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Artificial Intelligence for Sustainable Development: A Multidisciplinary Review of Applications, Challenges, and Future Research Directions

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Abstract

Artificial intelligence is increasingly shaping sustainable development by improving prediction, optimisation, monitoring, and decision-making across environmental, social, agricultural, industrial, and economic systems. This review examines the multidisciplinary applications of AI in climate prediction, renewable-energy management, biodiversity conservation, precision agriculture, food systems, water-resource management, healthcare, education, smart cities, green manufacturing, and supply-chain resilience. It also evaluates the technical, ethical, social, environmental, and regulatory challenges that influence the responsible use of AI. The reviewed evidence shows that AI can strengthen resource efficiency, enhance service delivery, support risk assessment, and improve institutional responses to complex sustainability problems. At the same time, its benefits are constrained by poor data quality, limited infrastructure, algorithmic bias, privacy concerns, unequal access, weak governance, and the growing energy and carbon costs of large-scale computing. The review highlights the need to distinguish between using AI for sustainability and ensuring the sustainability of AI itself. Responsible governance, transparent models, human oversight, inclusive datasets, impact assessment, and cross-sector collaboration are essential for aligning AI with the Sustainable Development Goals. Future research should prioritise low-energy systems, explainable models, locally relevant data, and evidence from low- and middle-income regions. A multidisciplinary approach can help ensure that AI contributes to resilient, equitable, and environmentally responsible development.

Keywords: Artificial intelligence, sustainable development, Sustainable Development Goals, responsible AI, environmental sustainability, multidisciplinary research

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1. Introduction

In recent years, artificial intelligence has proved to be an important enabler to solve complex environmental, social and economic issues related with sustainable development. It has found applications that go well beyond computer science, thanks to its ability to analyze vast amounts of data, uncover hidden patterns, automate decision making, predict future possibilities, and guide adaptive planning. AI has been deployed in climate modelling, managing renewable energy resources, precision agriculture, healthcare, education, industrial production, urban planning, financial systems, biodiversity conservation, and public administration. AI tools can be used to enhance resource efficiency, aid decision-making within institutions, and build more flexible systems for addressing complex, global challenges, as shown in these applications. Concurrently, its contribution is shaped by whether or not technological innovation is driven by an environmental focus, a social focus, an ethical governance, or a commitment to long-term public value, as well as by the drive for economic efficiency (Goralski & Tan, 2020).

This relationship is being accelerated by the growing pressures all around the world, such as climate change, biodiversity loss, food and water insecurity, unequal access to health care and education, rapid urbanisation, the increasing demand for energy and the socio-economic gap. These issues are addressed through integrated action across 17 goals in the United Nations Sustainable Development Goals. AI can help with many of these objectives, such as prediction, monitoring, optimisation, and service delivery. AI has been found to have the potential to contribute to a significant number of SDG targets, especially in the areas of health, education, clean energy, sustainable cities, climate action, and environmental protection. However, it can hinder progress in terms of energy usage, perpetuation of social bias, technological centralisation and digital inequalities (Vinuesa et al., 2020).

The concept of AI for social good also underscores the importance of channeled computational power to tangible and measurable human and social good. Interventions need to go beyond accurate models; they need to involve problem definition, stakeholder involvement, institutional capacity, local knowledge, good quality data, and processes to assess impact in the real world. Without these considerations, AI systems can come up with solutions that are difficult to implement, socially inappropriate or harmful to already disadvantaged communities (Tomašev et al., 2020). Regulatory oversight is thus a key element to safeguarding the coherence of AI applications with sustainable development objectives, fundamental rights, transparency and accountability, and environmental boundaries (Goh & Vinuesa, 2021).

Business and industrial organisations also play an important role in this transition. AI-powered business models can enhance production efficiency, supply-chain transparency, waste minimization, resource optimization, and sustainability reporting. Their broader impact, however, hinges on if firms incorporate the SDGs into their strategic planning rather than as a sideline technological by-product (Di Vaio et al. 2020). Recent scholarship reveals that research on AI and sustainable development has accelerated at a rapid pace, though it has not yet been evenly distributed across themes and geographical areas, and there are still challenges to integrate AI across disciplines and utilize evidence from developing regions (Gohr et al., 2025). The same reviews highlight the importance of guaranteeing a combination of sustainable applications powered by AI and carbon emissions concerns, data governance, algorithmic discriminatory effects, access and institutional readiness (Toderas, 2025).

In this context, this multi-disciplinary review explores the role of AI in sustainable development in environmental systems, agriculture, food and water management, health, education, social services, cities, industry, business and governance. It further links the applications of specific sectors and common technical, ethical, regulatory, and ecological issues. The review plays its role by providing a common analytical framework to the disparate evidence and in highlighting the need for responsible AI design, policy coordination, as well as multi-disciplinary research.

