which can be subdivided into two main risks. First, the use of AI more intensively potentially exposes sensitive data owned by companies. This increases the likelihood that important data sets are stolen or decrypted by criminals, posing a high legal and economic risk. The second main risk in the context of cybersecurity is that AI methods offer the inherent possibility of being sabotaged due to their digital and data-driven nature [8]. Especially given the tendency of AI methods to integrate with an external cloud computing infrastructure, there is a risk of external manipulation by competitors that is difficult to control. This will likely lead companies to be cautious about using AI methods in areas that are crucial to their economic stability and could hinder accelerated adoption. In particular, cybersecurity poses a disproportionately high hurdle for companies that have exposure to critical infrastructure (e.g., the energy industry), sensitive data (e.g. healthcare), or companies in areas that have only been moderately digitized to date (e.g. agriculture).

In addition, regulatory restrictions can present significant hurdles to the application of AI. The lack of clear and comprehensive regulations for AI technology is a major challenge, as existing laws and regulations may not always be sufficient to address its specific risks [82]. An associated challenge can be seen in the ethical and moral considerations surrounding AI [24], such as concerns about potential job loss, unequal distribution of benefits, and harm to individuals from biased or unfair AI systems [83]. Companies looking to implement AI on a larger scale should therefore assess the potential risk of encountering negative reactions from their employees or customers in the short term [84].

Furthermore, it is argued that the handling of personal data in AI systems raises crucial privacy and security concerns that need to be addressed through specific laws and regulations [83]. However, enforcing consistent regulations across borders is difficult, as AI algorithms and systems are often developed and operated by companies or organizations based

Fig. 6 Overview of key opportunities of AI methods for sustainability

Opportunities	
Mitigate Climate Change Conseq.	AI can play a significant role in addressing climate change e.g. by optimizing energy consumption and supporting climate adaptation strategies.
Governance	AI's versatility allows the adoption of insights from other fields and its integration into other domains to develop sustainable solutions across various disciplines.
Scientific Value	The responsible development and deployment of AI technologies can be assured by governance structures and policies that ensure ethical, transparent use in line with sustainability objectives.

in multiple countries with different circumstances [85]. In light of these challenges, it is fairly evident that regulation could prove a significant threat to the wider adoption of AI methods if a healthy balance between regulation and freedom of innovation cannot be found.

Another potential risk for the broader adoption of AI methods is the difficulty in assessing the business value of their application. Depending on the exact procedure, the implementation of AI methods can incur high costs without necessarily guaranteeing improvements of a certain magnitude. Especially for small and medium companies, this poses the risk of obtaining results that can only be used or interpreted to a limited extent, thus possibly preventing a fair amount of beneficial investments.

Additionally, small and medium-sized companies might also decide against making considerable investments due to their inability to efficiently spread the fixed cost [8]. The costs associated with data collection, technical expertise, and computing power for model training could pose significant challenges, particularly for small businesses that may require specialized approaches. When coupled with the inherent difficulty in evaluating the economic value of certain AI solutions, smaller companies may face a disproportionate risk compared to larger corporations. This could potentially impede the adoption of AI in economic sectors dominated by small and medium companies or even result in their business closures. For example, implementing AI solutions in the renewable energy sector requires specialized technical expertise, which can be a barrier for many organizations. In addition, the initial costs of developing and deploying AI systems can be prohibitive, particularly for smaller companies or regions with limited financial resources. In the renewable energy sector, acquiring comprehensive high-quality datasets can be challenging. Inadequate data can lead to inaccurate predictions and suboptimal performance of AI systems. Furthermore, the integration of various data sources requires sophisticated data management strategies to ensure reliability and accuracy [86]. These factors can slow the adoption and integration of AI technologies in renewable energy projects [87].

It is also outlined that AI can also serve as a facilitator for less environmentally friendly industries and procedures [54]. For example, AI methods could increase the efficiency and profitability of environmentally harmful processes, leading to lower prices and possibly fostering higher emissions, as well as less economic pressure to innovate for alternatives.

Furthermore, the rapid development of AI technologies could exacerbate inequalities and biases, potentially leading to negative social impacts and resistance to AI adoption in sustainability efforts [88]. Moreover, AI's potential to influence production and consumption patterns could result in unforeseen consequences, emphasizing the need for comprehensive evaluation and management of its societal impacts [89].

To expand upon this example and in relation to the AI alignment problem [90], it is essential for AI's interests to be aligned with preserving the environment (e.g., maintaining environmental stability). In a hypothetical scenario, should humans become obsolete as identified by Turchin [91], human values are not intrinsic to machines [91], an AI system can view the positive aspects of extreme weather conditions, such as their high energy yield, as favorable, while disregarding the negative environmental consequences due to the lack of biological needs.

AI faces several threats that could impede its role in sustainability. Ethical and privacy concerns are significant and require comprehensive regulatory oversight to ensure transparency, safety, and ethical standards [92].

The analysis section identified three main external risks that can mitigate the use of AI methods for a sustainable development: the concern over *cybersecurity*, *Regulations*, and the potential *economic risk*, as presented in Fig. 7.

Table 1 provides an overview of the articles included in the SWOT analysis, categorizing them based on the strengths, weaknesses, opportunities, and threats they address.

