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Artificial Intelligence for Sustainable Development: A Structured Critical Review of Applications, Benefits, Risks and Governance Priorities

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Abstract

This structured critical literature review examines the multidimensional role of artificial intelligence (AI) in advancing global sustainability and supporting progress towards the United Nations Sustainable Development Goals (SDGs). Drawing on multidisciplinary academic and institutional literature, the review critically synthesises AI applications, sustainability benefits, implementation challenges and associated risks. Particular attention is given to applications in energy management, agriculture, environmental monitoring, smart cities, circular economy practices and industrial processes, alongside their potential contributions to resource efficiency, decarbonisation and environmental resilience. The analysis also considers the ecological footprint of AI technologies, including energy consumption, carbon emissions, water requirements and electronic waste, together with data-related, algorithmic, socioeconomic and ethical concerns. These interconnected challenges are examined through the concept of the AI Green Paradox and an exploratory multidimensional risk-prioritisation framework incorporating indicative likelihood and severity assessments. The review highlights the importance of distinguishing improvements in technological performance from independently demonstrated sustainability outcomes, particularly where evidence is limited by differences in research methodologies, geographical contexts and implementation conditions. Responsible governance, Green AI development, international cooperation, technological accessibility and capacity building are identified as important priorities for supporting sustainable and equitable AI implementation. Overall, the review argues that AI's contribution to sustainable development depends not only on its technological capabilities but also on the effective management of its environmental and societal consequences.

1. Introduction

The twenty-first century is characterised by a defining duality: the unprecedented acceleration of technological innovation, particularly within the field of artificial intelligence (AI), alongside growing pressures on planetary and social systems. Global challenges, including climate change, natural resource depletion, biodiversity loss, socio-economic inequalities and threats to food security, require integrated solutions implemented on a large scale (Sachs, 2015; IPCC, 2023). Within this context, AI has emerged as a tool with substantial potential to address these complex challenges, providing new perspectives and capabilities for navigating the transition towards a more sustainable future.

1.1 The Global Context of Sustainability

The concept of sustainability has developed into a central paradigm within global discourse, recognising the interdependence of ecological well-being, economic prosperity and social equity. The influential definition introduced in the Brundtland Report, Our Common Future, describes sustainability as development that addresses present needs without limiting the capacity of future generations to meet their own needs (Brundtland Commission, 1987). This holistic vision was translated into practical action through the United Nations' adoption of the 2030 Agenda for Sustainable Development in 2015. Its 17 Sustainable Development Goals (SDGs) and 169 specific targets constitute a universal call for action to eliminate poverty, protect the planet and secure prosperity for all. These goals are inherently interconnected and indivisible (United Nations, 2015). At the same time, the urgency of restricting global warming to 1.5°C above pre-industrial levels has established carbon neutrality, or Net Zero, by the middle of the century as a global climate objective. Achieving this objective requires reducing greenhouse gas emissions while sequestering any remaining emissions (IPCC, 2018; IEA, 2021). Meeting these ambitious goals requires not only fundamental changes in policy and behaviour but also an unprecedented mobilisation of technological innovation.

1.2 The Rise of Artificial Intelligence (AI)

Over recent decades, artificial intelligence (AI) has expanded at an exceptional rate, progressing from a futuristic idea into a technological reality that is deeply embedded across almost every area of contemporary life (Russell and Norvig, 2021). This rapid development has been driven primarily by substantial increases in computational capacity, access to enormous quantities of data commonly referred to as Big Data, and the advancement of increasingly sophisticated algorithms, particularly within machine learning and deep learning (Goodfellow et al., 2016; LeCun et al., 2015).

Initially restricted to specialised tasks, including playing chess and performing basic pattern recognition, modern AI now demonstrates remarkable capabilities across a wide range of domains. Applications extend from autonomous vehicles and intelligent virtual assistants, such as Siri and Alexa, to personalised medicine involving AI-supported diagnosis and drug discovery, as well as the optimisation of industrial processes through automation and predictive maintenance. In these contexts, AI continues

to redefine efficiency, productivity and innovation (Brynjolfsson and McAfee, 2014). Its capacity to process and analyse extensive volumes of information at a speed and scale beyond human capability, identify concealed patterns and correlations, and support autonomous or semi-autonomous decision-making has fundamentally transformed operations across numerous fields.

This extensive computational and analytical capacity positions AI not only as a driver of economic development but also as a potentially transformative tool for addressing some of the most urgent and complex sustainability challenges. Through its capacity to predict future scenarios, optimise the use of resources, and automate processes of monitoring and management, AI introduces new perspectives and solutions for improving environmental management, reducing carbon footprints and accelerating progress towards a more equitable and resilient future (Cenek et al., 2018; Vinuesa et al., 2020). Integrating AI into sustainability strategies therefore becomes a strategic necessity, enabling global challenges to be transformed into opportunities for innovation and progress.

1.3 Aim, Research Questions and Objectives

Research Aim

The principal aim of this structured critical literature review is to critically examine and synthesise existing scientific literature concerning the applications, benefits, limitations and risks of artificial intelligence (AI) in advancing sustainable development and contributing to the United Nations Sustainable Development Goals (SDGs). The review evaluates AI applications across different sustainability domains, examines their reported environmental, social and economic outcomes, and identifies the technological, environmental, socioeconomic and ethical challenges associated with their implementation. Through this analysis, the study seeks to identify evidence-informed priorities for responsible AI development, governance and future research.

Research Questions

To address this aim, the study is guided by five research questions:

1. What are the principal applications of artificial intelligence across sustainability domains, and how do they relate to the United Nations Sustainable Development Goals?
2. What environmental, social and economic benefits of AI applications are reported in the existing literature?
3. What environmental, data-related, algorithmic, socioeconomic and ethical risks are associated with AI development and implementation?
4. What methodological limitations, implementation challenges and research gaps are identified in the existing evidence concerning AI's contribution to sustainability?
5. What technological, governance and policy strategies are identified in the literature to support responsible, equitable and environmentally sustainable AI development and implementation?

Research Objectives

The study seeks to achieve the following objectives:

- To identify and categorise AI applications across sustainability domains and examine their relationships with the SDGs.
- To synthesise and critically evaluate the reported environmental, social and economic benefits of AI applications.
- To identify and critically assess the environmental, technological, algorithmic, socioeconomic and ethical risks associated with AI development and implementation.
- To evaluate methodological limitations, implementation barriers and research gaps affecting the evidence concerning AI and sustainability.
- To synthesise evidence-based technological, governance and policy strategies for supporting responsible and sustainable AI implementation.

1.4 Scope and Structure of the Article

The scope of this review encompasses recent scientific literature examining the relationship between artificial intelligence and sustainable development, with particular emphasis on studies published from 2018 onwards. The analysis considers AI applications

across different sustainability domains, their contribution to the United Nations Sustainable Development Goals (SDGs), and their relevance to carbon neutrality (Net Zero). It also addresses the environmental, technological, socio-economic and ethical challenges associated with the development and implementation of AI technologies.

Two concepts are particularly relevant to this examination. “Green AI” refers to the development and application of energy-efficient artificial intelligence algorithms and systems intended to minimise the environmental impacts associated with their training and operation. Similarly, the “AI divide” describes inequalities in access to AI technologies, their utilisation and the distribution of their benefits across countries and communities.

The article is organised into six sections to provide a logical progression of the analysis. Following the introduction, Section 2 outlines the methodology adopted for identifying, selecting and synthesising the relevant literature. Section 3 establishes the theoretical foundations and key concepts, including sustainability, the Sustainable Development Goals, carbon neutrality and relevant AI methodologies. Section 4 examines the applications of artificial intelligence across different sustainability domains, supported by examples and findings from the reviewed literature. Section 5 critically discusses the environmental, algorithmic, socio-economic and ethical risks associated with AI, alongside mitigation strategies and future recommendations. Finally, Section 6 presents the principal conclusions of the study.

2. Methodology

This study adopts a structured critical literature review approach to examine the applications, reported sustainability outcomes, implementation challenges and multidimensional risks associated with artificial intelligence (AI) in sustainable development. The methodological approach combines the thematic organisation of relevant academic and institutional literature with a critical comparison of reported findings, methodological limitations and governance implications. The review considers AI applications across six sustainability domains: energy management, agriculture, environmental monitoring, smart cities, circular economy practices and industrial applications. Particular attention is given to their relationships with the United Nations Sustainable Development Goals (SDGs), alongside environmental, technological, socioeconomic and ethical considerations. The following subsections describe the literature-identification approach, source-selection considerations, classification framework and analytical synthesis used to examine the available evidence.

2.1 Literature Identification and Search Strategy

The identification of relevant literature was informed by searches of multidisciplinary academic databases and scholarly search platforms, including Scopus, Web of Science and Google Scholar. The reported search process was conducted on 18 May 2025 and focused on publications examining the relationship between artificial intelligence (AI), sustainability and sustainable development. Search concepts included artificial intelligence, machine learning, deep learning, sustainable development, Sustainable Development Goals (SDGs), Green AI, carbon neutrality, environmental sustainability, resource efficiency, algorithmic bias, ethical AI and AI governance. These concepts were considered individually and in relevant combinations to identify literature addressing both the potential benefits and the environmental, technological and socioeconomic implications of AI.

The review primarily considered literature published from 2018 onwards to reflect recent technological developments and emerging sustainability challenges. Earlier publications were retained where they provided foundational theoretical perspectives, established methodological approaches or important contributions to understanding AI and sustainable development. Academic research articles, review publications, conceptual studies and relevant institutional or policy documents were considered to support the multidisciplinary scope of the analysis.

Literature identification was guided by the five research questions and the six sustainability domains examined in this study: energy management, agriculture, environmental monitoring, smart cities, circular economy practices and industrial applications. Additional attention was given to cross-cutting issues, including the ecological footprint of AI systems, data governance, algorithmic transparency, technological inequalities, ethical accountability and responsible AI implementation.

The original database search exports, complete database-specific search expressions and detailed screening records are not available for independent reconstruction. Consequently, the search process cannot be presented as a fully reproducible systematic review, and the number of references cited in the manuscript should not be interpreted as the number of studies included through a

formally documented screening procedure. The present study therefore adopts a structured critical literature review approach, prioritising thematic relevance, comparative interpretation and methodological transparency rather than exhaustive coverage or statistical representativeness of the wider literature.

2.2 Eligibility Criteria and Study Selection

The selection of literature was guided by its relevance to the relationship between artificial intelligence (AI) and sustainable development. Priority was given to publications examining AI applications, environmental, social or economic sustainability outcomes, implementation challenges, technological limitations, ethical concerns and governance strategies. The review considered six principal application domains: energy management, agriculture, environmental monitoring, smart cities, circular economy practices and industrial applications.

Publications addressing cross-cutting concerns, including the environmental footprint of AI, algorithmic bias, data governance, technological inequalities and responsible implementation, were also considered relevant. Foundational theoretical publications, institutional reports and policy documents were incorporated where they contributed to the conceptual understanding, regulatory context or interpretation of sustainability-related challenges.

Sources without a substantive relationship to AI and sustainability, promotional materials and publications containing insufficient information to support meaningful critical interpretation were not considered appropriate for the review's substantive analysis. The review therefore prioritised thematic relevance, the nature of the available evidence and the contribution of individual publications to the research questions.

The literature was organised through a structured bibliographic register containing 138 references used throughout the manuscript. A bibliographic overview and preliminary thematic classification of the 138 cited references are provided in Supplementary File S1 (Appendix A), supporting transparency and traceability in the organisation of the literature. These references include research articles, review publications, conceptual contributions and institutional or policy sources. The register supports bibliographic traceability and thematic organisation but does not represent a formally verified population of studies selected through a reproducible systematic-review screening process. Accordingly, the review does not report PRISMA-derived inclusion counts or claim statistical representativeness of the wider literature.

Figure 1. PRISMA flowchart illustrating the study-selection process.

2.3 Literature Classification and Analytical Synthesis

The literature was organised and critically examined through a thematic analytical framework aligned with the five research questions. The framework considered six principal sustainability domains: energy management, agriculture, environmental monitoring, smart cities, circular economy practices and industrial applications. Cross-cutting issues relating to the environmental footprint of AI, algorithmic bias, data governance, technological inequalities and responsible implementation were examined across these domains.

The analytical framework considered the authorship and publication year of relevant sources, geographical context where identifiable, sustainability sector, research approach, AI application, reported sustainability outcomes, connections to the United Nations Sustainable Development Goals (SDGs), principal findings and acknowledged limitations. Publications were differentiated according to their contribution to the review, including empirical investigations, experimental or simulation-based research, case studies, review articles, conceptual studies and institutional or policy documents. These distinctions informed the interpretation of the available evidence rather than constituting a statistically representative classification of the wider literature.

The literature classification was undertaken collaboratively by two authors (S.S.D. and G.N.), who jointly reviewed and organised the publications according to their principal sustainability domains, methodological approaches, AI applications and reported sustainability outcomes. The classifications were cross-checked through joint review to ensure consistency in the thematic organisation of the literature. Publications addressing more than one sustainability domain were classified according to their primary research focus, while relevant cross-cutting contributions were acknowledged within the thematic synthesis. Where differences in interpretation or classification arose, these were discussed and resolved through agreement between the two authors.

The synthesis followed a comparative and critical approach. First, reported AI applications were examined across the six sustainability domains to identify their principal functions and potential contributions to sustainable development (RQ1). Second, the environmental, social and economic benefits associated with these applications were considered, with attention to the distinction between improvements in technological performance and demonstrated sustainability outcomes (RQ2). Third, environmental, data-related, algorithmic, socioeconomic and ethical risks were examined to identify challenges that may limit or undermine the sustainability benefits of AI implementation (RQ3). Fourth, methodological limitations, geographical differences, implementation barriers and gaps in the available evidence were considered across the reviewed literature (RQ4). Finally, technological, governance and policy responses were critically discussed to identify priorities for responsible, equitable and environmentally sustainable AI development (RQ5).