Objectives

1.To examine major artificial intelligence applications across the environmental, social, agricultural, industrial, and economic dimensions of sustainable development.

2.To evaluate the technical, ethical, social, environmental, and governance challenges that may limit the sustainable and responsible use of artificial intelligence.

3.To identify future research priorities and policy directions for developing inclusive, accountable, energy-efficient, and context-sensitive artificial intelligence systems.

2. Review Methodology

A structured literature review approach was used to examine the contribution of artificial intelligence to sustainable development across multiple disciplinary fields. Relevant studies published between 2016 and 2025 were identified through searches of Scopus, Web of Science, Google Scholar, ScienceDirect, SpringerLink, IEEE Xplore, PubMed, and multidisciplinary journal databases. The search strategy combined terms such as “artificial intelligence,” “machine learning,” “deep learning,” “sustainable development,” “Sustainable Development Goals,” “climate action,” “renewable energy,” “precision agriculture,” “healthcare,” “education,” “smart cities,” “circular economy,” “supply chain,” “AI ethics,” and “responsible AI.” Boolean operators were used to connect technological terms with sector-specific sustainability themes.

Studies were included when they directly examined AI applications, impacts, limitations, governance issues, or future directions related to environmental, social, or economic sustainability. Publications that discussed digital technologies without a clear AI component, lacked direct relevance to sustainable development, or provided insufficient information for thematic interpretation were excluded. Titles and abstracts were initially screened to assess relevance, followed by full-text examination of studies that met the review criteria. Duplicate records and sources with overlapping evidence were removed.

The selected literature was organised into thematic categories covering conceptual foundations, environmental sustainability, agriculture and water systems, human and social development, sustainable industry and cities, and governance challenges. Evidence was synthesised narratively to compare major applications, reported benefits, implementation barriers, ethical concerns, and research gaps across disciplines. Particular attention was given to cross-sector patterns, regional differences, environmental costs, social inclusion, data limitations, and policy requirements. The final synthesis was used to develop an integrated account of how AI can support sustainable development while identifying the conditions required for its responsible and equitable use.

3. Conceptual Foundations of AI and Sustainable Development

3.1 Artificial Intelligence Technologies and Capabilities

Artificial intelligence is the term used for a computer-based system that can carry out tasks normally performed by humans that involve learning, predicting, recognizing patterns, understanding language, interpreting visual information and making decisions. It has key sub-areas such as machine learning, deep learning, natural language processing, computer vision, robotics, and intelligent optimisation. These technologies can interpret enormous and complex data sets, find connections that traditional approaches might miss and make timely suggestions to institutions, businesses, and public agencies to help them make informed decisions. Transparency, accountability, equity, human control and respect for fundamental rights are the social values they require. How to embed ethical principles into the design and use of AI, instead of applying them as an afterthought to a deployed system, is therefore a crucial challenge (Floridi et al., 2018). As computational requirements intensify for cutting-edge models, there has also been an increasing focus on Green AI – a model that aims to optimize the use of resources, improve data reproducibility, and reduce resource usage while maintaining computational efficiency, alongside predictive performance (Schwartz et al., 2020).

3.2 Dimensions and Principles of Sustainable Development

Sustainable development is a development that takes into account the environmental, social and economic aspects and maintains the opportunity and available resources for future generations. It's core tenets are equitable, inclusive, resilient, resourceful, intergenerational and accountable to institutions. AI can help with these principles by improved planning and resource allocation, but the sustainability of the AI systems also needs to be considered. Reporting energy consumption and carbon emissions is required because the costs of the environment of developing and implementing models can be significant and may not be reported in standard performance evaluations (Henderson et al., 2020). This concern is highlighted by the power, monetary, and special hardware requirements that can arise during training processes for large-scale language models (Strubell et al., 2019). The use of AI to solve sustainability challenges, and the mitigation of the negative environmental and social impact of AI use, are therefore included in the concept of sustainable AI (van Wynsberghe, 2021).

3.3 Alignment of AI Applications with the Sustainable Development Goals

Climate modelling, clean-energy management, sustainable production, public health, education, resilient infrastructure, and environmental monitoring are just some of the ways AI contributes to reaching the SDGs. Machine learning can be used for better emissions estimation, optimisation of energy systems, transport planning, and technological innovation in climate mitigation, but its usefulness in this context would depend on the alignment to policy priorities and measurable mitigation outcomes (Kaack et al., 2022). AI can also contribute to the fight against global change by better forecasting and decision-making, but if regulation is weak and there is unequal access to the technology, and over-optimistic expectations, then this contribution may be constrained (Cowls et al., 2023). Considering the scientific, policy, community and technologists' viewpoints, successful alignment will be achieved only when human

judgment and machine intelligence are working synergistically to address planetary challenges (Debnath et al., 2023).
The major applications of artificial intelligence across sustainability domains, together with their expected contributions and relevant Sustainable Development Goals, are summarised in Table 1.