Fig. 7 Overview of key threats of AI methods for sustainability

Threats	
Cybersecurity	Cybersecurity plays a crucial role in protecting sensitive information.
Regulation	The advancement of AI technologies can outpace the creation of appropriate regulations, potentially leading to inadequate or outdated regulatory frameworks.
Economic Risk	The assessment of the economic value of AI methods can be difficult, which may result in economic risks for companies as they invest in AI technologies without knowing their potential return on investment.

5 Discussion

5.1 General discussion

The SWOT analysis conducted in Chapter 4 offers a comprehensive overview of the strengths, weaknesses, opportunities, and threats associated with AI in the realm of environmental sustainability. These findings underscore the multifaceted role that AI plays in improving sustainability efforts and the complexities involved in its deployment.

Among the most significant strengths identified is AI's capacity to process vast amounts of data and solve intricate problems that were previously deemed unsolvable without human intervention. This capability is particularly crucial in fields such as agriculture, where AI can markedly improve resource efficiency and crop yields through precision farming techniques. The ability of AI to learn from data with minimal prior knowledge of the underlying processes highlights its potential to drive innovations in sustainability in various sectors.

However, this potential is tempered by significant weaknesses, primarily the high energy consumption associated with AI technologies. Training large AI models often requires substantial computational resources, leading to considerable carbon emissions. This paradoxically undermines the environmental benefits that AI aims to deliver. Addressing this challenge requires advances in energy-efficient AI technologies and the integration of renewable energy sources into data centers.

The opportunities for AI in sustainability are expansive. The ability of AI to enhance climate change mitigation strategies through improved weather forecasting, disaster resilience, and optimization of renewable energy systems presents transformative potential. Additionally, AI can accelerate scientific research in fields critical to sustainability, such as materials science and chemistry, by providing advanced data analysis tools and predictive models.

Conversely, the threats to AI's role in sustainability are significant. Cybersecurity risks, regulatory challenges, and economic feasibility of AI implementations pose barriers to widespread adoption. The threat of algorithmic bias and the lack of explainability in AI decisions further complicate the deployment of AI solutions in critical sectors.

The distribution of articles included in the SWOT analysis, as illustrated in Table 1, indicates a balanced focus on the various dimensions of AI's impact on sustainability. The strengths, weaknesses, opportunities, and threats identified are supported by a diverse range of studies, reflecting a comprehensive examination of AI's role. The concentration of articles on the strengths of AI, particularly its speed and complexity, underscores the high potential recognized by the research community. Similarly, the considerable attention given to weaknesses, especially energy use and data bias, highlights the critical challenges that need to be addressed.

This distribution implies that while there is significant optimism about AI's capabilities, there is an equally strong awareness of the obstacles that must be overcome to realize its full potential in sustainability. The opportunities, particularly in mitigating climate change and advancing scientific research, are well supported, indicating clear pathways for AI to contribute positively. However, threats such as cybersecurity and regulatory issues receive substantial coverage, highlighting the need for robust strategies to mitigate these risks. This balanced distribution suggests a

Table 1 Overview of articles included in the SWOT analysis

SWOT	Description	Article
Strengths	Speed	[42, 48, 52]
	Complexity	[6, 41, 42, 49–53, 93]
	Separability	[44–46]
Weaknesses	Explainability	[59, 62, 63]
	Energy use	[24, 51, 60]
	Data bias	[8, 61, 64–69, 94]
Opportunities	Mitigate climate change conseq.	[8, 43, 70, 71, 74, 75]
	Governance	[8, 73]
	Scientific value	[9, 47–49, 72, 76–81, 95, 96]
Threats	Cybersecurity	[8, 88, 89]
	Regulation	[82–85, 92, 97]
	Economic risks	[7, 8, 54–58, 86, 87, 90, 91]

mature and realistic approach within the research community toward leveraging AI for environmental sustainability, recognizing both its transformative potential and the critical challenges that must be managed.

By comparing our results with related work, we find that our findings align closely with previous studies while also providing new insights into the evolving landscape of AI for sustainability. Palomares et al. [26] and Nishant et al. [27] both highlighted the synergy between AI and digital technologies [26], as well as the critical role of high-quality data [27], which our analysis also underscores. However, our study places greater emphasis on the latest advancements in AI, particularly the potential and challenges posed by Large Language Models (LLMs) and other recent developments.

Our analysis critically questions the results of Vinuesa et al. [98]. They highlighted that AI has an overall positive contribution towards sustainability. Their results show that AI significantly supports the achievement of Sustainable Development Goals (SDGs), contributing positively to 134 of the 169 targets. This is particularly evident in sectors such as healthcare, agriculture, and renewable energy [98]. However, we believe that this positive impact is highly dependent on how the threats and weaknesses of AI systems are addressed, and different scenarios can lead to varying outcomes. Therefore, these factors might need more careful consideration.

Our analysis expands on the work of Goralski and Tan [28] and Truby [29], which focused on the regulatory and ethical dimensions of AI. We delve deeper into the specific threats posed by cybersecurity and the economic risks associated with AI implementation, providing a more granular view of these challenges. This is consistent with the findings of Jobin et al. [85], who emphasized the global landscape of AI ethics guidelines.

Moreover, our analyses highlight the dynamic and unpredictable nature of AI advancements, echoing the sentiments of Reichstein et al. [43] and Vasudevan et al. [76] regarding the transformative potential of AI in scientific discovery and environmental monitoring.