The synthesis was qualitative and interpretative rather than statistical. Comparisons were made between sustainability domains, research approaches and reported outcomes where sufficient information was available. Given the absence of a reproducible screening record and a fully verified study-level dataset, frequencies and percentages describing the distribution of the 138 cited publications by sector, geographical region, methodology or SDG were not calculated. The findings therefore represent a structured critical interpretation of the available literature rather than a quantitative mapping of all published research in this field.

The multidimensional risk analysis presented in Section 5 builds on this thematic synthesis by considering the interactions between ecological, technological, socioeconomic and ethical challenges. The associated risk-prioritisation matrix uses indicative likelihood and severity ratings to illustrate potential areas of concern. These ratings are interpretative assessments rather than empirically validated probabilities or measurements of risk. The framework is intended to support critical discussion and identify governance priorities, not to provide a predictive or statistically validated risk-assessment model.

The bibliographic register described in Section 2.2 supports the identification and thematic organisation of the sources cited in this review. Its 138 references should not be interpreted as a statistically representative sample of empirical studies or as a verified systematic-review dataset. Where publication characteristics are available, they may support qualitative comparison, but no comprehensive quantitative distribution of the cited literature is claimed.

3. Theoretical Foundations and Key Concepts

A comprehensive understanding of the relationship between artificial intelligence and sustainability requires the fundamental concepts underlying this complex intersection to be clearly defined. This section explains the principal terms and establishes the theoretical foundation required for the subsequent examination of AI applications, challenges and future directions within the global context of sustainable development.

3.1. Sustainability and the Sustainable Development Goals (SDGs)

Sustainability is a normative and multidimensional concept whose interpretation has developed over time. The most widely recognised definition originates from the World Commission on Environment and Development, commonly referred to as the Brundtland Commission, in its report Our Common Future (1987). It describes sustainability as development that satisfies present needs while protecting the ability of future generations to fulfil their own needs (Brundtland Commission, 1987). This definition emphasises the importance of achieving balance both within the present generation and between current and future generations. It extends beyond environmental protection by incorporating economic and social dimensions (Kates et al., 2001).

The predominant framework for analysing sustainability consists of three interconnected pillars, as illustrated in Fig. 1: environmental or ecological, social and economic. The environmental pillar concerns the integrity of ecosystems, the conservation of natural resources, the protection of biodiversity, and the reduction of pollution and greenhouse gas emissions. It includes the transition towards a circular economy, the responsible management of water and land, and the protection of natural habitats (Rockström et al., 2009; Meadows et al., 1972). The social pillar focuses on social justice, equity, inclusion, health and education by promoting equal access to resources and opportunities while strengthening community cohesion (Costanza et al., 2014). The economic pillar involves establishing and sustaining long-term economic prosperity that is inclusive, resilient, resource efficient and separated from environmental degradation (Jackson, 2009). These three pillars do not function independently but are closely interconnected. Consequently, the most effective solutions are those that address environmental, social and economic considerations simultaneously (Sachs, 2015).

Figure 2. The three interconnected dimensions of sustainability: environmental, social and economic.

To translate sustainability into coordinated global action, the United Nations adopted the 2030 Agenda for Sustainable Development in September 2015. The Agenda introduced 17 Sustainable Development Goals (SDGs), commonly referred to as the Global Goals (United Nations, 2015). These universal, interconnected and indivisible goals provide a shared plan of action for advancing peace and prosperity for both people and the planet. Several of the 17 SDGs are directly connected to the role of AI in promoting sustainability, particularly Zero Hunger (SDG 2); Clean Water and Sanitation (SDG 6); Affordable and Clean Energy (SDG 7); Industry, Innovation and Infrastructure (SDG 9); Sustainable Cities and Communities (SDG 11); Responsible Consumption and Production (SDG 12); Climate Action (SDG 13); Life Below Water (SDG 14); and Life on Land (SDG 15). Through its capacity to optimize complex systems, AI represents an important tool for supporting the achievement of these goals (Vinuesa et al., 2020).

3.2. Carbon Neutrality (Net Zero)

Carbon neutrality and net-zero greenhouse gas emissions are closely related climate objectives, although their definitions and accounting boundaries are not necessarily identical. Carbon neutrality generally concerns balancing carbon dioxide (CO_2) emissions with equivalent removals or eligible offsets, whereas net-zero greenhouse gas emissions require balancing anthropogenic greenhouse gas (GHG) emissions and removals across the gases covered by the relevant accounting framework (IPCC, 2018). These objectives are central to limiting global warming in accordance with the Paris Agreement, adopted in 2015, which seeks to maintain the increase in global temperature well below 2°C while pursuing efforts to restrict it to 1.5°C (UNFCCC, 2015). Achieving net-zero emissions requires substantial reductions through decarbonisation, alongside the removal of residual emissions that cannot readily be eliminated (IEA, 2021). Decarbonisation depends on transitioning towards renewable energy sources (IRENA, 2020), improving energy efficiency (IEA, 2023b) and expanding electrification (BloombergNEF, 2024; World Economic Forum, 2023). Carbon dioxide removal may be achieved through nature-based approaches, including reforestation (IPCC, 2019; SCBD, 2020), and technological methods that remove CO_2 from the atmosphere and store it durably (National Academies of Sciences, Engineering, and Medicine, 2019). Carbon capture and storage (CCS) applied to industrial emissions can also contribute to decarbonisation by preventing CO_2 from entering the atmosphere, although it does not necessarily constitute carbon dioxide removal (IEA, 2023a). These transitions encourage investment in cleaner technologies and support the development of more resource-efficient and resilient economic systems.

3.3. Artificial Intelligence Methodologies and Techniques Relevant to Sustainability

Artificial intelligence (AI) is a multidisciplinary area of computer science concerned with developing systems capable of completing tasks that have traditionally required human intelligence (Russell and Norvig, 2021). Recent advances, particularly in the capacity to process enormous volumes of data, commonly known as Big Data, and in the development of advanced algorithms, have established AI as an important tool for responding to complex challenges, including those associated with sustainability. Within efforts to create a sustainable future, several specific AI branches and techniques are particularly significant.

Machine learning (ML) is a central branch of AI that enables systems to learn from data without being explicitly programmed to perform every individual task (Géron, 2019). Deep learning (DL) is an important subfield that applies neural networks to process complex and unstructured data, including images, audio and text (Goodfellow et al., 2016). For instance, Convolutional Neural Networks (CNNs) are particularly effective in analysing satellite imagery to monitor changes in land conditions. Recurrent Neural Networks (RNNs), by comparison, are applied to tasks involving time-series data, including weather forecasting (Ukoba et al., 2024; Hasanat et al., 2024).

Computer vision (CV) is a branch of artificial intelligence that enables computational systems to analyse and interpret visual information, including images and videos (Szeliski, 2022). It is particularly relevant to environmental monitoring, precision agriculture, including plant-health assessment and the detection of diseases and pests, and waste management, where it supports the automated identification and sorting of recyclable materials (Abdallah et al., 2020). Natural Language Processing (NLP), meanwhile, examines interactions between computers and human language, allowing machines to understand, interpret and produce human language (Jurafsky and Martin, 2025). More recent and powerful Transformer models have transformed NLP and can process extensive collections of sustainability reports (Vaswani et al., 2017).

When integrated with AI, robotics and autonomous systems can undertake complex tasks through automated processes (Siciliano and Khatib, 2016). In agriculture, for example, robotic systems may support planting, irrigation and harvesting. Within waste management, industrial robots can rapidly and efficiently sort different materials. Autonomous systems equipped with sensors may also be employed to monitor infrastructure and forest environments.

Multi-Agent Systems (MASs) consist of autonomous agents that interact with one another to address complex problems, while optimization algorithms identify the most appropriate solution from a range of possible alternatives (Wooldridge, 2009). Relevant applications include smart grids, in which AI agents coordinate energy distribution, and route optimisation systems designed to reduce fuel consumption. Federated Learning (FL) enables models to be trained across multiple decentralised devices without transferring raw data, making it particularly important for protecting privacy. Reinforcement Learning (RL) provides a powerful method for optimising complex and dynamic systems, while generative artificial intelligence introduces new possibilities for developing complex simulation scenarios and discovering innovative sustainable materials.

Through their capacity to analyse extensive datasets, identify complex patterns, automate processes and support optimised decision-making, AI technologies offer significant opportunities to address sustainability challenges. Their application may improve the efficiency, precision and responsiveness of environmental and resource-management practices, supporting a transition from reactive approaches towards predictive and proactive strategies. Nevertheless, the extent of these benefits depends on data quality, technological accessibility, implementation conditions and the environmental costs associated with developing and operating AI systems.

4. Applications of Artificial Intelligence in Sustainability

Artificial intelligence (AI) can serve as a powerful catalyst for sustainability by providing innovative solutions for optimising resources, reducing emissions and managing ecosystems more effectively. Its capacity to analyse extensive datasets, detect complex patterns and automate processes makes it an important tool for advancing the Sustainable Development Goals (SDGs) and achieving carbon-neutrality targets (Cenek et al., 2018; Vinuesa et al., 2020). From a critical perspective, however, the effectiveness of these solutions is frequently restricted by factors including data quality, scalability and implementation costs, which may contribute to the development of a technological divide. These limitations are examined in greater detail in the following section.

4.1. AI for Efficient Resource Management and Decarbonisation

The energy sector represents one of the most significant areas in which AI can generate an impact, given its essential role in global economic decarbonisation and the reduction of greenhouse gas emissions (Cenek et al., 2018; Priyanka and Memala, 2024). AI supports the dynamic operation of modern electricity grids by applying machine learning (ML) to balance energy demand and supply in real time. This process can minimize energy losses and reduce the need to activate fossil-fuel power stations (Huotari et al., 2024). For example, AI algorithms have been applied to optimize data-centre cooling systems, producing a substantial reduction in overall energy consumption (Evans and Gao, 2016). AI also supports the management of microgrids and distributed energy-storage systems, thereby strengthening the resilience of the wider energy network. To respond to the inherent intermittency of renewable energy sources, including wind and solar power, AI models can process meteorological and historical data to generate more accurate production forecasts. These forecasts improve operational planning and support the efficient integration of renewable energy (Ying et al., 2023; Gupta et al., 2025).

AI also performs a transformative function in reducing energy consumption within buildings and industry, both of which have substantial energy footprints (Pérez-Lombard et al., 2008). Through continuous sensor-based monitoring, AI systems can evaluate patterns of energy consumption and dynamically modify the operation of heating, ventilation and air-conditioning (HVAC) systems, resulting in considerable energy savings (Panchalingam and Chan, 2019; Zhou et al., 2023). In industrial settings, AI can optimize machinery and production processes by identifying inefficiencies and opportunities to conserve both energy and raw materials (Wuest et al., 2016). This capability is equally important for energy-storage management, where AI can optimize battery-charging and discharging strategies to maximise the use of surplus clean energy (Nazaralizadeh et al., 2024).

AI also has considerable potential to transform agriculture by improving efficiency and strengthening resilience in response to the challenges created by climate change (Kamilaris and Prenafeta-Boldú, 2018; Karim et al., 2025). These applications directly support

SDG 2 (Zero Hunger) and SDG 6 (Clean Water and Sanitation). AI-driven precision agriculture uses information collected through sensors and drones to calculate the precise water and fertiliser requirements of individual plants, thereby reducing excessive resource use and minimising pollution (Liakos et al., 2018; Talaviya et al., 2020). Computer-vision systems can identify weeds with high levels of accuracy, potentially reducing chemical use by up to 90% and directly benefiting soil health (Coleman et al., 2022). Deep-learning algorithms can also analyse aerial imagery to detect early indications of crop diseases and pests, enabling timely interventions and reducing dependence on extensive chemical treatments (Barbedo, 2019; Upadhyay et al., 2025). AI models may also forecast future crop yields and generate hyperlocal weather predictions, supporting production planning and the anticipation of potential shortages (Talaviya et al., 2020; Joshi et al., 2023; Hendy et al., 2023). In addition, AI can optimize irrigation by evaluating plant requirements and contribute to monitoring soil erosion and reducing waste through the optimisation of supply chains (Abdallah et al., 2020; Kalpana et al., 2024; Mavani et al., 2022).

Although the reviewed literature demonstrates the potential of AI to improve resource efficiency and support decarbonisation, the strength and transferability of the reported outcomes vary across application contexts. Improvements in prediction accuracy, operational efficiency or resource allocation do not necessarily establish equivalent reductions in environmental impacts. The sustainability benefits of AI applications depend on factors including the quality and representativeness of training data, the availability of appropriate technological infrastructure, implementation costs and the environmental footprint of the computational systems themselves. Consequently, reported improvements should be interpreted in relation to the methodologies, operational conditions and sustainability indicators employed in individual studies, rather than assumed to represent universally achievable outcomes.

4.2. AI for Environmental Resilience, Smart Cities and the Circular Economy

AI has become an important tool for understanding, monitoring and safeguarding the Earth's natural systems, supporting objectives such as SDG 13 (Climate Action) and SDG 15 (Life on Land) (Cenek et al., 2018; Vinuesa et al., 2020). Machine-learning and deep-learning algorithms can process enormous quantities of satellite information to monitor and evaluate large-scale deforestation (Reichstein et al., 2019; Hansen et al., 2013), the melting of polar ice (Kwok and Rothrock, 2009), atmospheric pollution (Guo et al., 2022), and water quality (Zhu et al., 2022). AI also provides effective methods for protecting species and their natural habitats (Mishra, 2023). By applying computer vision and acoustic analysis, AI systems can recognise animals within camera-trap recordings and identify illegal activities such as poaching (Kuruppu, 2023). Algorithms can combine diverse data sources to detect patterns and predict areas at high risk of illegal wildlife trade, allowing preventive measures to be implemented (Kumar and Ghosh, 2025). AI can further model the potential effects of climate change on habitats and species distribution, providing evidence to guide conservation strategies (Branco et al., 2023).