Table 1. Major AI Applications and Contributions to Sustainable Development

Sustainability domain	Major AI applications	Main sustainability contribution	Related SDGs	References
Climate and environment	Climate forecasting, emissions estimation, environmental monitoring, hazard prediction	Strengthens mitigation, adaptation, early warning, and evidence-based environmental planning	SDGs 6, 7, 11, 13, 15	Hino et al. (2018); Rolnick et al. (2022)
Renewable energy	Solar-output forecasting, fault detection, smart-grid control, predictive maintenance	Improves renewable-energy reliability, efficiency, and grid integration	SDGs 7, 9, 13	Kurukuru et al. (2021)
Biodiversity and ecosystems	Species identification, acoustic monitoring, habitat mapping, wildlife surveillance	Supports ecosystem assessment, conservation prioritisation, and biodiversity recovery monitoring	SDGs 13, 14, 15	Tuia et al. (2022); Müller et al. (2023)
Agriculture and food	Crop-disease detection, yield prediction, precision irrigation, food-quality monitoring	Reduces resource waste, improves productivity, and supports food security	SDGs 2, 6, 12, 13	Liakos et al. (2018); Misra et al. (2022)
Healthcare and education	Diagnostic support, disease surveillance, adaptive learning, student-risk prediction	Expands access to essential services and supports more personalised interventions	SDGs 3, 4, 10	Wahl et al. (2018); Ouyang et al. (2022)
Cities and industry	Traffic optimisation, digital twins, predictive maintenance,	Improves urban services, infrastructure resilience, and industrial resource	SDGs 9, 11, 12	Yigitcanlar et al. (2020); Bibri et al. (2024)

	cleaner production	efficiency		
Business and supply chains	Demand forecasting, supplier evaluation, disruption prediction, reverse logistics	Strengthens resilience, circularity, transparency, and sustainable production	SDGs 8, 9, 12	Toorajipour et al. (2021); Farshadfar et al. (2024)

The relationship between major AI application areas, core computational capabilities, responsible implementation conditions, and sustainable development outcomes is presented in Figure 1.

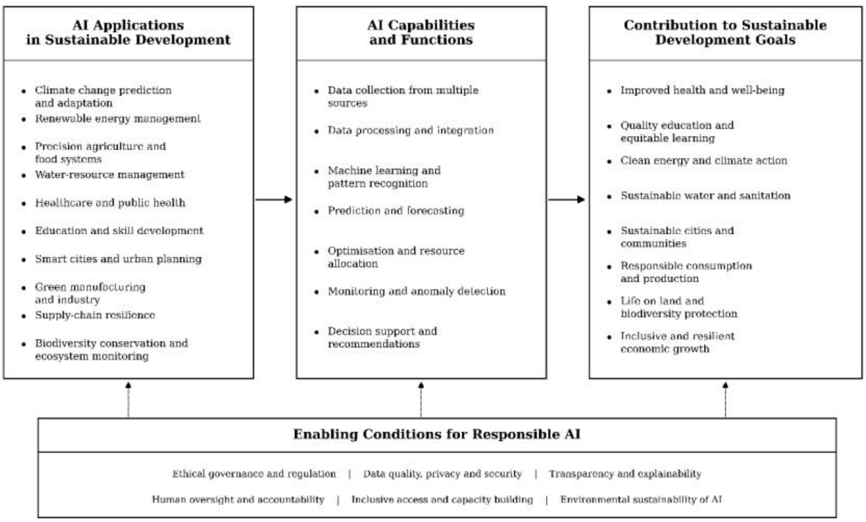

Figure 1. Conceptual Framework Linking AI Applications, Capabilities, and Sustainable Development Outcomes

4. AI Applications in Environmental and Ecological Sustainability

4.1 Climate Prediction, Adaptation, and Mitigation

The power of big data is being tapped by AI to enhance climate forecasting, adaptation, and mitigation efforts. Machine-learning models can detect intricate connections between temperature, rainfall, weather and human activities, and thus, more accurate predictions of droughts, floods, heatwaves and other climate hazards. They also can be used for environmental monitoring applications, to identify spatial and temporal changes that can be hard to spot using traditional observation methods. The usefulness of their application relies on reliable database availability, model design, and the use and interpretation of predictions with uncertainty (Hino et al., 2018). AI can also help with mitigation in the areas of energy demand forecasting, emissions monitoring, transport optimisation, carbon accounting, and better climate-policy modelling. It is useful complements scientific knowledge and public decision making, particularly when considering social, political and economic trade-offs in the context of climate responses (Rolnick et al., 2022).