5.2 Strategies to enhance AI's contribution to sustainability

To maximize the strengths and opportunities of AI while mitigating its weaknesses and threats, several strategic actions can be proposed:

(A) Enhance Data Availability and Quality

1. **Digitize Data Capture:** Implement advanced technologies to digitally capture more diverse and extensive datasets. This will provide a richer foundation for AI learning, improving the models' ability to recognize complex patterns and relationships.
2. **Concept Drift Detection** To address deficiencies in data quality, it is recommended to conduct thorough model maintenance, allowing for modifications when alterations in the database are observed. One method of exploring this issue is through the study of concept drift. The central objective of this approach is to identify and, consequently, address alterations within the system that can result in a reduction in the performance of AI models [94].
3. **Comprehensive Data Examination:** Regularly review and clean data sets to identify and correct errors and biases. This ensures the reliability and accuracy of the data, leading to more robust AI models. This is evident, for example, in agricultural applications, where large volumes of data must be efficiently organized to extract vital information [93].
4. **Facilitate Data Sharing:** Establish frameworks for data sharing between researchers, companies, and other stakeholders. This can be achieved through data sharing agreements and collaborations, while maintaining strict data privacy and security protocols.

Enhancing data availability and quality is fundamental to AI's success in sustainability. By ensuring data integrity and encouraging data sharing, AI models can be trained on richer and more accurate datasets, leading to better performance and more reliable results.

(B) Promote Collaborative Efforts

1. **Shared Infrastructure for SMEs:** Small and medium enterprises (SMEs) can reduce costs by building common infrastructures and sharing resources. Collaboration on topics like cybersecurity and AI business value can lead to collective improvements.
2. **Public-Private Partnerships:** Encourage partnerships between academia, industry, and policymakers to promote knowledge exchange and develop innovative solutions for sustainability challenges.

Promoting collaborative efforts is crucial for leveraging AI's full potential. By pooling resources and expertise, various stakeholders can overcome individual limitations, leading to more robust and innovative solutions for sustainability.

(C) Adopt Explainable AI and Ethical Standards

1. **Explainable AI (XAI):** Invest in developing and implementing XAI techniques such as layer-wise relevance propagation (LRP) [99] and counterfactual methods [100]. These methods improve the transparency of AI decisions, making them more understandable and trustworthy.
2. **AI Ethics:** Develop and adhere to ethical guidelines for AI usage. Transparent AI ethics can help mitigate social concerns and legal risks, ensuring that AI applications are aligned with societal values.

Adopting explainable AI and ethical standards is vital to gaining public trust and ensuring that AI applications are effective and socially responsible. By making AI decisions more transparent and adhering to ethical guidelines, stakeholders can address concerns related to AI's impact on society.

(D) Address Energy Consumption

1. **Renewable Energy Integration:** Locate data centers in regions with abundant renewable energy sources. Furthermore, optimize AI training processes to coincide with periods of surplus CO2-neutral energy.
2. **Greem AI:** Focus on the research and development of AI technologies that require less computational power and consequently lower energy consumption.

Addressing energy consumption is critical for ensuring that AI's environmental benefits are not offset by its energy requirements. By integrating renewable energy and developing energy-efficient AI technologies, the overall carbon footprint of AI can be minimized.

(E) Create Regulatory and Incentive Frameworks

1. **Incentivize Data Sharing:** Create incentives for companies to share data by offering benefits such as tax breaks or research grants.
2. **Robust Regulation:** Implement regulations that balance the need for data privacy and security with the benefits of data sharing. Effective data governance frameworks are essential to foster innovation while protecting stakeholders' interests [97].

Implementing regulatory and incentive frameworks is essential to guide the responsible development and deployment of AI. By incentivizing data sharing and establishing robust regulations, stakeholders can ensure that AI development aligns with societal values and sustainability goals.

By adopting these strategies, the potential of AI to contribute to sustainability efforts can be improved, addressing both current weaknesses and future opportunities. These measures can also mitigate threats and ensure that AI developments align with global sustainability goals.

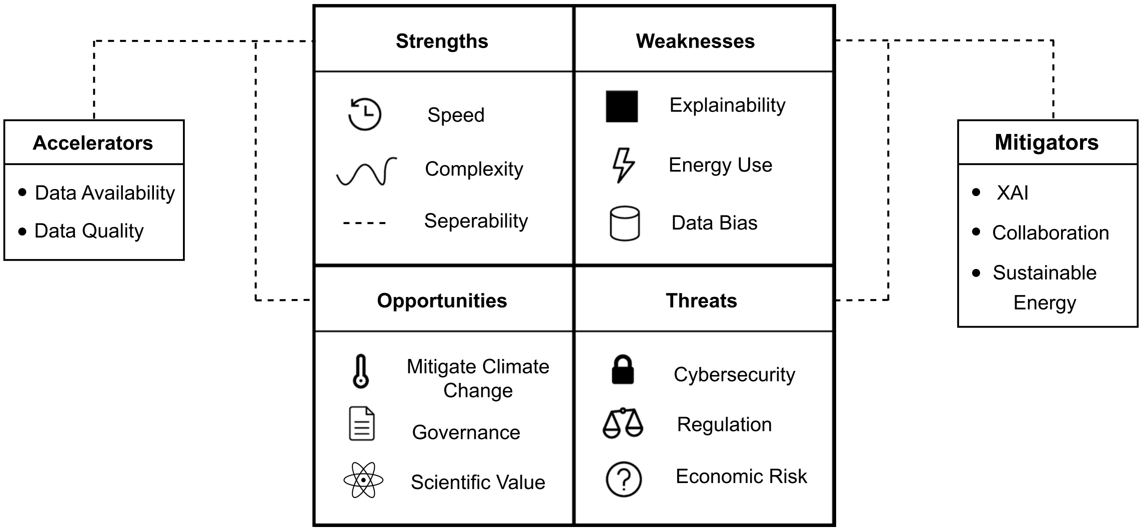


Fig. 8 Overview of key strengths, weaknesses, opportunities and threats found in the analysis in addition to discussed accelerators and mitigators