AI can also perform a central role in predicting and managing natural disasters, helping to reduce the consequences of extreme events and strengthen community resilience (Wibowo et al., 2025). AI models can integrate meteorological data, vegetation conditions and topographical information to predict wildfire risks and determine efficient intervention routes for emergency services (Alkhatib et al., 2023). Similarly, AI can process hydrological information to forecast flooding (Mosavi et al., 2018) and monitor ground stability to anticipate landslides (Rouet-Leduc et al., 2017). AI is equally important to the transition towards a circular economy, which seeks to preserve the value and usefulness of products and materials while eliminating waste and pollution (Ellen MacArthur Foundation, 2015; UNEP, 2018). Robotic systems incorporating computer vision and deep learning can sort different categories of waste rapidly and accurately, substantially improving the recovery of recyclable materials (Abdallah et al., 2020; Kiran et al., 2023). AI can also optimize industrial supply chains by detecting waste and operational inefficiencies (Olola and Olatunde, 2025), while accelerating the design and discovery of innovative sustainable materials (Zeng, 2024). These applications directly support the principles of circular design (de Padua Pieroni et al., 2019). AI additionally supports digital platforms that promote product sharing, reuse and repair (Geissdoerfer et al., 2020). Through Natural Language Processing (NLP), it can also examine sustainability reports and strengthen corporate transparency and accountability (Pardo Vásquez and Gómez Rodríguez, 2025).

As the world's population becomes increasingly urbanised, AI-supported solutions are becoming fundamental to the development of more sustainable smart cities in accordance with SDG 11 (Sustainable Cities and Communities) (Anthopoulos, 2017; Angelidou, 2017). A critical consideration, however, is that technological efficiency should not be prioritised at the expense of urban quality of life or community-centred design. As argued by urban theorist Michael Mehaffy, cities should not be understood as simple tree-like

structures but as complex and organic systems in which human and physical relationships are essential to resilience and prosperity (Mehaffy, 2023; UN-Habitat, n.d.). A holistic approach combining AI technologies with intelligent and equitable urban design is therefore necessary to prevent the creation of a technologically advanced urban vision that cannot be successfully realised in practice.

AI systems can examine traffic flows in real time, dynamically adjust traffic signals and improve public-transport schedules, thereby substantially reducing congestion and greenhouse gas emissions (Gracias et al., 2023; Kaur, 2025; Kriswardhana and Esztergár-Kiss, 2023). AI can also contribute to Mobility as a Service (MaaS) systems by integrating different transportation options and encouraging greater use of public transport and active forms of mobility (Albino et al., 2015; Syed et al., 2024; Khemakhem and Krichen, 2024). Furthermore, AI can improve the management of urban resources by optimising energy and water-distribution networks (Neema and Kaushal Gor, 2022; Ali et al., 2024). Smart buildings equipped with AI technologies can analyse sensor information and occupant-behaviour patterns to maintain comfortable internal conditions while minimising energy consumption (Ali et al., 2024). AI-enabled predictive maintenance can detect potential equipment failures before they occur, avoiding expensive periods of inactivity and extending equipment lifespans (Kari and Sierla, 2022). Urban air-quality sensor networks integrated with AI can continuously monitor and forecast pollutant concentrations (Morain et al., 2025). AI can also process extensive geographical and socio-economic datasets to support urban planning by identifying suitable locations for development and evaluating the potential sustainability effects of different scenarios (Neirotti et al., 2014; Mashhood et al., 2023).

The adoption of AI within the industrial sector contributes to a fundamental transition towards “Industry 4.0” or “Green Industry 4.0” (Müller et al., 2018; Stock and Seliger, 2016). AI supports predictive maintenance by processing sensor data to anticipate machinery failures, thereby reducing waste and costly production interruptions (Plathottam et al., 2023; Sohaib et al., 2021). It can also optimize energy and resource use throughout the production process by automatically modifying operational settings (Mhlanga, 2023). Within cement and steel manufacturing, AI can optimize combinations of raw materials to reduce emissions (Oguntola et al., 2024), while its application in the chemical industry can minimise waste generation (Wang et al., 2017). AI-supported quality-control systems can prevent the manufacture of defective products (Monsreal and Carmona Benitez, 2022). During the design stage, AI may also simulate and optimise the environmental performance of new industrial processes and equipment (Charles et al., 2023). Nevertheless, the potential of Green Industry 4.0 requires critical examination. High initial investment costs and the requirement for specialised knowledge may prevent small- and medium-sized enterprises (SMEs) from adopting these technologies, producing technological stratification in which their benefits remain accessible primarily to large corporations.

Across environmental monitoring, circular economy applications, smart-city systems and industrial processes, the literature identifies substantial opportunities for AI-supported sustainability improvements. Nevertheless, the evidence remains heterogeneous in terms of research design, geographical context, technological maturity and the indicators used to evaluate outcomes. Studies based on simulations, predictive models or controlled experimental settings may demonstrate technical feasibility without establishing comparable performance under real-world operational conditions. Furthermore, the benefits of AI adoption may be unevenly distributed, particularly where limited financial resources, digital infrastructure or specialist expertise restrict implementation. These considerations highlight the need to distinguish technological potential from independently demonstrated environmental and socioeconomic benefits when evaluating the contribution of AI to sustainable development.

4.3 Comparative Synthesis of the Reviewed Literature

A comparative synthesis of the reviewed literature provides a basis for examining the relationship between AI applications, sustainability outcomes and the methodological characteristics of existing research. The analytical categories established in Section 2.3 encompass publication year, geographical context, sustainability sector, research methodology, AI application, relevant Sustainable Development Goals (SDGs), reported sustainability benefits, associated risks and key findings.

The six principal application domains identified in this review-energy management, agriculture, environmental monitoring, smart cities, circular economy practices and industrial applications-provide a framework for comparing the evidence across different sustainability contexts. This classification also supports an examination of the extent to which AI-related sustainability research addresses environmental objectives alongside social and economic considerations.

Table 1 summarises the six principal sustainability domains examined in this review, highlighting their main artificial intelligence applications and corresponding relationships with the United Nations Sustainable Development Goals (SDGs).

Table 1
Overview of AI applications across sustainability domains and their alignment with the SDGs.

Sustainability domain	Principal AI applications	Relevant SDGs
Energy management	Smart grids, energy forecasting, HVAC optimisation	7, 9, 13
Agriculture	Precision irrigation, crop monitoring, disease detection	2, 6, 12
Environmental monitoring	Biodiversity monitoring, pollution detection, disaster prediction	13, 14, 15
Smart cities	Traffic management, intelligent buildings, urban planning	9, 11, 13
Circular economy	Waste sorting, material recovery, resource optimisation	9, 12
Industrial applications	Predictive maintenance, production optimisation, manufacturing efficiency	9, 12, 13

To complement the domain-level overview presented in Table 1, Table 2 provides a representative comparison of selected publications cited in this review. The comparison considers geographical context, research methodology, AI applications, reported sustainability outcomes and principal limitations. The selected publications illustrate different forms of evidence across the six sustainability domains, including computational modelling, literature reviews and conceptual contributions. They are not intended to constitute an exhaustive or statistically representative sample of the wider literature.

Table 2
Representative studies examining AI applications, sustainability outcomes and evidence limitations.

Source	Sustainability domain	Country/geographical context	Research methodology	AI application	Sustainability contribution or reported outcome	Evidence limitation
Cenek et al. (2018)	Energy management	Alaska, United States; rural electrical microgrids	Computational modelling and comparative neural-network forecasting	Long short-term memory networks and artificial neural networks for electricity-load prediction	Investigates electricity-demand forecasting to support power management and renewable-energy integration in isolated microgrids	Forecasting improvements do not independently establish reductions in fuel consumption or greenhouse gas emissions
Ali et al. (2024)	Energy management	International building energy-management literature	Literature review	AI-based energy forecasting, HVAC control and building energy optimisation	Synthesises applications supporting energy efficiency, operational control and potential energy savings	Reported energy savings and model performance vary across building types, datasets and operating conditions
Liakos et al. (2018)	Agriculture	International agricultural research	Literature review	Machine learning for crop management, agricultural monitoring and decision support	Reviews applications supporting precision agriculture and improved agricultural decision-making	Differences in datasets, agricultural conditions and evaluation methods limit the generalisability of reported performance
Barbedo (2019)	Agriculture	International agricultural monitoring literature	Critical literature review	UAV imagery, imaging sensors and machine learning for plant-stress detection	Reviews approaches for identifying crop stress associated with water availability, diseases, nutrient deficiencies and pests	Sensor limitations, environmental variability, image quality and practical deployment conditions constrain application
Reichstein et al. (2019)	Environmental monitoring	International Earth-system science research	Scientific perspective and critical synthesis	Deep learning for Earth-system modelling and geospatial data analysis	Identifies opportunities for improved environmental prediction, modelling and process understanding	Data-driven models may struggle to represent physical processes and generalise beyond observed conditions

Source	Sustainability domain	Country/geographical context	Research methodology	AI application	Sustainability contribution or reported outcome	Evidence limitation
Mosavi et al. (2018)	Environmental monitoring	International flood-prediction research	Literature review and comparative analysis	Machine-learning models for flood prediction and forecasting	Compares forecasting approaches and identifies opportunities to improve predictive performance and flood-risk assessment	Differences in datasets, model evaluation, forecasting horizons and geographical conditions limit direct comparisons
Gracias et al. (2023)	Smart cities	International smart-city literature	Structured literature review	Data analytics and intelligent technologies supporting transportation, infrastructure, energy and urban services	Synthesises smart-city concepts and applications associated with urban efficiency, service integration and sustainable development	Conceptual and methodological diversity limits direct comparison; the review does not independently establish measured emissions reductions
Abdallah et al. (2020)	Circular economy	International solid-waste management literature	Systematic literature review	AI for waste forecasting, collection planning, routing and solid-waste management optimisation	Reviews AI applications supporting waste-management decision-making and operational efficiency	Data availability, model interpretability and implementation conditions constrain transferability and practical adoption
Wuest et al. (2016)	Industrial applications	International manufacturing research	Literature review	Machine learning for manufacturing process monitoring, quality improvement and optimisation	Examines potential improvements in manufacturing performance and operational decision-making	Data quality, implementation complexity and methodological differences constrain wider application
Plathottam et al. (2023)	Industrial applications	International manufacturing literature	Literature review	AI and machine learning for predictive maintenance, quality assurance and process optimisation	Synthesises opportunities to improve manufacturing efficiency, productivity and operational decision-making	Data acquisition, infrastructure requirements, technical expertise, trust and security challenges can constrain implementation; environmental benefits are not independently quantified.

Note

The selected publications illustrate representative AI applications across the six sustainability domains and are not intended to constitute a statistically representative sample of the wider literature. Geographical context refers to the study setting for original investigations and the scope of the evidence examined for literature reviews. The limitations column incorporates constraints identified

in the publications and critical considerations arising from the present comparative synthesis. Reported improvements in technological performance should not automatically be interpreted as directly measured sustainability outcomes.

The reviewed literature demonstrates substantial variation in the types of evidence used to assess artificial intelligence applications across sustainability domains. Experimental investigations, computational simulations, case studies and conceptual analyses address different aspects of technological performance and sustainability. Improvements in predictive accuracy, automation or operational efficiency should therefore be distinguished from directly measured reductions in energy consumption, emissions, resource use or socioeconomic inequalities.

The six-domain comparison identifies important differences in the application and evaluation of AI technologies. Energy management and industrial applications emphasise optimisation and operational efficiency, while agricultural and environmental applications frequently focus on prediction, monitoring and resource management. Smart-city and circular-economy applications extend these approaches to urban systems, infrastructure and material flows. Across these domains, the principal analytical challenge concerns the extent to which reported technological improvements translate into demonstrable, transferable and long-term sustainability benefits. The absence of consistent outcome measures and differences between research contexts limit direct comparison and highlight the need for more standardised evaluation frameworks.

A further distinction concerns the strength and comparability of the evidence supporting AI-related sustainability claims. Studies reporting improved prediction accuracy, classification performance or computational efficiency provide evidence of technological capability but do not necessarily demonstrate corresponding reductions in environmental impacts. In contrast, investigations incorporating measured changes in energy consumption, emissions, water use, material efficiency or other sustainability indicators offer a more direct basis for evaluating environmental performance. Nevertheless, such findings must be interpreted in relation to the research design, geographical context, implementation scale and duration of observation. Consequently, improvements demonstrated under experimental or simulated conditions should not automatically be generalised to wider operational environments.

The geographical and socioeconomic context of AI implementation also influences the transferability of reported outcomes. Access to reliable datasets, computational infrastructure, technical expertise and financial resources varies between regions and organisations, potentially affecting both the effectiveness and accessibility of AI-based sustainability solutions. These differences are particularly relevant when considering applications developed in technologically advanced settings and their potential adoption in contexts characterised by limited infrastructure or institutional capacity. Accordingly, the assessment of AI's contribution to sustainable development requires attention not only to environmental performance but also to technological accessibility, social equity and the distribution of potential benefits.

Taken together, these comparisons indicate that AI's sustainability contribution cannot be evaluated through technological performance alone. A more comprehensive assessment requires measurable environmental and socioeconomic indicators, consideration of implementation conditions and recognition of the ecological costs associated with AI development and operation. These considerations establish the basis for the following discussion of the AI Green Paradox, multidimensional risks and governance priorities.

5. Discussion: A Critical Analysis of the Challenges and Future Directions of AI in Sustainability

The preceding sections have examined in detail the expanding role of artificial intelligence (AI) as a transformative force within global efforts to achieve sustainable development. The evidence presented from optimising energy use and transforming agricultural practices to strengthening environmental monitoring demonstrates AI’s potential to support a more efficient and resilient future. By offering unprecedented capabilities to analyse extensive and complex datasets and automate processes, AI can support a transition from reactive responses to predictive and proactive strategies for managing critical resources (Rolnick et al., 2022; Schwartz et al., 2020). This capacity positions AI not merely as a technological instrument but as an important driver for achieving the Sustainable Development Goals (SDGs) and responding to the challenges associated with climate change.

Nevertheless, AI must be approached from a critical and pragmatic perspective. Its integration into sustainability strategies involves considerable limitations and risks. A central contradiction becomes apparent: while AI offers potential solutions to some of the

world's most urgent challenges, its technological lifecycle simultaneously generates substantial ecological and socio-economic consequences.