4.2 Renewable Energy and Natural-Resource Management

AI plays a role in renewable energy systems, aiding in renewable energy forecasting, grid stability, equipment monitoring, and improving overall operational efficiency. In addition, solar and wind power are subject to weather influences, which generate uncertainty in electricity supply. The predictive models can forecast future production, anticipate fluctuations in grid activities, and detect problems before they cause serious losses. AI has been extended to grid-connected PV applications such as maximum power point tracking, fault detection and diagnosis, forecasting, inverter control, and maintenance planning. These functions can minimize energy losses and increase the reliability of integration of renewable energy (Kurukuru et al., 2021). AI can also contribute to more general natural resource management, by analysing the trend of forests, water bodies, soils and mineral use. Resource allocation, sensing, and predictive analytics can be used to inform resource allocation, detect degradation, and inform conservation planning. These systems need to be tailored to local ecological circumstances, and to not only consider efficiency as a metric of sustainable resource use.

4.3 Biodiversity Conservation and Ecosystem Monitoring

The conservation of biodiversity is one of the most promising fields for ecological AI. In the past, researchers have had to travel across vast and hard-to-reach terrain to track wildlife, but with the help of computer vision, acoustic recognition, drones, camera traps and automated species-identification systems, they can do so now. Machine learning can be used to classify species, estimate populations, to detect behavioural changes, and to detect threats like poaching or habitat disturbance. The tools can increase conservation capacity, but may lessen effectiveness if data are geographically restricted or include only well-studied species (Tuia et al., 2022). AI can also be used to prioritise protected areas using data on species distribution, extinction risk, land use, and conservation costs for more targeted and evidence-based biodiversity planning (Silvestro et al., 2022).

Analysis of ecological images, sounds and environmental signals has become a common field of application for deep-learning methods. They can be used to classify habitats, detect animals, assess vegetation and analyse changes in ecosystems, though they must be carefully validated as ecological data are often incomplete or unevenly distributed (Christin et al., 2019). Acoustic monitoring is of value, especially in forest restoration. Changes in bird, insect and other animal communities can be quantified by automated analysis of soundscapes, which can be used to monitor biodiversity recovery over time, without constant field work (Müller et al., 2023). AI and machine learning also have potential applications in forest-fire detection, habitat mapping, predicting wildlife conflicts, and evaluating the services provided to humans, but limited infrastructure and technical capacity could limit their application in countries like India (Shivaprakash et al., 2022).

4.4 Pollution Control and Disaster-Risk Management

AI supports pollution control by predicting air-quality changes, locating contamination sources, classifying waste, and identifying abnormal conditions in water and soil systems.

Sensor data combined with machine learning can provide early warnings and help authorities target inspections or interventions. In disaster-risk management, AI can analyse weather, terrain, satellite imagery, and historical records to estimate the likelihood and potential impact of floods, landslides, droughts, wildfires, and storms. Rapid image analysis can also assist post-disaster damage assessment and emergency-resource allocation. These applications can strengthen preparedness and response, but poor data quality, limited local representation, and weak institutional coordination may produce misleading results. Human oversight, transparent models, and community-based knowledge remain necessary to ensure that AI-supported environmental decisions are accurate, fair, and responsive to local needs.

5. AI Applications in Sustainable Agriculture, Food, and Water Systems

5.1 Precision Agriculture and Crop Management

AI is revolutionizing agriculture by providing farmers with more accurate, timely, and data-driven crop, soil, input and farm management. Satellite, drone, field sensor, weather station and farm data can be fed into machine-learning models to forecast crop yields, disease outbreaks, soil conditions and determine when to plant or harvest. These applications enable farmers to treat the variability of their fields instead of treating the whole farm which could lead to lower input waste and higher productivity (Liakos et al., 2018). AI can also help reduce the use of irrigation, pesticides and herbicides by determining when and where to intervene. This accuracy can help minimize production costs and eliminate overspending on chemicals and water consumption (Talaviya et al., 2020).

Advances in agricultural AI have evolved from predictive analytics to systems that can make integrated decisions. Weed identification, fruit counting, livestock monitoring, disease classification and autonomous machinery are all areas now covered by deep learning, computer vision, robotics and sensor-based analytics. However, their performance relies on the quality of the training data, local calibration, and digital infrastructure, and technical support for farmers (Benos et al., 2021). Big-data platforms also support precision agriculture by integrating climatic, biological, economic and operational data; however, related issues such as data ownership, interoperability, cyber-security and access to data are significant concerns (Bhat & Huang, 2021).