The comprehensive SWOT analysis conducted in Chapter 4 is summarized in Fig. 8, which illustrates the key strengths, weaknesses, opportunities, and threats associated with AI, as well as the key accelerators and mitigators of Chapter 5 in the realm of environmental sustainability.

6 Current trends and future work

Besides the aspects mentioned it should be considered that China and the U.S. appear to be at the forefront of both technological capabilities and investments in most of the areas discussed in this paper [101]. Assuming that these efforts do indeed result in technologies that have positive impacts on environmental sustainability, the extent of these impacts also depends on the geopolitical landscape, i.e., the willingness of nations to provide insights enabled by significant breakthroughs. Given the increasing tensions between China and the U.S., this will depend on many factors, including economic interests and the potential misuse of knowledge. On the other hand, the European Union is currently taking steps to establish the first regulation for AI through the AI-Act. This regulation aims to classify different AI methods according to their potential risks and prescribe the appropriate precautions accordingly. Risk is defined at the domain level where AI is applied. This approach is criticized because risk should not only be assessed at the level of specific domains, but also the potentially hazardous properties of individual models, arguing that even in perceived low-risk areas, sufficiently potent AI systems could pose significant threats [102]. The intention is to ensure that the development and deployment of AI technologies is carried out with careful consideration of the associated risks and the necessary measures are in place to mitigate them. This development is simultaneously positive and negative. On the one hand, these regulations are urgently needed. However, it would be preferable for the regulation to be pursued at the international level. Since it only applies to the European Union, it could potentially increase the gap in AI research.

Although it remains a long and complex journey to establish AGI, its potential future applications for sustainability can be envisioned in various roles, including "Guidance Counselors," "Awareness Creators," or "Creative Assistants." These roles could be employed at both the personal and governmental levels to promote sustainable practices and decision making. On a personal level, AGI can assist individuals by answering questions like "What can I do to reduce my carbon footprint?" and providing personalized recommendations for adopting sustainable habits and choices. At the governmental level, AGI can support leaders in formulating effective strategies to reduce their nation's ecological footprint within specific timeframes. By considering a country's unique setup and circumstances, AGI can provide well-informed analyses and weigh the pros and cons of various policy options, ultimately aiding decision-makers in implementing sustainable practices and policies. DeepMind [102] expressed similar thinking, highlighting the urgent need for model evaluations that secure the alignment and dangerous capabilities of the system as input for risk assessment. Especially with regard to future models with increasing capabilities because even current models already show potential outcomes which were not intended [103]. Similar challenges are encountered in the domain of sustainability, given its expansive scope and the crucial nature of strategic orientation. Hence, a risk assessment for future AI models deployed to enhance sustainability appears to be indispensable. In a 2022 survey by Michael et al. 36% of AI researchers and other stakeholders expressed concern that AI systems could trigger a disaster this century equivalent to or worse than a nuclear war [102, 104], highlighting the perceived significance of extreme AI risks to society and the environment.

In the short term, current AI models, such as LLMs, are already being positively evaluated for their potential as assistants in medical education [95, 96] showing a high level of concordance and insight in its explanations. These models could also be adapted to serve as guides and assistants in the sustainability domain.

Future research could focus on exploring how LLMs can facilitate progress towards climate objectives, by generating new insights and using the reasoning capabilities of LLMs to provide practical recommendations. Additionally, more comprehensive risk assessment methodologies, specifically tailored to address unique aspects and challenges related to environmental sustainability, are needed.

7 Conclusions

In summary, the insights presented in this study support that AI has the potential to contribute considerably to advancements in environmental sustainability.

However, it is important to recognize that AI, if viewed only as a tool, does not intrinsically possess an agenda. Rather, it can be viewed as an accelerator of human intentions, with a particular focus on those parts of society or geopolitical entities that have the most advanced technological capabilities.

Whether AI eventually has a positive impact on the environment will therefore depend largely on whether the leading nations and companies at the forefront of technological progress are able to develop a shared understanding of AI ethics that prioritizes environmental concerns. Stephen Hawking argued similarly, stressing the need for engineers to understand the ethics behind AI, to prevent harmful consequences [105].

In addition to the threats, it is worth highlighting the extensive list of strengths and opportunities identified in Sect. 3.

In order to foster these, the issue of explainability, i.e. the need for XAI is particularly important, and the increasing interest in this domain [106] shows promising potential.

As the development of AI systems accelerates, resulting in increased computational power and expanded generalization capabilities [18], their prospective utilization within the sustainability sector represents a significant field of investigation.

Despite the prevailing focus on enhancing AI model capabilities, the integration of sustainability factors, particularly in light of the substantial carbon emissions generated during training procedures, remains an underexplored area of research. As such, monitoring the evolution of these processes towards encompassing sustainability aspects will be an intriguing focus of future study.