5.1. The "AI Green Paradox" and Key Challenges

One of the principal contradictions associated with applying AI to sustainability is the "AI Green Paradox," in which AI's capacity to support environmental solutions is counterbalanced by the ecological costs of developing and operating these technologies (Schwartz et al., 2020; Strubell et al., 2019; Patterson et al., 2021). Training deep-learning models, particularly Large Language Models (LLMs), requires enormous quantities of energy and can produce a substantial carbon footprint (Akter et al., 2024). The paradox also includes the electronic waste generated through rapid cycles of hardware replacement (AlSagri and Sohail, 2024; Chen, 2025; Katirai, 2024) and the water required to cool data centres, which may intensify water scarcity within local communities (Ewim et al., 2023). Responding to this paradox requires a fundamental strategic commitment to developing and adopting the "Green AI" paradigm. Within this discussion, "digital pollution" refers to the combined ecological effects of digital infrastructure, including the extensive energy requirements of data centres and the carbon emissions associated with manufacturing and disposing of electronic equipment (Chen, 2025; Ewim et al., 2023). The related concept of "green debt" describes the possibility that the immediate sustainability benefits provided by AI may eventually be exceeded by the long-term ecological and resource costs associated with its development and operation, resulting in an overall environmental deficit (Schwartz et al., 2020).

The performance and reliability of AI systems are also determined by the quality, quantity and ethical integrity of the data used for training. Data bias represents a significant concern because historical datasets may reproduce existing social inequalities or inadequately represent particular regions and communities (Hayes et al., 2020; Caliskan et al., 2022; Donoho, 2017). Consequently, AI applications may not adequately respond to the needs of marginalised groups, further widening the digital and social "AI divide." In addition, many deep-learning systems operate as "black boxes," making the processes through which they reach particular conclusions difficult to understand (Ching et al., 2018; Belenguer, 2022). This absence of transparency can weaken public confidence, particularly in critical applications, and complicate the establishment of algorithmic accountability when incorrect decisions occur (Castelvecchi, 2016; Adadi and Berrada, 2018). Explainable AI (XAI) is therefore essential for managing these risks because it improves the transparency and interpretability of AI models and enables human oversight and auditing (Gunning et al., 2019; Jobin et al., 2019; Crawford, 2021; Kitsara, 2022). Appropriate data-governance frameworks are also required to encourage the collection of diverse and equitable datasets, minimise bias and safeguard ethical data practices (Floridi and Cowls, 2019).

The implementation of AI also creates socio-economic risks, including substantial initial costs and dependence on advanced technologies, which may be unaffordable for developing countries and small- and medium-sized enterprises (SMEs) (Băbut et al., 2021; Acemoglu and Restrepo, 2019). Consequently, the sustainability benefits of AI may remain concentrated among a limited number of corporations and countries, potentially intensifying existing inequalities (European Commission, 2021; Dutta and Bharali, 2021). Addressing these disparities requires coordinated technological, financial and educational measures, which are discussed in greater detail in Section 5.3.

5.2. Critical Risk Analysis

Although artificial intelligence (AI) offers transformative potential for advancing sustainability objectives, its widespread adoption involves significant challenges and inherent risks. A critical perspective requires these risks to be examined systematically to support the responsible, ethical and efficient integration of AI into global environmental and social strategies. Identifying, evaluating and prioritising these risks are essential steps in developing suitable mitigation measures and preventing undesirable outcomes. As illustrated in Fig. 2, the risks can be organised into three principal categories: the inherent environmental risks associated with AI, particularly its ecological footprint; risks connected with data and algorithms; and socio-economic and ethical risks.

Analysing the risks associated with implementing AI for sustainability becomes particularly complex where these principal categories overlap. These intersections reveal multifactorial challenges that require an integrated and carefully balanced response.

Figure 3. Intersection of artificial intelligence risk categories within the context of sustainability.

Ecological Risks and Socio-Economic and Ethical Risks

This intersection concerns the environmental effects of AI and their related social, economic and ethical consequences. It introduces the concept of inequitable green debt, which reflects the central contradiction of applying AI to sustainability. Although AI promises to support environmental solutions, its energy consumption, electronic waste and water requirements produce an ecological footprint that creates a form of "green debt" (Crawford, 2021; UNEP, 2021). If this debt is ignored or inadequately managed, it may intensify social and economic inequalities. Its unequal effects on particular communities, combined with disparities in access to AI's benefits, can transform green debt into an inequitable burden (Crawford, 2021). This relationship also creates the risk of unsustainable AI development, in which AI's substantial ecological footprint (Chen, 2025; Ewim et al., 2023), when disregarded, contradicts the fundamental principles of sustainable development (UNEP, 2021). If the processes used to develop and operate AI are themselves unsustainable, they may reproduce or worsen existing environmental and social inequalities. This can further generate green disparities, whereby AI's environmental consequences are distributed unevenly and vulnerable communities carry a disproportionate share of pollution, resource depletion and electronic-waste management. Finally, the perspective of a human and natural resource crisis connects AI's reliance on energy, water and rare minerals with its effects on communities and workers. This dependence may contribute to social conflict, population displacement and inequitable labour conditions (Crawford, 2021; UNEP, 2021).

Ecological Risks and Data Algorithm-Related Risks

This intersection considers how the quantity, quality and management of data, together with algorithmic efficiency, directly affect the environmental footprint of AI systems. This relationship produces a computational footprint, referring to the direct ecological consequences of the extensive computational resources required to train and operate AI models (Schwartz et al., 2020; Strubell et al., 2019; Patterson et al., 2021). The substantial energy and resource demands of data centres increase alongside algorithmic complexity and data volume, contributing to carbon emissions and resource depletion. The problem is intensified by computational inefficiency, which occurs when algorithms are poorly optimised or data are inadequately managed, causing unnecessary energy and resource consumption (Schwartz et al., 2020). Such inefficiency needlessly increases AI's ecological footprint. This consequence is frequently described as digital pollution, a metaphor for the negative environmental effects of the digital infrastructure required to process large datasets and operate complex algorithms. It encompasses energy use, carbon emissions and electronic waste (Schwartz et al., 2020; Patterson et al., 2021). Another important challenge concerns inaccessible "green" data. When the information needed to develop effective Green AI applications, for example, systems supporting climate monitoring or energy optimization, is difficult to collect, store or process because of technical or financial restrictions, progress towards sustainable AI and wider environmental objectives is obstructed.

Socio-Economic and Ethical Risks in Data Algorithm-Related Risks

This intersection represents one of the most critical areas of concern because the properties of data and algorithms may generate inequality, ethical challenges and threats to fundamental rights. It includes systemic digital bias, which occurs when biases contained within training datasets are reproduced and amplified by algorithms, eventually becoming a systemic form of social discrimination (Caliskan et al., 2022; Belenguer, 2022). This may result in inequitable decisions concerning employment, lending, justice and access to essential services, thereby reinforcing existing inequalities. A lack of algorithmic transparency, commonly described as the "black box" problem, together with concerns regarding confidentiality, can also contribute to the erosion of digital trust (Castelvecchi, 2016). This weakens public confidence not only in AI technologies but also in the institutions that employ them, creating substantial social consequences. The expression "black box" responsibility describes the fundamental difficulty of assigning responsibility for errors or harm produced by opaque AI systems, making legal and ethical accountability challenging to establish (Adadi and Berrada, 2018; Gunning et al., 2019). Finally, this intersection strengthens the concept of the ethical digital divide, suggesting that unequal access to advanced AI systems and their benefits, when combined with inadequate data governance, may widen global socio-economic and ethical inequalities (Kitsara, 2022).

The Complex Intersection of All Three Risk Categories

The most complicated intersection occurs when ecological, socioeconomic and ethical, and data- and algorithm-related risks emerge simultaneously. This situation demonstrates the potential for a failure of integrated AI governance. If regulatory systems do not address all three dimensions collectively, the result may be a systemic failure of sustainability (Floridi and Cowls, 2019; OECD, 2019; UNESCO, 2021). Any partial benefits generated by AI may consequently be outweighed by negative and multidimensional outcomes. This produces what may be described as AI's Green Paradox, reinforcing the concern that despite its capacity to support

sustainability, AI may create a threefold negative effect through intensive resource use, the reproduction of bias and inequality, and problems associated with data management and algorithmic opacity (Schwartz et al., 2020; Crawford, 2021; UNEP, 2021). These interconnected risks ultimately provide a significant warning regarding an unsustainable AI future. Without holistic, proactive and integrated risk management, AI development may contribute to a future that is environmentally, socially and ethically unsustainable, undermining international efforts to establish an equitable society and maintain a healthy natural environment (Crawford, 2021).

To support a structured comparison of the sustainability risks associated with artificial intelligence, an exploratory semi-quantitative risk-prioritisation framework is presented through the assessment scale in Table 3 and the detailed risk matrix in Table 4. The framework combines indicative likelihood and severity ratings on five-point ordinal scales, with comparative scores calculated by multiplying likelihood by severity (P × I), producing values ranging from 1 to 25. These scores provide a heuristic basis for comparing potential areas of concern and identifying corresponding mitigation priorities. As the ratings represent interpretative analytical judgements rather than empirically validated measurements, the resulting scores should not be interpreted as measured probabilities, statistically established risk levels or universally applicable thresholds.

For the purposes of this exploratory framework, likelihood and severity are interpreted using five-point ordinal scales. Likelihood is classified as very unlikely (1), unlikely (2), possible (3), likely (4) and very likely (5), while severity is classified as negligible (1), minor (2), moderate (3), major (4) and severe (5). Likelihood refers to the indicative potential for a particular risk to arise within relevant AI applications, whereas severity concerns the potential environmental, technological, socioeconomic or ethical consequences if that risk occurs. The numerical ratings presented in Table 3 are illustrative analytical judgements informed by the risk categories discussed in the literature; they are not presented as the results of a formal expert-elicitation or empirical validation exercise.

For interpretative purposes, the resulting scores are grouped into five indicative risk levels using classification thresholds adopted for this exploratory framework. These categories provide a consistent basis for discussing relative risk significance and prioritising potential mitigation measures:

- Very low risk (green; score of 1–4): These risks are generally insignificant and require only minimal monitoring.
- Low risk (yellow; score of 5–8): These risks are usually manageable and require routine monitoring.
- Moderate risk (orange; score of 9–15): These risks require targeted attention and proactive management measures.
- High risk (red; score of 16–19): These risks require immediate and substantial mitigation measures because of their potentially severe impact or high probability of occurrence.
- Critical risk (dark red; score of 20–25): These are the most severe risks and require urgent, high-priority interventions supported by robust governance frameworks.

Table 3. Risk-assessment matrix for evaluating the effects of AI on sustainability.

	Likelihood				
Risk Classification (Impact)	**1 (Minimal)**	**2 (Low)**	**3 (Moderate)**	**4 (High)**	**5 (Critical)**
5 (Catastrophic)	5	10	15	20	25
4 (Major)	4	8	12	16	20
3 (Moderate)	3	6	9	12	15
2 (Minor)	2	4	6	8	10
1 (Negligible)	1	2	3	4	5

Table 4
Comprehensive assessment of AI-related sustainability risks and corresponding mitigation measures.

Risk Domain	Specific Risk	Likelihood (1–5)	Severity (1–5)	Combined Score (P × I)	Risk Level	Recommended Mitigation Strategies
	Intensive energy use during the training and operation of AI models	**4**	**4**	**16**	**High**	**Prioritise computationally efficient algorithms, such as compact, sparse and TinyML models; increase the use of renewable electricity in data centres; and enhance the performance of cooling technologies.**
Environmental burden generated by AI (AI-related "green debt")	Embodied carbon associated with hardware manufacturing and discarded electronic equipment	3	4	12	Moderate	Adopt lifecycle-based hardware management by improving equipment design, prolonging operational life and supporting effective recycling; introduce consistent methods for calculating and reporting hardware-related emissions.
	Use of water to regulate data-centre temperatures	3	3	9	Moderate	Reduce cooling-related water demand by incorporating recycled water, improving system efficiency and investigating alternative cooling methods that rely less heavily on water.
	Dependence on substantial quantities of data and the financial costs involved	4	3	12	Moderate	Expand investment in openly accessible data infrastructure; develop collaborative arrangements for gathering and managing data; and remove unnecessary barriers to data access.
Data reliability, accessibility and representativeness	Unrepresentative or biased data that may reproduce or intensify social inequalities	4	5	20	Critical	Introduce policies governing ethical data use and bias prevention; apply explainable AI approaches; broaden the range of data sources; and involve diverse stakeholder groups in development and oversight processes.
	Limited consistency, compatibility and availability across datasets	3	4	12	Moderate	Establish shared and openly available data standards; promote international cooperation to improve interoperability; and encourage the wider use of open-source AI technologies.
	Limited understanding of how AI systems reach particular conclusions—the	3	4	12	Moderate	Advance the design of interpretable and dependable AI models and establish specific transparency

Risk Domain	Specific Risk	Likelihood (1–5)	Severity (1–5)	Combined Score (P × I)	Risk Level	Recommended Mitigation Strategies
	Intensive energy use during the training and operation of AI models	**4**	**4**	**16**	**High**	**Prioritise computationally efficient algorithms, such as compact, sparse and TinyML models; increase the use of renewable electricity in data centres; and enhance the performance of cooling technologies.**
	"black-box" challenge					requirements for systems used in sensitive or high-risk contexts.
System complexity, opacity and confidence (Explainable AI—XAI)	Obstacles affecting the verification, auditing and practical acceptance of AI systems	3	3	9	Moderate	Make algorithms more transparent, create reliable procedures for independently evaluating AI systems and use XAI methods to improve confidence among users and institutions.
	Uncertainty regarding responsibility when AI systems produce errors or cause harm	2	4	8	Low	Define legal responsibilities for algorithmic outcomes and strengthen public understanding of both the capabilities and limitations of artificial intelligence.
	Considerable start-up expenditure and the need for capital-intensive infrastructure	4	4	16	High	Provide grants, financial support and other incentives for Green AI research; encourage cooperation between public and private organisations; and widen access to shared cloud resources.
Financial barriers, unequal access and technological disparities	Unequal access to AI technologies and their benefits—the "AI divide"	4	5	20	Critical	Increase access to open-source systems and shared digital infrastructure while supporting technological training and capacity development, particularly in developing countries.
	Reliance on a limited number of technology providers and increasing market concentration	3	4	12	Moderate	Support competitive markets, interoperable standards and open-source alternatives; apply appropriate competition and antitrust measures where market dominance becomes problematic.
	Ethical data management and the protection of personal privacy	4	4	16	High	Strengthen privacy and data-protection regulations; apply comprehensive data-governance procedures; and openly communicate how information is obtained, processed and utilised.