5.2 Sustainable Food Production and Supply Chains

AI can enhance sustainability in the food production, processing, storage, distribution, and retail. The forecasting systems are used to estimate requirement, inventory planning, quality monitoring and to minimize post-harvest losses. Computer vision can identify defects and contamination and automated systems can also assist with sorting, grading, packaging and traceability. These applications can enhance the food safety and minimize waste, and help production systems to adapt to market and environmental changes (Javaid et al., 2023). AI can also be used to continuously monitor temperature, humidity, transport conditions and storage facilities, thanks to the combination of the Internet of Things and big data analysis. This helps to have greater visibility of the supply chain and helps take timely action in case the quality of food or its safety is compromised (Misra et al., 2022). AI-powered supply chains can also leverage to better match supply and demand, optimize shipping routes, and pinpoint inefficiencies that lead to higher emissions or waste. However, there is a risk that these systems will not be taken up by small farmers and enterprises as a result of their cost, limited connectivity, lack of technical skills, and reliance on private technology providers. It is necessary to have affordable tools, shared data, and sustainable implementation; in terms of standards, and support for users in low resource areas.

5.3 Water-Resource Monitoring and Management

In agricultural and urban water management, increasing use of AI and connected sensing technologies is aiding in management. Smart water systems can monitor water usage, identify leaks and predict usage, inspect water quality, and improve the water system. These functions are particularly relevant in areas with water stress, population growth, and water scarcity (Singh & Ahmed, 2021). Within the agricultural context, machine learning models can be used in irrigation systems, merging soil moisture readings, weather forecasts, crop needs, and field conditions to enable an automated system. Water is then provided as and when required, which helps curb the waste of water and minimises the impact of over-irrigation and degradation of soil (Vij et al., 2020). The greater adoption of such systems has the potential to enhance water security, but it requires dependable sensors, local maintenance, accurate data, and engagement of farmers and communities in decision making.

6. AI Applications in Human and Social Development

6.1 Healthcare and Public-Health Systems

AI is emerging as a powerful tool to enhance healthcare provision, epidemiological surveillance, diagnostics and treatment planning. Machine-learning systems can review medical images, lab data, patient records and epidemiological information to determine risk factors and guide clinical care. AI can be used in resource-limited areas to manage shortages of specialists, including screening, triage, tele-consultation and early detection of disease. Its value is particularly high in scenarios where access to health services is unequal, there are large populations and limited health infrastructure (Wahl et al., 2018). AI also plays a role in global health by helping to forecast outbreaks, discover drugs, allocate resources, or monitor population levels. The benefits, however, rely on the availability of reliable data, appropriate regulation, and safeguarding against bias or exclusion (Schwalbe & Wahl, 2020).

While AI can enhance the efficiency of health systems in low- and middle-income countries, its implementation is context-dependent, given the capacity of the health system, digital infrastructure, workforce readiness, and availability of health data in the country. A high-resources developed system might not be readily transferable to others or to other clinical settings without adaptation (Ciecierski-Holmes et al., 2022). In the healthcare industry as a whole, AI is best suited to augment, rather than substitute for, human clinical practice, process efficiency, and decision-making within an evidence-based framework (Secinaro et al., 2021).

6.2 Education, Skills Development, and Digital Inclusion

Some educational applications of AI are intelligent tutors, automated assessment, learning analytics, adaptive content, student-risk prediction, and administrative support. These tools can create personalised learning pathways, be able to identify students who need extra support and offer timely feedback. In higher education, research has accelerated in recent years, but has been mostly technology-focused and failed to sufficiently consider the role of teachers, pedagogy and institutional practice (Zawacki-Richter et al., 2019). AI also helps with analyzing participation, suggesting resources, and aiding in engagement on online learning platforms. They rely on good instructional design, teacher participation and clear utilization of student data (Ouyang et al., 2022).

AI could also play a role in digital inclusion for translating texts, speech recognition, accessibility features, and adaptive learning for remote and underserved populations. However, inequalities in device access, internet connectivity, technical skills and access to good quality digital content can exacerbate existing educational inequalities. Educational infrastructure, teacher training and affordability and inclusive system design are therefore necessary for sustainable use.

6.3 Poverty Reduction, Social Welfare, and Humanitarian Support

AI can help in poverty reduction by processing data from household surveys, satellite imagery, mobile telephony and economic indicators to pinpoint vulnerable groups and measure deprivation. These models could enhance targeting of social protection and development interventions and emergency services where standard data collection is slow or expensive (Usmanova et al., 2022). AI can help in crisis mapping, disaster response, food distribution, migration analysis, and resource prioritisation in social welfare and humanitarian settings. It can also support public agencies in identifying service gaps and be able to respond faster to the evolving needs.