On a positive note, we believe that, particularly with respect to sustainability, the potential of AI outweighs threats, which is consistent with previous studies suggesting that AI will help rather than hinder most of the SDGs focused on environmental issues [24].

Together, the potential impact of AI on society, beyond environmental sustainability, is not yet fully established, and future research is needed. It is important to note that AI is not the only relevant technology to achieve sustainable improvements. For example, industrially scalable quantum computing could also offer new opportunities. Achieving ambitious climate goals will require a combination of technical solutions as well as sufficiency-based approaches and consistency-based approaches. Further research is also necessary to make progress in this direction. In particular, there is great value in exploring how AI can improve sustainability in specific sectors through detailed technical approaches.

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References

1. European Commission: The European Green Deal. Accessed: 2023-02-01 (2019). https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en
2. Huber J. Towards industrial ecology: sustainable development as a concept of ecological modernization. J Environ Policy Plan. 2000;2(4):269–85.
3. Allievi F, Vinnari M, Luukkanen J. Meat consumption and production-analysis of efficiency, sufficiency and consistency of global trends. J Clean Prod. 2015;92:142–51.
4. Fauth R, Pieper M. Designing sustainable office spaces - how to combine workspace characteristics with sufficiency strategies. In: IOP Conference Series: Earth and Environmental Science, 2022;1078.
5. Shah F, Wu W. Soil and crop management strategies to ensure higher crop productivity within sustainable environments. Sustainability. 2019. https://doi.org/10.3390/su11051485.
6. Rai R, Tiwari MK, Ivanov D, Dolgui A. Machine learning in manufacturing and industry 4.0 applications. Oxfordshire: Taylor & Francis; 2021.
7. Igliński H, Babiak M. Analysis of the potential of autonomous vehicles in reducing the emissions of greenhouse gases in road transport. Proced Eng. 2017;192:353–8.
8. Galaz V, Centeno MA, Callahan PW, Causevic A, Patterson T, Brass I, Baum S, Farber D, Fischer J, Garcia D, et al. Artificial intelligence, systemic risks, and sustainability. Technol Soc. 2021;67: 101741.
9. Ben Ayed R, Hanana M. Artificial intelligence to improve the food and agriculture sector. J Food Qual. 2021. https://doi.org/10.1155/2021/5584754.
10. Helm JM, Swiergosz AM, Haeberle HS, Karnuta JM, Schaffer JL, Krebs VE, Spitzer AI, Ramkumar PN. Machine learning and artificial intelligence: definitions, applications, and future directions. Curr Rev Musculoskelet Med. 2020;13:69–76.
11. Morandín-Ahuerma F. What is artificial intelligence? International Journal of Research Publication and Reviews 2022.
12. Haga C. Artificial intelligence in nursing. Okayama Igakkai Zasshi (J Okayama Med Assoc). 2022;134:28.
13. Hamet P, Tremblay J. Artificial intelligence in medicine. Metab: Clin Exp. 2017;69S:36–40.
14. Turing AM. Computing machinery and intelligence. Berlin: Springer; 2009.
15. McCarthy J, Minsky ML, Rochester N, Shannon CE. A proposal for the dartmouth summer research project on artificial intelligence, august 31, 1955. AI Mag. 2006;27(4):12–12.
16. Huang M-H, Rust RT. Artificial intelligence in service. J Serv Res. 2018;21(2):155–72.
17. Salehi H, Burgueño R. Emerging artificial intelligence methods in structural engineering. Eng Struct. 2018;171:170–89.
18. Bubeck S, Chandrasekaran V, Eldan R, Gehrke J, Horvitz E, Kamar E, Lee P, Lee YT, Li Y, Lundberg S, et al. Sparks of artificial general intelligence: early experiments with gpt-4. arXiv preprint. 2023. https://doi.org/10.4855/arXiv.2303.12712.
19. Gubrud MA. Nanotechnology and international security. In: Fifth Foresight Conference on Molecular Nanotechnology, 1997;1.
20. Pennachin C, Goertzel B. Contemporary approaches to artificial general intelligence. Artif Gen Intell. 2007. https://doi.org/10.1007/978-3-540-68677-4_1.
21. Goertzel B, Potapov A, Iklé M. Artificial general intelligence: conceptual advances and preliminary investigations. J Artif Gen Intell. 2014;5:1–30.
22. Brown B, Hanson M, Liverman D, Merideth R. Global sustainability: toward definition. Environ Manag. 1987;11:713–9.
23. Mog J. Struggling with sustainability-a comparative framework for evaluating sustainable development programs. World Dev. 2004;32:2139–60.
24. Vinuesa R, Azizpour H, Leite I, Balaam M, Dignum V, Domisch S, Felländer A, Langhans SD, Tegmark M, Fuso Nerini F. The role of artificial intelligence in achieving the sustainable development goals. Nat Commun. 2020;11(1):1–10.
25. Stockholm Resilience Centre, S.U.C.B.-N...: The SDGs wedding cake 2016.