Risk Domain	Specific Risk	Likelihood (1–5)	Severity (1–5)	Combined Score (P × I)	Risk Level	Recommended Mitigation Strategies
	Intensive energy use during the training and operation of AI models	**4**	**4**	**16**	**High**	**Prioritise computationally efficient algorithms, such as compact, sparse and TinyML models; increase the use of renewable electricity in data centres; and enhance the performance of cooling technologies.**
Ethics, governance and broader societal effects	Employment disruption and the possible displacement of workers	3	3	9	Moderate	Provide opportunities for professional reskilling and upskilling and prepare long-term workforce strategies that support a fair transition towards an AI-enabled economy.
	Deficiencies in legislation and unresolved questions of accountability	3	3	9	Moderate	Accelerate the preparation of appropriate legal and ethical provisions and encourage international coordination to achieve greater consistency between national regulatory systems.
	Autonomous decision-making and the need to retain meaningful human supervision	2	4	8	Low	Ensure that people remain directly involved in decisions with serious consequences and establish ethical standards governing the scope and operation of autonomous AI technologies.

The risk-prioritisation matrix offers an integrated perspective on the environmental, technological, socioeconomic and ethical challenges associated with AI adoption. Within the illustrative assessment, risks relating to biased datasets and unequal access to AI technologies receive the highest combined scores (20), reflecting their potential implications for social equity, technological inclusion and responsible decision-making. Intensive energy consumption, substantial infrastructure investment and data-privacy concerns are also assigned comparatively high scores (16), highlighting the importance of resource efficiency, financial accessibility and effective governance. These rankings should not be interpreted as universal measurements of risk, since their significance may differ according to technological application, geographical context, infrastructure conditions and the populations affected. Furthermore, the individual scores and classification thresholds have not been independently validated. The framework should therefore be regarded as a preliminary analytical tool requiring further empirical investigation, expert consultation and sensitivity testing before its application to operational risk-management decisions.

Figure 4. Comprehensive risk matrix for evaluating sustainability-related AI risks and their corresponding mitigation measures.

5.3. Mitigation Strategies and Future Recommendations

The critical assessment undertaken in this study demonstrates that artificial intelligence represents a powerful instrument for advancing sustainability, although its potential benefits remain closely connected to a range of complex challenges. The central argument is that fully realising AI's capabilities requires a strategic and proactive approach that acknowledges its inherent risks and introduces appropriate measures to reduce them. Future progress therefore depends on a commitment to developing "Green AI", with particular emphasis on energy efficiency and responsible hardware management, while creating systems that are transparent, equitable and accountable. Combined with robust governance frameworks and international cooperation, these measures can help

ensure that the continued development of AI supports a genuinely sustainable and socially just future for all (Crawford, 2021; UNEP, 2021).

Clearly defined strategic recommendations are consequently required. First, funding and incentive policies should establish dedicated financial support for “Green AI” innovation and introduce fiscal incentives for technological solutions that contribute to sustainability (Schwartz et al., 2020; Patterson et al., 2021). International cooperation and public–private partnerships (PPPs) constitute another essential element of this process (UNEP, 2018; Hinton et al., 2015; Siqueira et al., 2024). Such collaborations can support the transfer of knowledge, expertise and technology while promoting a more equitable global distribution of the benefits generated by AI (Tejaswini et al., 2020; Luccioni et al., 2022). The expansion of open-source platforms is equally important, particularly through the development of openly accessible algorithms and datasets that reduce barriers to technological participation (Fauzi, 2023; Ham et al., 2019; van Klompenburg et al., 2020). Finally, education and capacity building remain fundamental priorities. Targeted training programmes can help prepare a new generation of “Green AI engineers” while strengthening technological knowledge and professional skills in developing countries (OECD, 2019; UNESCO, 2019, 2021; UNEP, 2021).

Beyond these strategic recommendations, the reviewed literature highlights several areas requiring further investigation. First, although AI applications demonstrate considerable potential to improve resource efficiency and environmental management, further research is needed to establish their long-term sustainability performance, particularly when the energy consumption, water requirements and embodied environmental impacts of AI infrastructure are considered. Second, additional investigation is required into the effectiveness of AI applications across different geographical and socio-economic contexts, particularly in developing countries and resource-constrained organisations where technological accessibility, financial capacity and data availability remain significant challenges. Third, the relationship between algorithmic transparency, data governance and sustainability outcomes requires further examination to establish how responsible AI practices can be consistently implemented and evaluated. Finally, future studies should investigate the effectiveness of integrated governance approaches that address environmental, technological and socio-economic risks simultaneously. Addressing these gaps would strengthen the evidence base for assessing AI's contribution to the Sustainable Development Goals and support the development of more accountable, equitable and environmentally responsible AI systems.

6. Conclusions

This study critically examined the evolving and multidimensional role of artificial intelligence (AI) in advancing global sustainability and supporting the United Nations Sustainable Development Goals (SDGs). The analysis highlighted AI's applications across energy management, agriculture, environmental monitoring, smart cities, circular economy practices and industrial processes (RQ1). Across these domains, AI demonstrates considerable potential to improve resource efficiency, support environmental monitoring, optimise complex systems and contribute to environmental, social and economic sustainability objectives (RQ2). Nevertheless, improvements in technological performance do not necessarily establish measurable sustainability benefits, emphasising the importance of evaluating outcomes within their specific implementation contexts.

Despite these opportunities, AI adoption presents significant environmental, technological, socioeconomic and ethical challenges (RQ3). The analysis highlighted the AI Green Paradox, whereby technologies intended to support sustainability may simultaneously generate substantial ecological pressures through energy consumption, carbon emissions, water requirements and electronic waste. Additional concerns include algorithmic bias, limited transparency, data-governance challenges, substantial implementation costs and unequal access to technological infrastructure and expertise. These interconnected issues demonstrate that AI's sustainability contribution depends on both its capabilities and the consequences of its development and implementation.

The review also identified methodological and practical limitations within the available literature (RQ4), including differences in research approaches, geographical contexts, evaluation criteria and implementation conditions. These variations complicate comparisons between studies and limit the transferability of reported findings. In particular, evidence derived from simulations, predictive models or experimental settings should be distinguished from demonstrated environmental and socioeconomic improvements in operational contexts. Further research incorporating measurable sustainability indicators, longitudinal evaluation and diverse geographical settings is therefore necessary to strengthen the evidence supporting AI-based sustainability interventions.

The principal contribution of this review lies in integrating the opportunities and challenges of AI within a multidimensional sustainability perspective. Rather than presenting the AI Green Paradox as an entirely new phenomenon, the study employs it as an organising concept connecting AI's potential sustainability benefits with its ecological, technological and socioeconomic consequences. The accompanying exploratory risk-prioritisation framework further supports the structured interpretation of interconnected challenges and the identification of potential mitigation priorities. Maximising AI's benefits while reducing associated risks requires continued development of Green AI, transparent and accountable governance frameworks, international cooperation, technological accessibility, education and professional capacity building (RQ5).

The study is subject to methodological limitations. As a structured critical literature review, it draws on a multidisciplinary body of published literature without a fully reproducible systematic screening record or a statistically representative study-level dataset. Consequently, its findings should be interpreted as a critical synthesis of the available evidence rather than an exhaustive or quantitative assessment of the wider research landscape. Nevertheless, the review provides an integrated basis for examining AI's sustainability implications and identifying priorities for future investigation. AI has substantial potential to support a more sustainable future, but realising this potential requires responsible technological development, measurable sustainability outcomes and coordinated action addressing environmental protection, social equity and ethical accountability.

Declarations

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Data Availability Statement: This study draws on previously published academic and institutional literature cited in the reference list. No new empirical datasets were generated. The bibliographic sources supporting the critical synthesis are identified in the manuscript. The original database search exports and screening records are not available; consequently, the literature-identification and selection process cannot be independently reconstructed in full.

Supplementary Materials: Supplementary File S1 (Appendix A) provides a bibliographic overview and preliminary thematic classification of the 138 references cited in this review. The accompanying Excel spreadsheet includes bibliographic information and classifications by publication type, sustainability domain, AI application and thematic alignment with the Sustainable Development Goals (SDGs). This register supports bibliographic transparency and thematic organisation but does not represent a systematically screened or statistically representative dataset of included studies.

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Clinical Trial Registration: Not applicable. This study is a structured critical literature review and does not involve clinical research, medical interventions or experimental clinical procedures.

References

1. Abdallah M, Talib MA, Feroz S, Nasir Q, Abdalla H, Mahfood B (2020) 'Artificial intelligence applications in solid waste management: A systematic research review', *Waste Management*, 109, pp. 231–246. Available at: https://doi.org/10.1016/j.wasman.2020.04.057
2. Acemoglu D, Restrepo P (2019) 'Automation and new tasks: How technology displaces and reinstates labour', *Journal of Economic Perspectives*, 33(2), pp. 3–30. Available at: https://doi.org/10.1257/jep.33.2.3
3. Adadi A, Berrada M (2018) 'Peeking inside the black box: A survey on explainable artificial intelligence (XAI)', *IEEE Access*, 6, pp. 52138–52160. Available at: https://doi.org/10.1109/ACCESS.2018.2870052
4. Akter S, Babu MM, Hani U, Sultana S, Bandara R, Grant D (2024) 'Unleashing the power of artificial intelligence for climate action in industrial markets', *Industrial Marketing Management*, 117, pp. 92–113. Available at: https://doi.org/10.1016/j.indmarman.2023.12.011
5. Albino V, Berardi U, Dangelico RM (2015) 'Smart cities: Definitions, dimensions, performance, and initiatives', *Journal of Urban Technology*, 22(1), pp. 3–21. Available at: https://doi.org/10.1080/10630732.2014.942092
6. Ali DMTE, Motuzienė V, Džiugaitė-Tumėnienė R (2024) 'AI-driven innovations in building energy management systems: A review of potential applications and energy savings', *Energies*, 17, 4277. Available at: https://doi.org/10.3390/en17174277
7. Alkhatib R, Sahwan W, Alkhatieb A, Schütt B (2023) 'A brief review of machine learning algorithms in forest fires science', *Applied Sciences*, 13, 8275. Available at: https://doi.org/10.3390/app13148275
8. AlSagri HS, Sohail SS (2024) 'Evaluating the role of artificial intelligence in sustainable development goals with an emphasis on quality education', *Discover Sustainability*, 5, 458. Available at: https://doi.org/10.1007/s43621-024-00682-9
9. Angelidou M (2017) 'The role of smart city characteristics in the plans of fifteen cities', *Journal of Urban Technology*, 24(4), pp. 3–28. Available at: https://doi.org/10.1080/10630732.2017.1348880
10. Anthopoulos L (2017) 'Smart utopia versus smart reality: Learning by experience from 10 smart city cases', *Cities*, 63, pp. 128–148. Available at: https://doi.org/10.1016/j.cities.2016.10.005
11. Băbuț G, Moraru RI, Cioca LI (2021) 'Kinney methods: Useful or harmful tools in the risk assessment and management process?', in *Proceedings of the Manufacturing Science and Education Conference*, Sibiu, Romania, 2–4 June, pp. 315–318
12. Barbedo JGA (2019) 'A review on the use of unmanned aerial vehicles and imaging sensors for monitoring and assessing plant stresses', *Drones*, 3, 40. Available at: https://doi.org/10.3390/drones3020040
13. Belenguer L (2022) 'AI bias: Exploring discriminatory algorithmic decision-making models and the application of possible machine-centric solutions adapted from the pharmaceutical industry', *AI and Ethics*, 2, pp. 771–787. Available at: https://doi.org/10.1007/s43681-022-00138-8
14. BloombergNEF (2024) *Long-Term Electric Vehicle Outlook 2024*. London: BloombergNEF
15. Branco VV, Correia L, Cardoso P (2023) 'The use of machine learning in species threats and conservation analysis', *Biological Conservation*, 283, 110091. Available at: https://doi.org/10.1016/j.biocon.2023.110091
16. Brundtland Commission (1987) Our Common Future: Report of the World Commission on Environment and Development. Oxford University Press, Oxford
17. Brynjolfsson E, McAfee A (2014) The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. W.W. Norton & Company, New York
18. Caliskan A, Ajay PP, Charlesworth T, Wolfe R, Banaji MR (2022) 'Gender bias in word embeddings: A comprehensive analysis of frequency, syntax, and semantics', in *Proceedings of the AAAI/ACM Conference on Artificial Intelligence, Ethics, and Society (AIES '22)*, Oxford, UK, 1–3 August. New York: ACM. Available at: https://doi.org/10.1145/3514094.3534162
19. Castelvecchi D (2016) 'Can we open the black box of AI?', *Nature*, 538, pp. 20–23. Available at: https://doi.org/10.1038/538020a
20. Cenek M, Haro R, Sayers B, Peng J (2018) 'Climate change and power security: Power-load prediction for rural electrical microgrids using long short-term memory and artificial neural networks', *Applied Sciences*, 8, 749. Available at: https://doi.org/10.3390/app8050749