The concept of AI for social good emphasizes that while technology is a key driver, it is not enough to ensure positive outcomes. Effective systems should be designed to meet the needs of communities affected and incorporate protections from discrimination and accountability to public institutions. Models may be poorly designed, leading to misidentification of vulnerable individuals, exclusion of individuals with less digital documentation, or more surveillance. Therefore, when utilizing AI for social and humanitarian decision-making, human oversight, participatory design, and careful impact evaluation are needed (Shi et al., 2020).

7. AI Applications in Sustainable Industry, Cities, and Economic Systems

7.1 Smart Cities and Sustainable Infrastructure

In the era of smart cities, AI's ability to assist in real-time monitoring, predictive planning, and optimizing urban resources is becoming integral to the development of smart cities. AI is used in traffic control, transport management, waste collection, energy distribution, emergency services and infrastructure management etc. These tools can use information from sensors, cameras, connected devices and administrative systems to help cities predict congestion, detect service problems, and enhance public decision making. But their benefits rely on good governance, trustworthy data infrastructure, and equitable access to digitally enabled services, with the potential risks of poorly regulated urban AI being a source of surveillance, exclusion, and dependence on private technology suppliers (Yigitcanlar et al., 2020).

Digital twins take these capabilities one step further, by simulating virtual replicas of buildings, transport networks, utilities and urban environments. Together with AI they can simulate different scenarios, understand the impact on the environment, and anticipate infrastructure's reaction to population growth, climate hazards, or resource limitations. This integration can assist in more adaptive and environmentally responsive urban planning, but with reliable data, interoperability, and robust institutional coordination (Bibri et al., 2024).

7.2 Green Manufacturing, Transportation, and Circular Economy

AI and Industry 4.0 technologies can enhance industrial sustainability by implementing predictive maintenance, automated quality control, energy optimisation, process monitoring, and minimising material waste. With intelligent manufacturing systems, the inefficiencies can be detected, or the equipment failure can be predicted, and the operation can be adjusted accordingly. These capabilities can reduce emissions and resources used, while enhancing productivity, but this is not guaranteed unless firms link digital transformation with their environmental objectives (Ghobakhloo, 2020).

Sensors, robotics, data analytics and connected production systems can also help to produce cleaner and more efficient transport operations. Optimization of routes, fleet monitoring and forecasting demand can help reduce fuel consumption, delivery times and avoid unnecessary movement of goods. The availability of these technologies would help to reinforce environmental performance, but due to high implementation costs, skills shortages, and the lack of infrastructure, smaller companies may be limited in their access to them (Javaid et al. 2022).

In circular economy, machine learning has the potential to aid in product tracking, reverse logistics, product remanufacturing, material recycling, and material recovery. It is also used to predict product returns, classify waste and enhance re-use or disposal decision-making. The functions aim to reinforce circular supply chains, prolong the lifespan of the product, and minimize reliance on virgin resources (Farshadfar et al., 2024).

7.3 Sustainable Business, Finance, and Supply-Chain Management

AI is increasingly being employed by businesses to enhance their sustainability planning, supplier assessment, inventory management, risk analysis, and environmental reporting. Digital technologies can be used to support green supply-chain practices, which can improve the coordination, resource efficiency, and business performance when implemented as part of an overall business strategy (Bag et al., 2021). AI can also aid companies in analysing demand, supplier selection, disruption identification, and optimizing logistics in intricate networks. As a tool for use in supply-chain management, it has increased rapidly as it helps in decision making and visibility along the entire supply chain, including procurement, production and distribution (Toorajipour et al., 2021).

These tools are particularly useful in times of crisis when companies have to adjust to an unexpected increase in demand, transportation disruptions or even the failure of suppliers. Resilience can be fortified with AI, as it pinpoints the risk areas, predicts disruption, and aids in planning for alternate sourcing or distribution arrangements (Modgil et al., 2022).

Sustainable finance applications could also benefit environment risk assessment and investment screening, but transparent models, reliable sustainable data and protection against false and misleading classifications are essential for achieving the trustworthiness needed in sustainable finance.

Despite its broad applications, AI adoption across sustainability sectors remains constrained by technical, social, environmental, and institutional challenges, as outlined in Table 2.