26. Palomares I, Martínez-Cámara E, Montes R, García-Moral P, Chiachio M, Chiachio J, Alonso S, Melero FJ, Molina D, Fernández B, Moral C, Marchena R, Vargas JP, Herrera F. A panoramic view and swot analysis of artificial intelligence for achieving the sustainable development goals by 2030: progress and prospects. Appl Intell. 2021;51:6497–527.
27. Nishant R, Kennedy M, Corbett J. Artificial intelligence for sustainability: challenges, opportunities, and a research agenda. Int J Inform Manag. 2020;53: 102104.
28. Goralski MA, Tan TK. Artificial intelligence and sustainable development. Int J Manag Educ. 2020;18(1): 100330.
29. Truby J. Governing artificial intelligence to benefit the un sustainable development goals. Sustain Dev. 2020;28(4):946–59.
30. Naz F, Agrawal R, Kumar A, Gunasekaran A, Majumdar A, Luthra S. Reviewing the applications of artificial intelligence in sustainable supply chains: exploring research propositions for future directions. Bus Strategy Environ. 2022;31(5):2400–23.
31. Kar AK, Choudhary SK, Singh VK. How can artificial intelligence impact sustainability: a systematic literature review. J Clean Prod. 2022. https://doi.org/10.1016/j.jclepro.2022.134120.
32. Sætra HS. A framework for evaluating and disclosing the esg related impacts of ai with the sdgs. Sustainability. 2021;13(15):8503.
33. Leigh D. Swot analysis. Handb Improv Perform Workplace: Vol. 2009;1–3:115–40.
34. Glaister KW, Falshaw JR. Strategic planning: still going strong? Long Range Plan. 1999;32(1):107–16.
35. Yuan H. A swot analysis of successful construction waste management. J Clean Prod. 2013;39:1–8.
36. Hajizadeh Y. Machine learning in oil and gas; a swot analysis approach. J Petrol Sci Eng. 2019;176:661–3.
37. Farrokhnia M, Banihashem SK, Noroozi O, Wals A. A swot analysis of chatgpt: implications for educational practice and research. Innov Educ Teach Int. 2023. https://doi.org/10.1080/14703297.2023.2195846.
38. Peterson NG, Jeanneret PR. Job analysis: overview and description of deductive methods. Appl Meas: Ind Psychol Human Resour Manag. 2007. https://doi.org/10.4324/9780203936412-2.
39. Kandakoglu A, Celik M, Akgun I. A multi-methodological approach for shipping registry selection in maritime transportation industry. Math Comput Model. 2009;49(3–4):586–97.
40. Azimi R, Yazdani-Chamzini A, Fouladgar MM, Zavadskas EK, Basiri MH. Ranking the strategies of mining sector through anp and topsis in a swot framework. J Bus Econ Manag. 2011;12(4):670–89.
41. Brunton SL. Applying machine learning to study fluid mechanics. Acta Mechan Sin. 2021;37(12):1718–26.
42. Roszyk K, Nowicki MR, Skrzypczyński P. Adopting the yolov4 architecture for low-latency multispectral pedestrian detection in autonomous driving. Sensors. 2022;22(3):1082.
43. Reichstein M, Camps-Valls G, Stevens B, Jung M, Denzler J, Carvalhais N, et al. Deep learning and process understanding for data-driven earth system science. Nature. 2019;566(7743):195–204.
44. Bas TG, Astudillo P, Rojo D, Trigo A. Opinions related to the potential application of artificial intelligence (ai) by the responsible in charge of the administrative management related to the logistics and supply chain of medical stock in health centers in north of chile. Int J Environ Res Public Health. 2023;20:4839.
45. Hadjiiski L, Cha K, Chan H-P, Drukker K, Morra L, Näppi JJ, Sahiner B, Yoshida H, Chen Q, Deserno TM, et al. Aapm task group report 273: recommendations on best practices for ai and machine learning for computer-aided diagnosis in medical imaging. Med Phys. 2023;50(2):1–24.
46. Harsono AB, Susiarno H, Suardi D, Owen L, Fauzi H, Kireina J, Wahid RA, Carolina JS, Mantilidewi KI, Hidayat YM. Cervical pre-cancerous lesion detection: development of smartphone-based via application using artificial intelligence. BMC Res Notes. 2022. https://doi.org/10.1002/mp.16188.
47. Zhang P, Guo Z, Ullah S, Melagraki G, Afantitis A, Lynch I. Nanotechnology and artificial intelligence to enable sustainable and precision agriculture. Nat Plants. 2021;7(7):864–76.
48. Lakshmi V, Corbett J. How artificial intelligence improves agricultural productivity and sustainability: A global thematic analysis 2020.
49. Dharmaraj V, Vijayanand C. Artificial intelligence (ai) in agriculture. Int J Curr Microbiol Appl Sci. 2018;7(12):2122–8.
50. Nishant R, Kennedy M, Corbett J. Artificial intelligence for sustainability: challenges, opportunities, and a research agenda. Int J Inf Manag. 2020;53: 102104.
51. Nicodeme C. Ai legitimacy for sustainability. In: 2021 IEEE Conference on Technologies for Sustainability (SusTech), pp. 1–5. IEEE, 2021.
52. Gomes C. Ai for scientific discovery and a sustainable future. Proceedings of the Genetic and Evolutionary Computation Conference 2023.
53. Swarnkar M, Chopra M, Dhote V, Nigam N, Upadhyaya K, Prajapati M. Use of ai for development and generation of renewable energy. In: 2023 IEEE Renewable Energy and Sustainable E-Mobility Conference (RESEM), pp. 1–5. IEEE, 2023.
54. Khakurel J, Penzenstadler B, Porras J, Knutas A, Zhang W. The rise of artificial intelligence under the lens of sustainability. Technologies. 2018;6(4):100.
55. Al-Jarrah O, Abu-Qdais H. Municipal solid waste landfill siting using intelligent system. Waste Manag. 2006;26(3):299–306.
56. Sanders NR, Boone T, Ganeshan R, Wood JD. Sustainable supply chains in the age of ai and digitization: research challenges and opportunities. J Bus Logist. 2019;40(3):229–40.
57. Liao M, Lan K, Yao Y. Sustainability implications of artificial intelligence in the chemical industry: a conceptual framework. J Ind Ecol. 2022;26(1):164–82.
58. Cioffi R, Travaglioni M, Piscitelli G, Petrillo A, De Felice F. Artificial intelligence and machine learning applications in smart production: progress, trends, and directions. Sustainability. 2020;12(2):492.
59. Shin D. The effects of explainability and causability on perception, trust, and acceptance: implications for explainable ai. Int J Human-Comput Stud. 2021;146: 102551.
60. Strubell E, Ganesh A, McCallum A. Energy and policy considerations for deep learning in nlp. arXiv preprint. 2019. https://doi.org/10.4855/arXiv.1906.02243.
61. Blumenstock J. Don't forget people in the use of big data for development. Berlin: Nature Publishing Group; 2018.