21. Charles A, Bayat M, Elkaseer A, Scholz S (2023) 'Simulation in additive manufacturing and its implications for sustainable manufacturing in the era of Industry 4.0', in Scholz, S.G., Howlett, R.J. and Setchi, R. (eds.) *Sustainable Design and Manufacturing*. Singapore: Springer. Available at: https://doi.org/10.1007/978-981-19-9205-6_36
22. Chen S (2025) 'How much energy will AI really consume? The good, the bad and the unknown', *Nature*, 639, pp. 22–24. Available at: https://doi.org/10.1038/d41586-025-00616-z
23. Ching T, Himmelstein DS, Beaulieu-Jones BK, Kalinin AA, Do BT, Way GP, Ferrero E, Agapow PM, Zietz M, Hoffman MM et al (2018) 'Opportunities and obstacles for deep learning in biology and medicine', *Journal of the Royal Society Interface*, 15, 20170387. Available at: https://doi.org/10.1098/rsif.2017.0387
24. Coleman GRY, Bender A, Hu K, Sharpe SM, Schumann AW, Wang Z, Bagavathiannan MV, Boyd NS, Walsh MJ (2022) 'Weed detection to weed recognition: Reviewing 50 years of research to identify constraints and opportunities for large-scale cropping systems', *Weed Technology*, 36, pp. 741–757. Available at: https://doi.org/10.1017/wet.2022.84
25. Costanza R, Hart M, Talberth S, Moeller L (2014) An Introduction to Ecological Economics. CRC, Boca Raton, FL
26. Crawford K (2021) *Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence*. New Haven, CT: Yale University Press. Available at: https://yalebooks.yale.edu/book/9780300264630/atlas-of-ai/
27. de Padua Pieroni M, McAloone T, Pigosso D (2019) 'Business model innovation for the circular economy: Integrating literature and practice into a conceptual process model', *Proceedings of the Design Society: International Conference on Engineering Design*, 1, pp. 2517–2526. Available at: https://doi.org/10.1017/dsi.2019.258
28. Donoho D (2017) '50 years of data science', *Journal of Computational and Graphical Statistics*, 26(4), pp. 745–766. Available at: https://doi.org/10.1080/10618600.2017.1384734
29. Dutta L, Bharali S (2021) 'TinyML meets IoT: A comprehensive survey', *Internet of Things*, 16, 100461. Available at: https://doi.org/10.1016/j.iot.2021.100461
30. Ellen MacArthur Foundation (2015) Towards a Circular Economy: Business Rationale for an Accelerated Transition. Ellen MacArthur Foundation, Cowes
31. European Commission (2021) *Proposal for a Regulation Laying Down Harmonised Rules on Artificial Intelligence*. Brussels: European Commission. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52021PC0206
32. Evans R, Gao J (2016) 'DeepMind AI reduces Google data centre cooling bill by 40%', *Google DeepMind Blog*, 20 July. Available at: https://deepmind.google/blog/deepmind-ai-reduces-google-data-centre-cooling-bill-by-40/
33. Ewim DRE, Ninduwezuor-Ehiobu N, Orikpete OF, Egbokhaebho BA, Fawole AA, Onunka C (2023) 'Impact of data centres on climate change: A review of energy-efficient strategies', *Journal of Engineering and Exact Sciences*, 9, 16397-01e. Available at: https://doi.org/10.18540/jcecvl9iss6pp16397-01e
34. Fauzi C (2023) 'A review of geospatial artificial intelligence (Geo-AI): Implementation of machine learning in urban planning', in Al Rasyid, M.U.H. and Mufid, M.R. (eds.) *Proceedings of the International Conference on Applied Science and Technology on Engineering Science 2023*. Dordrecht: Atlantis Press. Available at: https://doi.org/10.2991/978-94-6463-364-1_30
35. Floridi L, Cowls J (2019) 'A unified framework of five principles for AI in society', *Harvard Data Science Review*, 1, pp. 2–15. Available at: https://doi.org/10.2139/ssrn.3831321
36. Geissdoerfer M, Pieroni MP, Pigosso DC, McAloone OC (2020) 'Circular business models: A review', *Journal of Cleaner Production*, 277, 123741. Available at: https://doi.org/10.1016/j.jclepro.2020.123741
37. Géron A (2019) Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems, 2nd edn. O'Reilly Media, Sebastopol, CA
38. Goodfellow I, Bengio Y, Courville A (2016) *Deep Learning*. Cambridge, MA: MIT Press. Available at: https://www.deeplearningbook.org/
39. Gracias JS, Parnell GS, Specking E, Pohl EA, Buchanan R (2023) 'Smart cities: A structured literature review', *Smart Cities*, 6, pp. 1719–1743. Available at: https://doi.org/10.3390/smartcities6040080
40. Gunning D, Stefik M, Choi J, Haake T, Ding Y (2019) 'XAI—Explainable artificial intelligence', *Science Robotics*, 4, eaay7120. Available at: https://doi.org/10.1126/scirobotics.aay7120
41. Guo R, Qi Y, Zhao B, Pei Z, Wen F, Wu S, Zhang Q (2022) 'High-resolution urban air-quality mapping for multiple pollutants based on dense monitoring data and machine learning', *International Journal of Environmental Research and Public Health*, 19, 8005.

Available at: https://doi.org/10.3390/ijerph19138005

42. Gupta M, Arya A, Varshney U, Mittal J, Tomar A (2025) 'A review of PV power forecasting using machine-learning techniques', *Progress in Engineering Science*, 2, 100058. Available at: https://doi.org/10.1016/j.pes.2025.100058
43. Ham Y, Kim J, Luo J (2019) 'Deep learning for multi-year ENSO forecasts', *Nature*, 573, pp. 568–572. Available at: https://doi.org/10.1038/s41586-019-1559-7
44. Hansen MC, Potapov PV, Moore R, Hancher M, Turubanova SA, Tyukavina A, Thau D, Stehman SV, Goetz SJ, Loveland TR et al (2013) 'High-resolution global maps of twenty-first-century forest-cover change', *Science*, 342, pp. 850–853. Available at: https://doi.org/10.1126/science.1244693
45. Hasanat SM, Younis R, Alahmari S, Ejaz MT, Haris M, Yousaf H, Watara S, Kaleem Ullah K, Ullah Z (2024) 'Enhancing load-forecasting accuracy in smart grids: A novel parallel multichannel network approach using 1D CNN and Bi-LSTM models', *International Journal of Energy Research*, 2024, 2403847. Available at: https://doi.org/10.1155/2024/2403847
46. Hayes P, van de Poel I, Steen M (2020) 'Algorithms and values in justice and security', *AI & Society*, 35, pp. 533–555. Available at: https://doi.org/10.1007/s00146-019-00932-9
47. Hendy ZM, Abdelhamid MA, Gyasi-Agyei Y, Mokhtar A (2023) 'Estimation of reference evapotranspiration based on machine-learning models and time-series analysis: A case study in an arid climate', *Applied Water Science*, 13, 216. Available at: https://doi.org/10.1007/s13201-023-02016-y
48. Hinton G, Vinyals O, Dean J (2015) 'Distilling the knowledge in a neural network', *arXiv*, arXiv:1503.02531. Available at: https://doi.org/10.48550/arXiv.1503.02531
49. Huotari M, Malhi A, Främling K (2024) 'Machine-learning applications for smart-building energy utilisation: A survey', *Archives of Computational Methods in Engineering*, 31, pp. 2537–2556. Available at: https://doi.org/10.1007/s11831-023-10054-7
50. International Energy Agency (IEA) (2021) *Net Zero by 2050: A Roadmap for the Global Energy Sector*. Paris: IEA Publishing. Available at: https://www.iea.org/reports/net-zero-by-2050 (Accessed: 14 September 2024)
51. International Energy Agency (IEA) (2023a) *Carbon Capture, Utilisation and Storage 2023*. Paris: IEA Publishing. Available at: https://www.iea.org/energy-system/carbon-capture-utilisation-and-storage (Accessed: 24 April 2025)
52. International Energy Agency (IEA) (2023b) *Energy Efficiency 2023*. Paris: IEA Publishing. Available at: https://www.iea.org/reports/energy-efficiency-2023 (Accessed: 11 May 2025)
53. Intergovernmental Panel on Climate Change (IPCC) (2018) 'Summary for policymakers', in Masson-Delmotte, V., Zhai, P., Pörtner, H.-O., Roberts, D., Skea, J., Shukla, P.R. (eds.) *Global Warming of 1.5°C*. Cambridge: Cambridge University Press, pp. 3–24. Available at: https://doi.org/10.1017/9781009157940.001
54. Intergovernmental Panel on Climate Change (IPCC) (2019) *Climate Change and Land: An IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse-Gas Fluxes in Terrestrial Ecosystems*. Geneva: World Meteorological Organization. Available at: https://www.ipcc.ch/srccl/
55. Intergovernmental Panel on Climate Change (IPCC) (2023) *AR6 Synthesis Report: Climate Change 2023*. Geneva: IPCC. Available at: https://www.ipcc.ch/report/ar6/syr/
56. International Renewable Energy Agency (IRENA) (2020) *Renewable Power Generation Costs in 2019*. Abu Dhabi: IRENA. Available at: https://www.irena.org/publications/2020/Jun/Renewable-Power-Costs-in-2019
57. Jackson T (2009) Prosperity Without Growth: Economics for a Finite Planet. Earthscan, London
58. Jobin A, Ienca M, Vayena E (2019) 'The global landscape of AI ethics guidelines', *Nature Machine Intelligence*, 1, pp. 389–399. Available at: https://doi.org/10.1038/s42256-019-0088-2
59. Joshi R, Gurav O, Jadhav R, Shinde T (2023) Crop prediction using machine-learning algorithms. Int J Multidisciplinary Res 5:IJFMR230611095
60. Jurafsky D, Martin JH (2025) *Speech and Language Processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition with Language Models*. 3rd edn. Stanford, CA: Stanford University. Available at: https://web.stanford.edu/~jurafsky/slp3/
61. Kalpana P, Smitha L, Madhavi D, Nabi SA, Kalpana G, Kodati S (2024) 'A smart irrigation system using the IoT and an advanced machine-learning model: A systematic literature review', *International Journal of Computational and Experimental Science and Engineering*, 10, 526. Available at: https://doi.org/10.22399/ijcesen.526

62. Kamilaris A, Prenafeta-Boldú FX (2018) 'Deep learning in agriculture: A survey', *Computers and Electronics in Agriculture*, 147, pp. 70–90. Available at: https://doi.org/10.1016/j.compag.2018.02.016
63. Kari A, Sierla S (2022) 'An overview of machine-learning applications for smart buildings', *Sustainable Cities and Society*, 76, 103445. Available at: https://doi.org/10.1016/j.scs.2021.103445
64. Karim S, Hussain K, Alvi MB, Rahu MA, Kaloi MA, Haleem H (2025) 'Artificial intelligence in sustainable smart agriculture: Concepts, applications, and challenges', *VAWKUM Transactions on Computer Sciences*, 13, pp. 307–342. Available at: https://doi.org/10.21015/vtcs.v13i1.2151
65. Kates RW, Clark WC, Corell RJ, Hall M, Jaeger CC, Lowe I, McCarthy JJ, Schellnhuber HJ, Bolin B, Dickson NM et al (2001) 'Sustainability science', *Science*, 292, pp. 641–642. Available at: https://doi.org/10.1126/science.1059386
66. Katirai A (2024) 'The environmental costs of artificial intelligence for healthcare', *Asian Bioethics Review*, 16, pp. 527–538. Available at: https://doi.org/10.1007/s41649-024-00295-4
67. Kaur A (2025) 'Artificial intelligence in traffic management', *International Journal of Science and Technology*, 16. Available at: https://doi.org/10.71097/IJSAT.v16.i1.2824
68. Khemakhem S, Krichen L (2024) 'A comprehensive survey of an IoT-based smart public street-lighting system application for smart cities', *Franklin Open*, 8, 100142. Available at: https://doi.org/10.1016/j.fraope.2024.100142
69. Kiran SP, Sneha ML, Aiswarya S, Arya BA, Geena P (2023) 'Municipal solid-waste management: A review of machine-learning applications', *E3S Web of Conferences*, 455, 02018. Available at: https://doi.org/10.1051/e3sconf/202345502018
70. Kitsara I (2022) 'Artificial intelligence and the digital divide: From an innovation perspective', in Bounfour, A. (ed.) *Platforms and Artificial Intelligence*. Cham: Springer. Available at: https://doi.org/10.1007/978-3-030-90192-9_12
71. Kriswardhana W, Domokos Esztergár-Kiss D (2023) 'A systematic literature review of Mobility as a Service: Examining the socio-technical factors in MaaS adoption and bundling packages', *Travel Behaviour and Society*, 31, pp. 232–243. Available at: https://doi.org/10.1016/j.tbs.2022.12.007
72. Kumar B, Ghosh O (2025) 'An overview of AI applications in wildlife conservation', in Raghav, Y., Chauhan, A., Pandey, P. and Khan, S. (eds.) *AI and Machine Learning Techniques for Wildlife Conservation*. Hershey, PA: IGI Global, pp. 19–48. Available at: https://doi.org/10.4018/979-8-3693-6935-7.ch002
73. Kuruppu S (2023) 'AI system to protect endangered animal populations and prevent poaching threats using weapon detection', *International Journal of Innovative Science and Research Technology*, 8, pp. 1270–1275. Available at: https://doi.org/10.5281/zenodo.8395158
74. Kwok R, Rothrock DA (2009) 'Decline in Arctic sea-ice thickness from submarine sonars: Data extension and insights from seasonal cycles', *Geophysical Research Letters*, 36. Available at: https://doi.org/10.1029/2009GL039035
75. LeCun Y, Bengio Y, Hinton G (2015) 'Deep learning', *Nature*, 521, pp. 436–444. Available at: https://doi.org/10.1038/nature14539
76. Liakos KG, Busato P, Moshou D, Pearson S, Bochtis D (2018) 'Machine learning in agriculture: A review', *Sensors*, 18, 2674. Available at: https://doi.org/10.3390/s18082674
77. Luccioni AS, Viguier S, Ligozat A-L (2022) 'Estimating the carbon footprint of BLOOM, a 176B parameter language model', *arXiv*, arXiv:2211.02001. Available at: https://doi.org/10.48550/arXiv.2211.02001
78. Mashhood M, Salman H, Amjad R, Nisar H (2023) 'The advantages of using artificial intelligence in urban planning: A review of literature', *Statistics, Computing and Interdisciplinary Research*, 5, pp. 1–12. Available at: https://doi.org/10.52700/scir.v5i2.125
79. Mavani NR, Ali JM, Othman S, Hussain MA, Hashim H, Abd Rahman N (2022) 'Application of artificial intelligence in the food industry: A guideline', *Food Engineering Reviews*, 14, pp. 134–175. Available at: https://doi.org/10.1007/s12393-021-09290-z
80. Meadows DH, Meadows DL, Randers J, Behrens WW III (1972) The Limits to Growth. Universe Books, Los Angeles, CA
81. Mehaffy MW (2023) Notes on an Incomplete Architecture: On the Bewitchment of Intelligence and the Nature of Habitat. Mijnbestseller.nl, Rotterdam
82. Mhlanga D (2023) 'Artificial intelligence and machine learning for energy consumption and production in emerging markets: A review', *Energies*, 16, 745. Available at: https://doi.org/10.3390/en16020745
83. Mishra AK (2023) 'Artificial intelligence in wildlife conservation', *International Journal of Avian & Wildlife Biology*, 7, p. 67. Available at: https://doi.org/10.15406/ijawb.2023.07.00192