Table 2. Key Challenges Affecting Sustainable AI Adoption

Challenge category	Main issues	Sustainability implications	Required response	References
Data limitations	Incomplete, biased, fragmented, or geographically unrepresentative datasets	Reduces model reliability and may exclude vulnerable communities or regions	Develop locally relevant, interoperable, and representative datasets	Ciecierski-Holmes et al. (2022); Bhat and Huang (2021)
Infrastructure and capacity	High costs, weak connectivity, limited computing resources, skills shortages	Restricts adoption in low-resource settings and widens the digital divide	Invest in affordable infrastructure, training, and context-sensitive technologies	Wahl et al. (2018); Singh and Ahmed (2021)
Bias and fairness	Discriminatory predictions, unequal error rates, limited transparency	Reinforces social inequalities and weakens public trust	Use fairness testing, inclusive design, audits, and human oversight	Jobin et al. (2019); Bender et al. (2021)
Privacy and surveillance	Extensive collection of health, education, mobility, and welfare data	Threatens individual rights and may discourage public participation	Apply data minimisation, consent, security, and clear accountability rules	Floridi et al. (2018); Hagendorff (2020)
Environmental cost	High electricity demand, hardware use, and carbon emissions	Undermines the environmental benefits claimed for AI systems	Report energy use, compare model efficiency, and adopt Green AI practices	Henderson et al. (2020); Luccioni et al. (2023)
Governance gaps	Voluntary principles, unclear liability, weak institutional enforcement	Creates inconsistent standards and limited accountability	Establish impact assessments, procurement rules, monitoring, and regulatory oversight	Morley et al. (2020); Sigfrids et al. (2022)

8. Challenges, Governance, and Future Research Directions

8.1 Technical, Data, and Infrastructure Challenges

Unbalanced data quality, limited access to digital infrastructure, low regional technical capacity, and low interoperability are current obstacles that hinder the effective use of AI for sustainable development. Sustainability-related data are often unevenly distributed, incomplete, and scarce in low-income areas, a problem that many AI systems rely on large, representative, and regularly updated databases. This can lead to a drop in model accuracy and less suitability for local use. However, the lack of computing infrastructure, poor connection, lack of qualified staff and the cost of implementation also limit adoption in low-resource settings. If these barriers are not addressed in future AI systems, they could exacerbate inequality.Unless future AI systems are designed to be affordable, adaptable, and locally deployable.

8.2 Ethical, Social, Environmental, and Regulatory Concerns

Bias, privacy, surveillance, accountability, loss of jobs and lack of access to benefits are concerns when it comes to AI. While fairness, transparency, human autonomy, and non-maleficence are highlighted and elaborated upon in many ethical guidelines, they are not identical and can be challenging to apply to practice (Jobin et al., 2019). The ethical frameworks can also be symbolic if there is a lack of monitoring, sanctions or institutional responsibility (Hagendorff, 2020). Large AI models generate further risks, as they can amplify harmful social patterns, make it harder to trace data origins, and centralise the power of the technology with a few organisations (Bender et al., 2021). They also have a large footprint in terms of environment, because the training and deployment of the models can be energy intensive and produce measurable carbon emissions (Luccioni et al., 2023).

The major technical, ethical, social, environmental, governance, and economic barriers affecting the responsible use of AI, together with the principal pathways for addressing them, are illustrated in Figure 2.

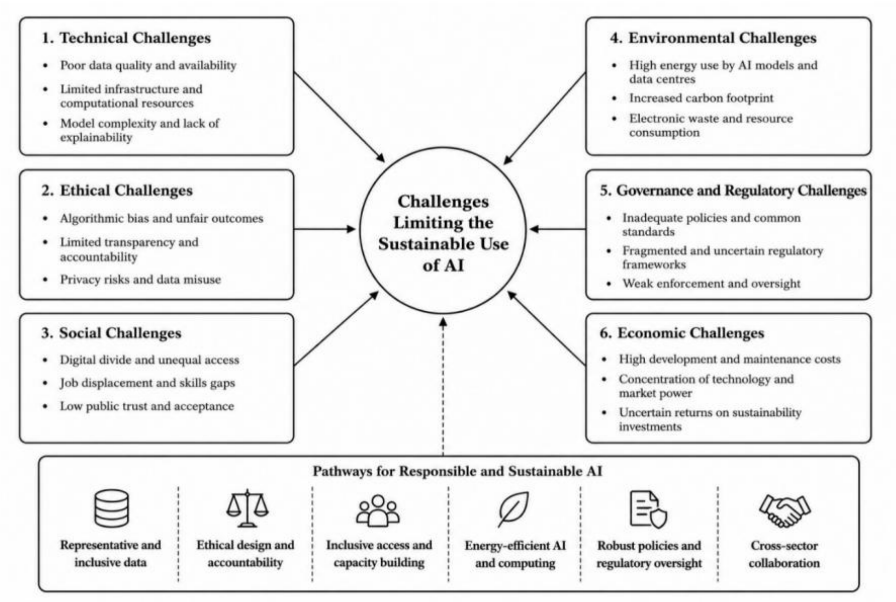

Figure 2. Major Challenges Limiting the Responsible and Sustainable Use of Artificial Intelligence