62. Holzinger A, Langs G, Denk H, Zatloukal K, Müller H. Causability and explainability of artificial intelligence in medicine. Wiley Interdiscip Rev: Data Min Knowl Discov. 2019. https://doi.org/10.1002/widm.1312.
63. Holzinger A. From machine learning to explainable ai. 2018 World Symposium on Digital Intelligence for Systems and Machines (DISA), 2018;55–66.
64. Fox MP, MacLehose RF, Lash TL. Applying quantitative bias analysis to epidemiologic data. Berlin: Springer; 2022.
65. Jiménez D, Delerce S, Dorado H, Cock J, Muñoz LA, Agamez A, Jarvis A. A scalable scheme to implement data-driven agriculture for small-scale farmers. Glob Food Secur. 2019;23:256–66.
66. Tsymbal A. The problem of concept drift: definitions and related work. Comput Sci Dep, Trinity Coll Dublin. 2004;106(2):58.
67. Hastings A, Wysham DB. Regime shifts in ecological systems can occur with no warning. Ecol Lett. 2010;13(4):464–72.
68. Chouldechova A, Roth A. The frontiers of fairness in machine learning. arXiv preprint. 2018. https://doi.org/10.4855/arXiv.1810.08810.
69. Pal S. Integrating ai in sustainable supply chain management: a new paradigm for enhanced transparency and sustainability. Int J Res Appl Sci Eng Technol. 2023;11:2979–84.
70. Yadav M, Singh G. Environmental sustainability with artificial intelligence. EPRA Int J Multidiscip Res (IJMR). 2023;9(5):213–7.
71. Hantson S, Arneth A, Harrison SP, Kelley DI, Prentice IC, Rabin SS, Archibald S, Mouillot F, Arnold SR, Artaxo P, et al. The status and challenge of global fire modelling. Biogeosciences. 2016;13(11):3359–75.
72. Tanveer M, Hassan S, Bhaumik A. Academic policy regarding sustainability and artificial intelligence (ai). Sustainability. 2020;12:9435.
73. Hashlamoun NA, Barghuthi NBA, Tamimi H. Exploring the intersection of ai and sustainable computing: Opportunities, challenges, and a framework for responsible applications. 2023 9th International Conference on Information Technology Trends (ITT), 2023;220–225.
74. Baklaga L. Revolutionizing sustainable energy production with quantum artificial intelligence: Applications in autonomous robotics and data management. Green and Low-Carbon Economy 2023.
75. Pandey AK. Development and deployment of green artificial intelligence. INTERNATIONAL JOURNAL OF MATHEMATICS AND COMPUTER RESEARCH 2023.
76. Vasudevan RK, Choudhary K, Mehta A, Smith R, Kusne G, Tavazza F, Vlcek L, Ziatdinov M, Kalinin SV, Hattrick-Simpers J. Materials science in the artificial intelligence age: high-throughput library generation, machine learning, and a pathway from correlations to the underpinning physics. MRS Commun. 2019;9(3):821–38.
77. Choudhary K, DeCost B, Chen C, Jain A, Tavazza F, Cohn R, Park CW, Choudhary A, Agrawal A, Billinge SJ, et al. Recent advances and applications of deep learning methods in materials science. Npj Computat Mater. 2022;8(1):59.
78. Stein HS, Soedarmadji E, Newhouse PF, Guevarra D, Gregoire JM. Synthesis, optical imaging, and absorption spectroscopy data for 179072 metal oxides. Sci Data. 2019;6:9.
79. Butler KT, Davies DW, Cartwright H, Isayev O, Walsh A. Machine learning for molecular and materials science. Nature. 2018;559(7715):547–55.
80. Venkatasubramanian V, Mann V. Artificial intelligence in reaction prediction and chemical synthesis. Curr Opin Chem Eng. 2022;36: 100749.
81. Yano J, Gaffney KJ, Gregoire J, Hung L, Ourmazd A, Schrier J, Sethian JA, Toma FM. The case for data science in experimental chemistry: examples and recommendations. Nat Rev Chem. 2022;6(5):357–70.
82. Cath C. Governing artificial intelligence: ethical, legal and technical opportunities and challenges. Philos Trans Royal Soc A: Math, Phys Eng Sci. 2018;376(2133):20180080.
83. Coeckelbergh M. Artificial intelligence: some ethical issues and regulatory challenges. Technol Regul. 2019;2019:31–4.
84. McClure PK. "you're fired", says the robot: the rise of automation in the workplace, technophobes, and fears of unemployment. Soc Sci Comput Rev. 2018;36(2):139–56.
85. Jobin A, Ienca M, Vayena E. The global landscape of ai ethics guidelines. Nat Mach Intell. 2019;1(9):389–99.
86. Ohalete NC, Aderibigbe AO, Ani EC, Ohenhen PE, Daraojimba DO, Odulaja BA. Ai-driven solutions in renewable energy: a review of data science applications in solar and wind energy optimization. World J Adv Res Rev. 2023. https://doi.org/10.3057/wjarr.2023.20.3.2433.
87. Zitouna B, Tlig M, Hedia S, Slama JBH. An emc study for renewable energy applications using ai algorithms. In: 2023 IEEE International Conference on Artificial Intelligence & Green Energy (ICAIGE), pp. 1–5. IEEE, 2023.
88. Camaréna S. Engaging with artificial intelligence (ai) with a bottom-up approach for the purpose of sustainability: victorian farmers market association, melbourne Australia. Sustainability. 2021. https://doi.org/10.3390/su13169314.
89. Akavova A, Beguyev S, Zaripova R. How ai and machine learning can drive sustainable development. E3S Web Conf. 2023. https://doi.org/10.1051/e3sconf/202346004018.
90. Yudkowsky E. The ai alignment problem: why it is hard, and where to start. Symb Syst Disting Speak. 2016;4:1.
91. Turchin A. Ai alignment problem:"human values" don't actually exist 2019.
92. Fan Z, Yan Z, Wen S. Deep learning and artificial intelligence in sustainability: a review of sdgs, renewable energy, and environmental health. Sustainability. 2023. https://doi.org/10.3390/su151813493.
93. De Alwis S, Hou Z, Zhang Y, Na MH, Ofoghi B, Sajjanhar A. A survey on smart farming data, applications and techniques. Comput Ind. 2022;138: 103624.
94. Bayram F, Ahmed BS, Kassler A. From concept drift to model degradation: an overview on performance-aware drift detectors. Knowl-Based Syst. 2022;245: 108632.
95. Kung TH, Cheatham M, Medenilla A, Sillos C, De Leon L, Elepaño C, Madriaga M, Aggabao R, Diaz-Candido G, Maningo J, et al. Performance of chatgpt on usmle: potential for ai-assisted medical education using large language models. PLoS Digit Health. 2023;2(2):0000198.
96. Gilson A, Safranek CW, Huang T, Socrates V, Chi L, Taylor RA, Chartash D, et al. How does chatgpt perform on the united states medical licensing examination? the implications of large language models for medical education and knowledge assessment. JMIR Med Educ. 2023;9(1):45312.