84. Monsreal MM, Carmona Benitez RB (2022) 'Impact of IoT on supply-chain performance', *Journal of Applied Research and Technology*, 20, pp. 584–593. Available at: https://doi.org/10.22201/icat.24486736e.2022.20.5.1957
85. Morain A, Nedd R, Poole K, Hawkins L, Jones M, Washington B, Anandhi A (2025) 'Artificial-intelligence application in nonpoint-source pollution management: A status update', *Sustainability*, 17, 5810. Available at: https://doi.org/10.3390/su17135810
86. Mosavi A, Ozturk P, Chau K-W (2018) 'Flood prediction using machine-learning models: Literature review', *Water*, 10, 1536. Available at: https://doi.org/10.3390/w10111536
87. Müller JM, Kiel D, Voigt K-I (2018) 'What drives the implementation of Industry 4.0? The role of opportunities and challenges in the context of sustainability', *Sustainability*, 10, 247. Available at: https://doi.org/10.3390/su10010247
88. National Academies of Sciences, Engineering, and Medicine (2019) *Negative Emissions Technologies and Reliable Sequestration: A Research Agenda*. Washington, DC: National Academies Press. Available at: https://doi.org/10.17226/25259
89. Nazaralizadeh S, Banerjee P, Srivastava AK, Famouri P (2024) 'Battery energy-storage systems: A review of energy-management systems and health metrics', *Energies*, 17, 1250. Available at: https://doi.org/10.3390/en17051250
90. Neema S, Kaushal Gor K (2022) 'Smart waste management using IoT', *International Journal of Scientific Research in Science, Engineering and Technology*, 9, pp. 16–21. Available at: https://doi.org/10.32628/IJSRSET229529
91. Neirotti P, De Marco A, Cagliano AC, Mangano G, Scorrano F (2014) 'Current trends in smart-city initiatives: Some stylised facts', *Cities*, 38, pp. 25–36. Available at: https://doi.org/10.1016/j.cities.2013.12.010
92. Organisation for Economic Co-operation and Development (OECD) (2019) *Recommendation of the Council on Artificial Intelligence*. OECD/LEGAL/0449. Paris: OECD Publishing. Available at: https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449
93. Oguntola O, Boakye K, Simske S (2024) 'Towards leveraging artificial intelligence for sustainable cement manufacturing: A systematic review of AI applications in electrical-energy-consumption optimisation', *Sustainability*, 16, 4798. Available at: https://doi.org/10.3390/su16114798
94. Olola TM, Olatunde TI (2025) 'Artificial intelligence in financial and supply-chain optimisation: Predictive analytics for business growth and market stability in the USA', *International Journal of Applied Science and Research*, 2, 18. Available at: https://doi.org/10.22399/ijasrar.18
95. Panchalingam R, Chan KC (2019) 'A state-of-the-art review of artificial intelligence for smart buildings', *Intelligent Buildings International*, 13, pp. 203–226. Available at: https://doi.org/10.1080/17508975.2019.1613219
96. Pardo Vásquez CY, Gómez Rodríguez G (2025) 'Artificial intelligence and its impact on corporate social responsibility', *Southern Perspective/Perspectiva Austral*, 3, 32. Available at: https://doi.org/10.56294/pa202532
97. Patterson D, Gonzalez J, Le Q, Liang C, Munguia LM, Rothchild D, So D, Texier M, Dean J (2021) 'Carbon emissions and large neural-network training', *arXiv*, arXiv:2104.10350. Available at: https://doi.org/10.48550/arXiv.2104.10350
98. Pérez-Lombard L, Ortiz J, Pout C (2008) 'A review of building energy-consumption information', *Energy and Buildings*, 40, pp. 394–398. Available at: https://doi.org/10.1016/j.enbuild.2007.03.007
99. Plathottam SJ, Rzonca A, Lakhnori R, Iloeje CO (2023) 'A review of artificial-intelligence applications in manufacturing operations', *Journal of Advanced Manufacturing and Processing*, 5, e10159. Available at: https://doi.org/10.1002/amp2.10159
100. Priyanka KD, Memala WA (2024) 'Artificial-intelligence applications in renewable-energy systems', *Journal of Electrical Systems*, 20, pp. 1903–1916. Available at: https://doi.org/10.52783/jes.2983
101. Reichstein M, Camps-Valls G, Stevens B, Jung J, Denzler J, Oh IS (2019) 'Deep learning and process understanding for data-driven Earth-system science', *Nature*, 566, pp. 195–204. Available at: https://doi.org/10.1038/s41586-019-0912-1
102. Rockström J, Steffen W, Noone K, Persson Å, Chapin FS III, Lambin EF, Lenton TM, Scheffer M, Folke C, Schellnhuber HJ et al (2009) 'A safe operating space for humanity', *Nature*, 461, pp. 472–475. Available at: https://doi.org/10.1038/461472a
103. Rolnick D, Donti PL, Kaack LH, Kochanski K, Lacoste A, Sankaran K, Ross AS, Milojevic-Dupont N, Jaques N, Waldman-Brown A et al (2022) 'Tackling climate change with machine learning', *ACM Computing Surveys*, 55, 42. Available at: https://doi.org/10.1145/3485128
104. Rouet-Leduc B, Hulbert C, Carpenter B, Lechmann A, Bolton D, Guyer RA (2017) 'Machine learning predicts laboratory earthquakes', *Geophysical Research Letters*, 44, pp. 9276–9282. Available at: https://doi.org/10.1002/2017GL074677
105. Russell SJ, Norvig P (2021) Artificial Intelligence: A Modern Approach, 4th edn. Pearson, London

106. Sachs JD (2015) The Age of Sustainable Development. Columbia University, New York
107. Secretariat of the Convention on Biological Diversity (SCBD) (2020) Global Biodiversity Outlook 5. SCBD, Jakarta
108. Schwartz R, Dodge J, Smith NA, Etzioni O (2020) 'Green AI', *Communications of the ACM*, 63, pp. 54–63. Available at: https://doi.org/10.1145/3381831
109. Siciliano B, Khatib O (eds) (2016) *Springer Handbook of Robotics*. Berlin and Heidelberg: Springer. Available at: https://doi.org/10.1007/978-3-319-32552-1
110. Siqueira MB, Santos VM, dos Diniz EH, Cruz APA (2024) 'Artificial intelligence for sustainability: A systematic literature review in information systems', *Revista de Gestão Social e Ambiental*, 18, e07885. Available at: https://doi.org/10.24857/rgsa.v18n3-178
111. Sohaib M, Mushtaq S, Uddin J (2021) 'Deep learning for data-driven predictive maintenance', in Ahad, M.A.R. and Inoue, A. (eds.) *Vision, Sensing and Analytics: Integrative Approaches*. Cham: Springer. Available at: https://doi.org/10.1007/978-3-030-75490-7_3
112. Stock T, Seliger G (2016) 'Opportunities for sustainable manufacturing in Industry 4.0', *Procedia CIRP*, 40, pp. 536–541. Available at: https://doi.org/10.1016/j.procir.2016.01.129
113. Strubell E, Ganesh A, McCallum A (2019) 'Energy and policy considerations for deep learning in NLP', *arXiv*, arXiv:1906.02243. Available at: https://doi.org/10.48550/arXiv.1906.02243
114. Syed TA, Khan MY, Jan S, Albouq S, Alqahtany SS, Naqash MT (2024) 'Integrating digital twins and artificial-intelligence multimodal transformers into water-resource management: Overview and advanced predictive framework', *AI*, 5, pp. 1977–2017. Available at: https://doi.org/10.3390/ai5040098
115. Szeliski R (2022) *Computer Vision: Algorithms and Applications*. 2nd edn. Berlin and Heidelberg: Springer Nature. Available at: https://doi.org/10.1007/978-3-030-34372-9
116. Talaviya T, Shah D, Patel N, Yagnik H, Shah M (2020) 'Implementation of artificial intelligence in agriculture for the optimisation of irrigation and the application of pesticides and herbicides', *Artificial Intelligence in Agriculture*, 4, pp. 58–73. Available at: https://doi.org/10.1016/j.aiia.2020.04.002
117. Tejaswini TN, Pooja VR, Shruti HH, Nalina V (2020) Energy efficiency in green data centres: A review. J Netw Commun Emerg Technol 10:1–7
118. Ukoba K, Onisuru OR, Jen TC (2024) 'Harnessing machine learning for sustainable futures: Advancements in renewable energy and climate-change mitigation', *Bulletin of the National Research Centre*, 48, 99. Available at: https://doi.org/10.1186/s42269-024-01254-7
119. United Nations (2015) *Transforming Our World: The 2030 Agenda for Sustainable Development*. New York: United Nations. Available at: https://sdgs.un.org/2030agenda
120. United Nations Environment Programme (UNEP) (2018) The Weight of Cities: Resource Requirements of Future Urbanization. UNESCO, Paris
121. United Nations Environment Programme (UNEP) (2021) Artificial Intelligence End-to-End: The Environmental Impact of the Full AI Lifecycle Needs to Be Comprehensively Assessed. UNEP, Nairobi
122. United Nations Educational, Scientific and Cultural Organization (UNESCO) (2019) Artificial Intelligence in Education: Compendium of Promising Initiatives—Mobile Learning Week 2019. UNESCO, Paris
123. United Nations Educational, Scientific and Cultural Organization (UNESCO) (2021) *Recommendation on the Ethics of Artificial Intelligence*. Paris: UNESCO. Available at: https://unesdoc.unesco.org/ark:/48223/pf0000381137
124. United Nations Framework Convention on Climate Change (UNFCCC) (2015) *The Paris Agreement*. Bonn: UNFCCC. Available at: https://unfccc.int/process-and-meetings/the-paris-agreement (Accessed: 11 May 2025)
125. UN-Habitat (2025) (n.d.) 'Combating the growth of sprawl and the decline of healthy public-space systems'. Available at: https://unhabitat.org/combating-the-growth-of-sprawl-and-the-decline-of-healthy-public-space-systems (Accessed: 12 August
126. Upadhyay A, Chandel NS, Singh KP, Subeesh A, Chakraborty SK, Nandede BM, Kumar M, Upendar K, Salem A, Elbeltagi A (2025) 'Deep learning and computer vision in plant-disease detection: A comprehensive review of techniques, models, and trends in precision agriculture', *Artificial Intelligence Review*, 58, 92. Available at: https://doi.org/10.1007/s10462-024-11100-x
127. van Klompenburg T, Kassahun A, Catal C (2020) 'Crop-yield prediction using machine learning: A systematic literature review', *Computers and Electronics in Agriculture*, 177, 105709. Available at: https://doi.org/10.1016/j.compag.2020.105709

128. Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gomez AN, Polosukhin I (2017) 'Attention is all you need', in *Proceedings of the 31st International Conference on Neural Information Processing Systems*, Long Beach, CA, 4–9 December, pp. 5998–6008
129. Vinuesa R, Azizpour H, Leite I, Balaam M, Dignum V, Domisch S, Fennell P, Georgieff R, Jacobsson A, Jernberg J et al (2020) 'The role of artificial intelligence in achieving the Sustainable Development Goals', *Nature Communications*, 11, 233. Available at: https://doi.org/10.1038/s41467-019-14108-y
130. Wang J, Ma Y, Zhang L, Gao RX, Wu D (2017) 'Deep learning for smart manufacturing: A review', *Journal of Manufacturing Systems*, 48, pp. 114–121. Available at: https://doi.org/10.1016/j.jmsy.2018.01.003
131. Wibowo A, Amri I, Surahmat A, Rusdah R (2025) 'Leveraging artificial intelligence in disaster management: A comprehensive bibliometric review', *Jàmbá: Journal of Disaster Risk Studies*, 17, 1776. Available at: https://doi.org/10.4102/jamba.v17i1.1776
132. Wooldridge M (2009) An Introduction to MultiAgent Systems, 2nd edn. Wiley, Hoboken, NJ
133. World Economic Forum (2023) *Mission Possible Partnership Reports and Initiatives*. Cologny: World Economic Forum. Available at: https://www.missionpossiblepartnership.org/
134. Wuest T, Weimer D, Irgens C, Thoben KD (2016) 'Machine learning in manufacturing: Advantages, challenges, and applications', *Production & Manufacturing Research*, 4, pp. 23–41. Available at: https://doi.org/10.1080/21693277.2016.1192517
135. Ying C, Wang W, Yu J, Li Q, Yu D, Liu J (2023) 'Deep learning for renewable-energy forecasting: A taxonomy and systematic literature review', *Journal of Cleaner Production*, 384, 135414. Available at: https://doi.org/10.1016/j.jclepro.2022.135414
136. Zeng X (2024) 'A review of the design of sustainable advanced materials using artificial intelligence', *Advanced Materials in Sustainable Manufacturing*, 1, 10006. Available at: https://doi.org/10.35534/amsm.2024.10006
137. Zhou SL, Shah AA, Leung PK, Zhu X, Liao Q (2023) 'A comprehensive review of the applications of machine learning for HVAC', *DeCarbon*, 2, 100023. Available at: https://doi.org/10.1016/j.decarb.2023.100023
138. Zhu M, Wang J, Yang X, Zhang Y, Zhang L, Ren H, Wu B, Ye L (2022) 'A review of the application of machine learning in water-quality evaluation', *Eco-Environment & Health*, 1, pp. 107–116. Available at: https://doi.org/10.1016/j.eehl.2022.06.001