8.3 Responsible AI Governance and Policy Frameworks

From principles to tools, standards, impact assessments, audits, and accountability mechanisms – all in the name of responsible governance. A number of ethical checklists, model documentation, risk-assessment procedures and oversight procedures can support the practice, but if there is to be any benefit, they must be supported by institutional commitments and regular assessment (Morley et al., 2020). Cooperative governance models are particularly significant because it is necessary to have governments, researchers, businesses, civil society and affected communities involved in sustainable AI. Shared decision making can contribute to greater legitimacy and decision making that is responsive to social and environmental considerations (Gianni et al., 2022). Clear procurement rules, transparency requirements, and review mechanisms for AI systems that are deployed in public services, are also necessary for public administrations (Sigfrids et al., 2022).

8.4 Emerging Research Priorities and Multidisciplinary Opportunities

Special focus should be given to the development of explainable models, inclusive datasets, low-energy computing, context-sensitive evaluation, and long-term assessment of social and environmental effects in future research. Additionally, more focus should be given to the principles of Green AI which seek to minimize computational waste, and to benchmark the performance of AI models against the energy consumption and the carbon cost (Verdecchia et al., 2023). Multidisciplinary collaboration can link technical

innovation and law, ethics, policy, ecology, economics and community knowledge, ensuring that AI does not generate new sources of risk and exclusion that are linked to sustainability.
Based on the synthesis of evidence across the reviewed sectors, the main priorities for future multidisciplinary research are presented in Table 3.

Table 3. Priority Directions for Future Multidisciplinary Research

Research priority	**Current gap**	**Recommended research direction**	**Expected contribution**
Energy-efficient AI	Model accuracy is often reported without energy or carbon costs	Develop lightweight models and standardised energy-reporting frameworks	Reduces the environmental footprint of AI development and deployment
Explainability and accountability	Complex models are difficult for users and regulators to interpret	Design explainable systems, audit procedures, and responsibility frameworks	Improves trust, transparency, and institutional accountability
Inclusive and localised datasets	Evidence is concentrated in technologically advanced regions	Build datasets reflecting local languages, environments, populations, and social conditions	Improves relevance and reduces geographic and demographic bias
Long-term impact evaluation	Many studies focus on short-term technical outcomes	Conduct longitudinal studies covering environmental, economic, and social effects	Clarifies whether AI produces sustained development benefits
Human–AI collaboration	AI is often examined separately from human and institutional decision-making	Study participatory design and collaboration among experts, communities, and AI systems	Supports context-sensitive and socially legitimate decisions
Cross-sector governance	Policies are commonly developed within isolated sectors	Compare governance across health, agriculture, cities, industry, and public services	Enables coherent standards and transferable governance practices

9. Conclusion

AI has emerged as a key enabler for sustainable development in environmental, social, agricultural, industrial and economic systems. The potential advantages of its capacity to process vast amounts of data, enhance predictions, automate intricate tasks, and guide timely decision-making are significant for the fields of climate modeling, renewable energy management, biodiversity conservation, precision agriculture, healthcare, education, smart city, green manufacturing, and resilient supply chains. The applications demonstrate AI's potential to support institutions in achieving greater efficiency in their utilization of resources, addressing new risks, and delivering critical services with greater reach and quality. But the advantages of AI can't be taken for granted. Poor data quality, inadequate infrastructure, implementation costs, access disparities, model bias, privacy issues and lack of technical capacity can diminish its effectiveness. Large-scale computing also presents concerns for the environmental impact of the technology, including energy consumption, carbon emissions, and the sustainability of these AI systems. In this regard, it is crucial to consider AI for sustainability and the sustainability of AI in the pursuit of sustainable development. Adoption into the future should be guided by responsible governance. To ensure AI is working towards social and environmental objectives, there is a need for clear standards, transparent models, human oversight, impact assessment, public accountability, and stakeholder participation. The success of implementing AI systems in the local context requires collaboration among policymakers, researchers, enterprises, and communities to tailor the technology to the local environment and avoid centralizing the benefits of AI technologies into advanced technological institutions or regions. Future research could be aimed at low-energy models, datasets which are inclusive, explainable models, evaluation across sectors, and evidence from low- and middle-income settings. To link technical innovation with ethics, policy, ecology, and economics and public needs, a multi-disciplinary approach will be crucial. AI can be used in a responsible way to help ensure more resilient, equitable and environmentally sustainable paths to development.

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