97. Bessen JE, Impink SM, Reichensperger L, Seamans R. Gdpr and the importance of data to ai startups. NYU Stern School Bus. 2020. https://doi.org/10.2139/ssrn.3576714.
98. Vinuesa R, Azizpour H, Leite I, Balaam M, Dignum V, Domisch S, Felländer A, Langhans S, Tegmark M, Nerini FF. The role of artificial intelligence in achieving the sustainable development goals. Nat Commun. 2019;2(8):674–80.
99. Montavon G, Binder A, Lapuschkin S, Samek W, Müller K-R. Layer-wise relevance propagation: an overview. Explainable AI: interpreting, explaining and visualizing deep learning, 2019;193–209.
100. Keane MT, Kenny EM, Delaney E, Smyth B. If only we had better counterfactual explanations: five key deficits to rectify in the evaluation of counterfactual xai techniques. arXiv preprint. 2021. https://doi.org/10.4855/arXiv.2103.01035.
101. Lee K-F. Ai superpowers: China, silicon valley, and the new world order. Boston: Houghton Mifflin; 2018.
102. Shevlane T, Farquhar S, Garfinkel B, Phuong M, Whittlestone J, Leung J, Kokotajlo D, Marchal N, Anderljung M, Kolt N, et al. Model evaluation for extreme risks. arXiv preprint. 2023. https://doi.org/10.4855/arXiv.2305.15324.
103. Ganguli D, Hernandez D, Lovitt L, Askell A, Bai Y, Chen A, Conerly T, Dassarma N, Drain D, Elhage N, et al. Predictability and surprise in large generative models. In: 2022 ACM Conference on Fairness, Accountability, and Transparency, 2022;1747–1764.
104. Michael J, Holtzman A, Parrish A, Mueller A, Wang A, Chen A, Madaan D, Nangia N, Pang RY, Phang J, et al. What do nlp researchers believe? results of the nlp community metasurvey. arXiv preprint. 2022. https://doi.org/10.4855/arXiv.2208.12852.
105. Rossi F. Building trust in artificial intelligence. J Int Aff. 2018;72(1):127–34.
106. Brasse J, Broder HR, Förster M, Klier M, Sigler I. Explainable artificial intelligence in information systems: a review of the status quo and future research directions. Electron Mark. 2023;33(1):26.