Figures

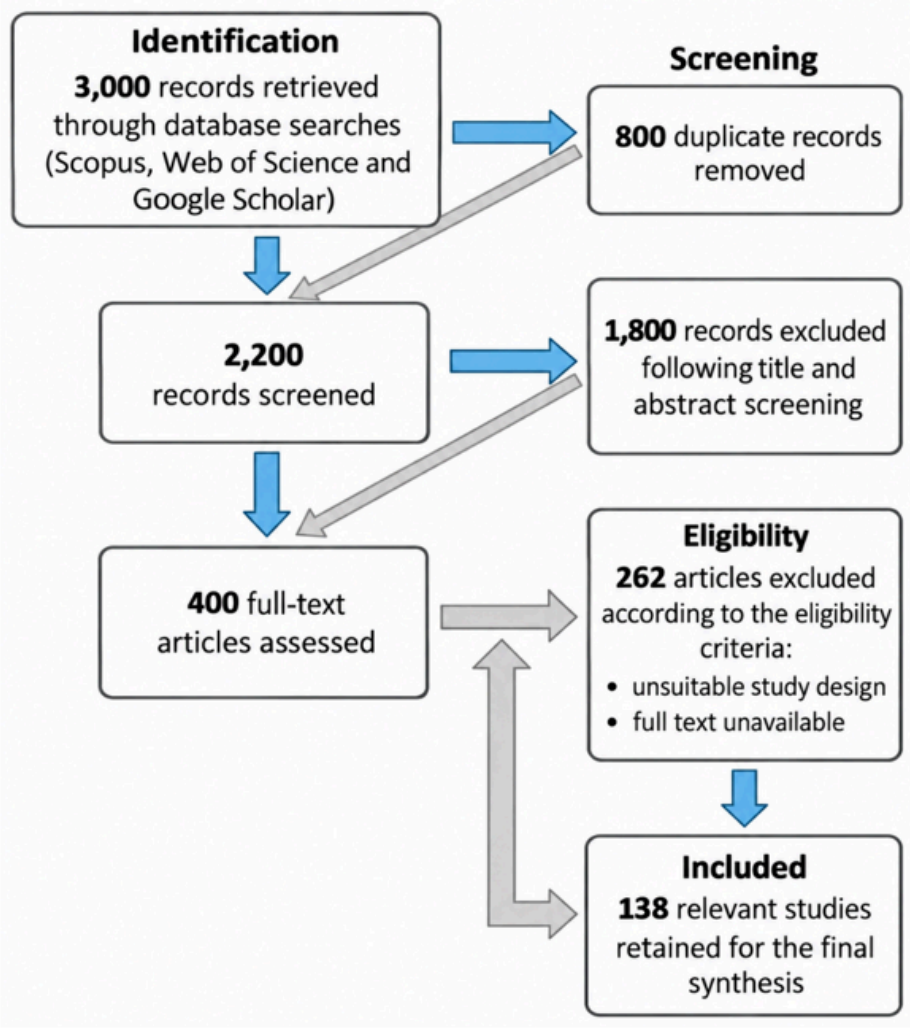


Figure 1

PRISMA flowchart illustrating the study-selection process.

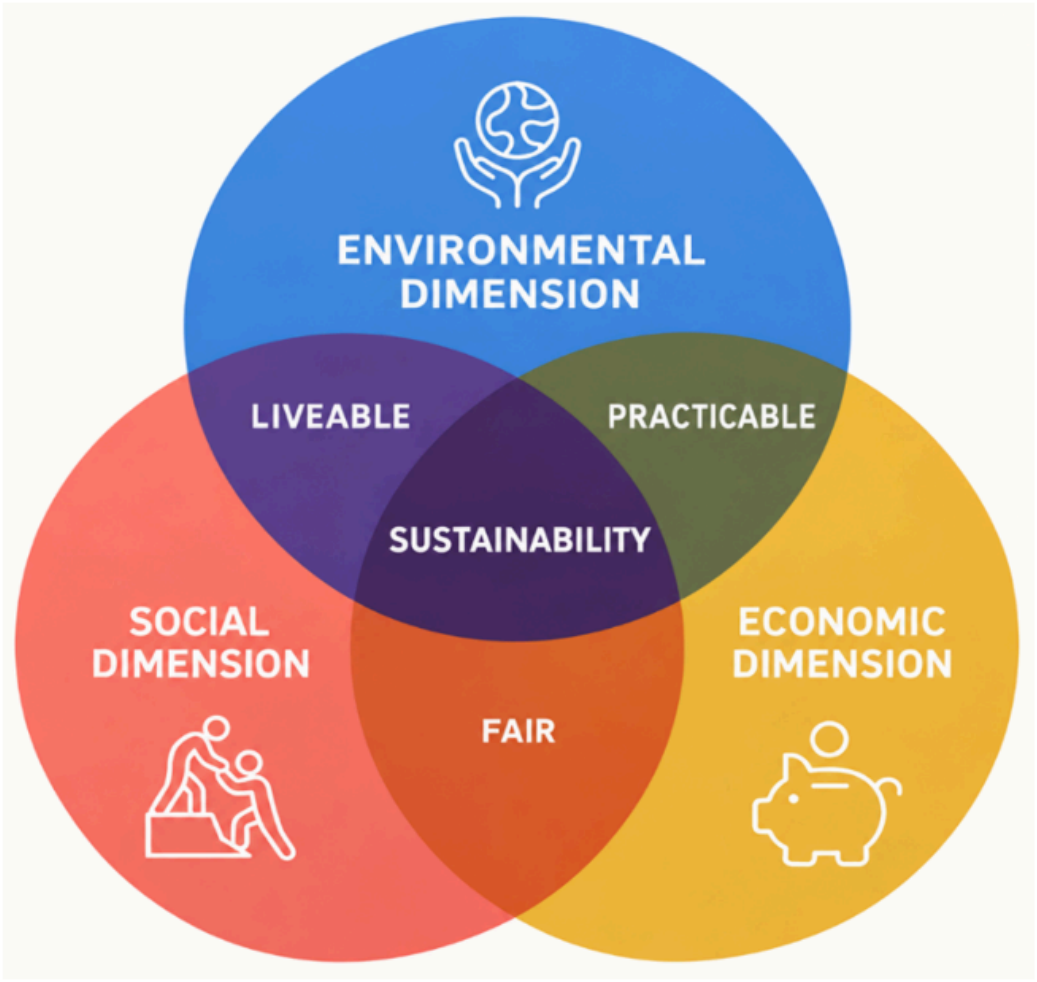


Figure 2

The three interconnected dimensions of sustainability: environmental, social and economic.

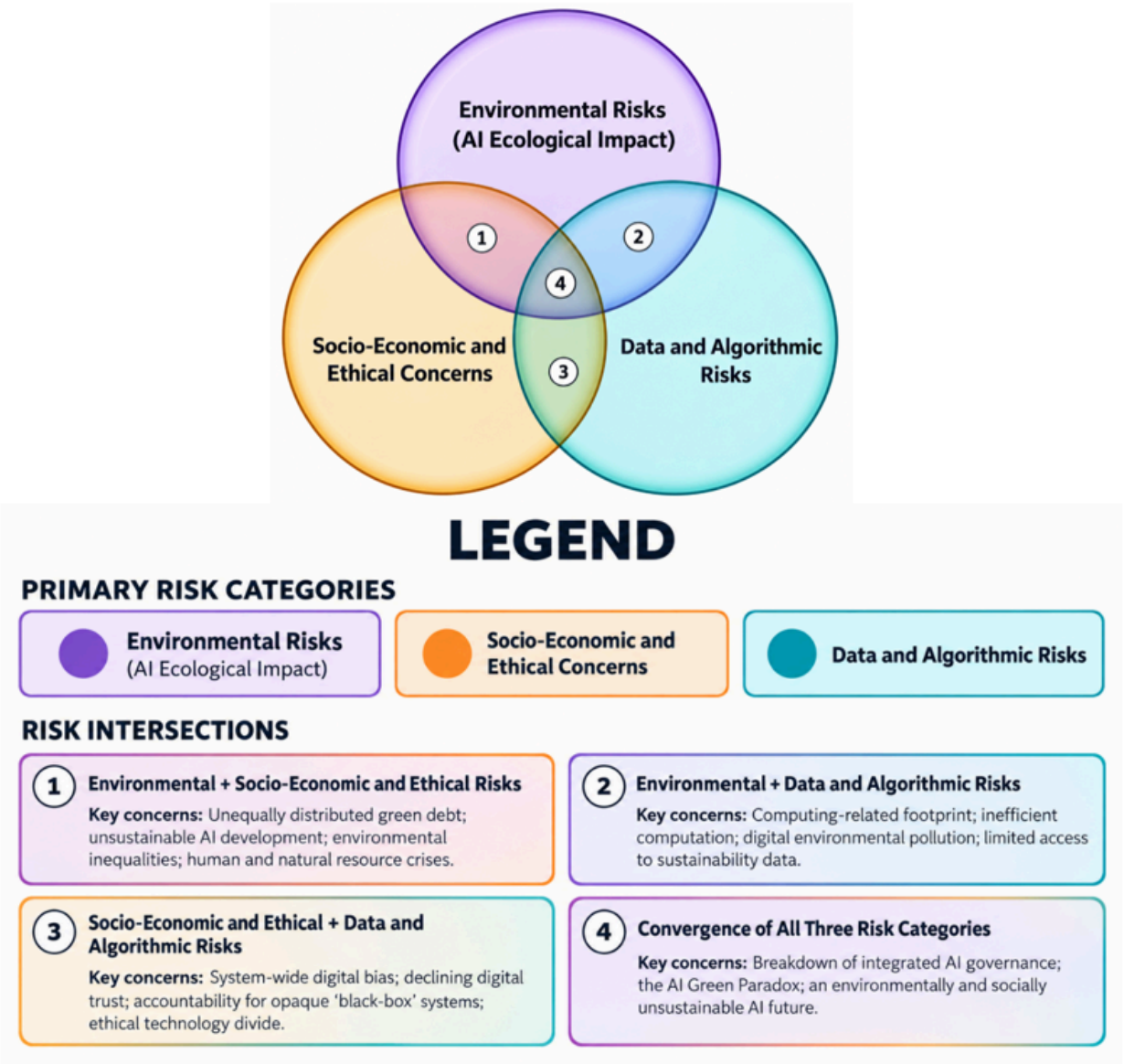


Figure 3

Intersection of artificial intelligence risk categories within the context of sustainability.

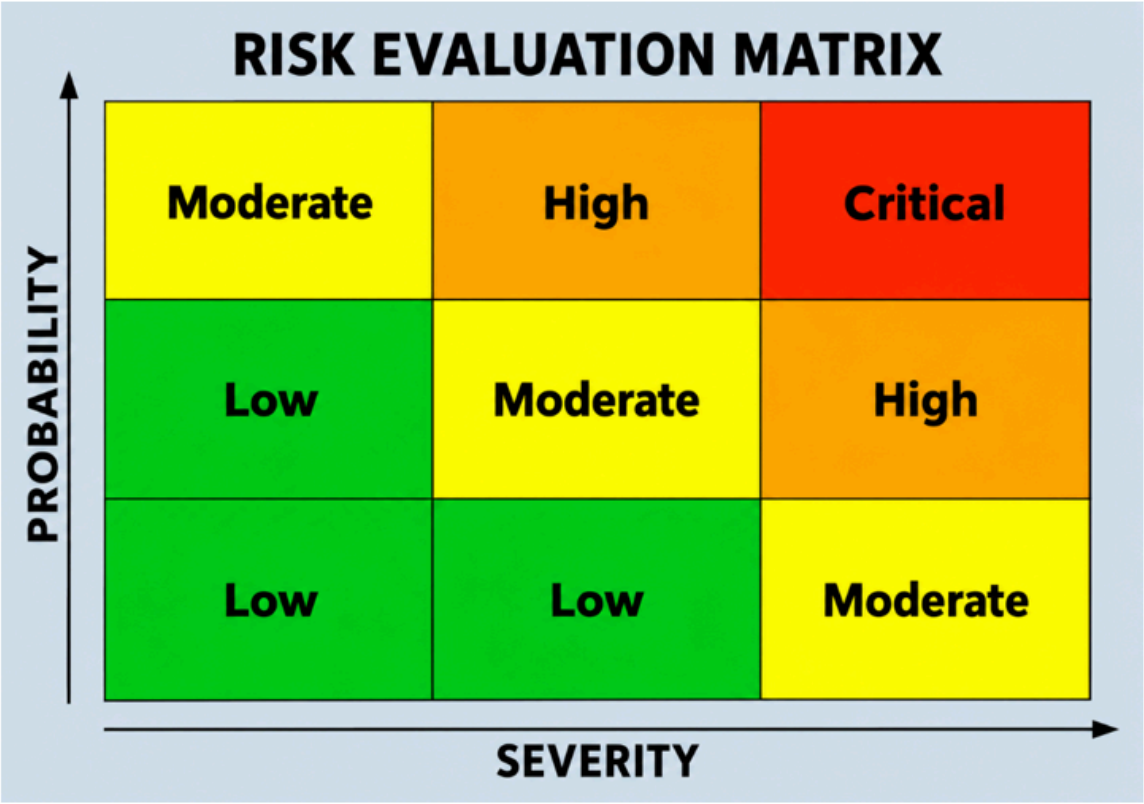


Figure 4

Comprehensive risk matrix for evaluating sustainability-related AI risks and their corresponding mitigation measures.

Supplementary Files

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- AppendiceAReferenceList.xlsx
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