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Abstract

The intersection of Sustainability and Digital Transformation exemplifies the role of Artificial Intelligence in leveraging global efforts toward the United Nations' 17 Sustainable Development Goals (SDGs). We provide a systematic review of AI's role—specifically Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), and Computer Vision (CV)—in monitoring, modelling, and achieving targets across all 17 SDGs. The analysis is contextualized by two different approaches: the first relates to AI applications in scientific research, and the second explores how AI can be utilized to achieve the targets of an SDG. Regarding the former, it is demonstrated how AI-powered tools for sustainability tracking, human security analysis, and green workforce skills mapping contribute to the scientific research of the Ae4ria research network, a dynamic international scientific research network that pursues a multitude of environmental research goals and activities (Ae4ria.org). As for the latter, a detailed case study on SDG 7 (Affordable and Clean Energy) illustrates AI's technical capability in managing the complexity of modern power systems, using dynamic reserve dimensioning, optimization of continuous intraday trading strategies, and multi-agent reinforcement learning for computing economic equilibria in balancing markets. Yet, despite the breadth and high potential of AI in monitoring, assessing, and ultimately achieving the SDGs, we need to address the policy paradox presented by AI's rapidly growing environmental footprint, particularly the substantial energy demands and carbon emissions associated with data centers and large model training. This highlights the need for innovative policy instruments, such as "Green AI" incentives and governance frameworks, that can promote circular economies for digital infrastructures underpinning the development of AI. Realizing AI's transformative potential is ultimately contingent upon addressing critical economic, institutional, and ethical dimensions, ensuring that its deployment fosters an equitable and truly sustainable digital transition for all.

Keywords: AI for SDGs; Sustainable Development Goals; SDG; Energy; AI models;

1. Artificial Intelligence for the Sustainable Development Goals

Artificial intelligence (AI), human well-being, and environmental sustainability are converging in significant ways as we strive to address the pressing challenges of our time—such as climate change, biodiversity loss, and widening social disparities. Utilizing AI in environmental management offers new opportunities to utilize resources wisely, make informed decisions, and accelerate progress toward greener economies. Recent studies (Koundouri et al., 2025) have shown that machine learning can facilitate an understanding of the relationships between various aspects of human security and the Sustainable Development Goals (SDGs).

The United Nations' 17 Sustainable Development Goals (SDGs) demand timely, disaggregated data to assess global progress. As traditional monitoring methods—such as surveys, censuses, and administrative reports—often lag behind real-world developments, AI has become indispensable in extracting, analyzing, and forecasting sustainability indicators from complex environmental and socioeconomic datasets. Its applications across the SDS are described next.

Regarding the role of AI in SDG 1 (No Poverty), AI methods can be utilized to conduct nearly real-time poverty assessments in low-income areas, regions, and countries. These can be utilized, for instance, by applying Natural Language Processing (NLP) models, such as BERT, to analyze social media or other datasets for employment and cost-of-living indicators, or Convolutional Neural Networks (CNNs) trained on nighttime lights to predict village-level wealth with high precision (Jean et al., 2016).

In the context of SDG 2 (Zero Hunger), achieving zero hunger entails manifold AI applications for agricultural monitoring and early warning. Platforms like the Radiant Earth Foundation utilize U-Net-based CNNs on Sentinel imagery to estimate crop yields, whereas LSTM and Recursive Neural Networks can be employed to forecast food prices and climate-related shocks. For instance, the Famine Early Warning Systems Network (FEWS NET) integrates these predictive tools to mitigate hunger crises (You et al. 2017).

In terms of AI applied to SDG 3 (Good Health and Well-being), deep learning methods can be utilized for disease detection and health surveillance. For instance, ResNet-50 and EfficientNet can be used to diagnose tuberculosis and COVID-19 from imaging data, while LSTM models are useful in epidemiological forecasts. Depending on the health and/or well-being sector, GPT-4 and related NLP-driven sentiment models can serve in various types of analyses, which may even extend to mental health, i.e., assessing depression trends through AI-driven analyses of social media (Esteva et al., 2019).

Considering the importance of AI for SDG 4 (Quality Education), AI-powered analyses of educational data can enhance broader access and equity in learning. UNICEF's "Mapping Schools" project utilized CNNs to locate previously unmapped schools, while Random Forest and LSTM models have been found useful for predicting student dropout risks. Additionally, NLP helps governments analyze educational quality and identify curriculum gaps (Holmes et al., 2021).

Regarding the role of AI in achieving SDG 5 (Gender Equality), NLP and fairness-aware ML help identify gender bias and representation gaps. UN's "Global Pulse" employed BERT to detect online harassment and stereotypes, while IBM's "AI Fairness 360 Toolkit" audits bias in institutional decision-making. Computer vision models also estimate gender participation in political or corporate imagery, supporting equitable policy interventions (Buolamwini & Gebru, 2018).

In the framework of the targets and indicators of SDG 6 (Clean Water and Sanitation), AI enhances water monitoring and sanitation management. The European Space Agency (ESA) utilizes CNNs to analyze Sentinel satellite data for tracking freshwater quality. Meanwhile, IoT sensors can be combined with Autoencoders to detect contamination anomalies in real-time, thereby enhancing global access to safe water (see also Mandal et al., 2025).

Regarding the application of AI in SDG 7 (Affordable and Clean Energy), multiple companies worldwide incorporate AI-powered optimizers to enhance sound energy consumption and renewable energy generation. Google's "DeepMind" has reduced data-center energy use by 40% by utilizing AI methods. Meanwhile, LSTM models have been found useful in forecasting solar and wind output, and CNNs applied to nighttime lights have estimated electrification levels in remote regions (Rolnick et al., 2019).

Focusing on the contribution of AI towards SDG 8 (Decent Work and Economic Growth), in the same way as with other socioeconomic data, AI has been employed to monitor labor markets and productivity. NLP models can analyze millions of job postings to map skills demand, while predictive analytics can improve manufacturing efficiency. OECD's "AI Observatory" tracks digital job trends, and computer vision can ensure workplace safety through real-time anomaly detection (Brynjolfsson & McAfee, 2017).

Regarding AI and SDG 9 (Industry, Innovation, and Infrastructure), AI can serve as a foundation for smart manufacturing and infrastructure management (Phatthanachaisuksiri et al., 2025). Siemens, for instance, applies LSTM-based predictive maintenance for equipment monitoring, and the World Bank's AI program uses U-Net for road mapping. NLP models, such as SciBERT, analyze patent data to track innovation patterns, etc.

Addressing the significance of AI for SDG 10 (Reduced Inequalities), AI exposes and mitigates inequality through spatial and institutional analysis. Vision Transformers detect urban poverty patterns from satellite imagery, while Google's "What-If Tool" can audit bias in public services. GNNs model access to health or transport networks, guiding inclusive policymaking (Mehrabi et al., 2021).

Pertaining to the impact of AI on SDG 11 (Sustainable Cities and Communities), urban AI systems model traffic, pollution, and housing. Hangzhou's "CityBrain" utilizes reinforcement learning to optimize traffic signals and reduce emissions (Yan and Li, 2022). CNNs such as the U-Net++ can monitor urban sprawl, and ML-driven sensors can assess housing quality and disaster vulnerability.

Although perhaps not immediately evident, AI can be utilized to promote circular economies and waste reduction within the context of SDG 12 (Responsible Consumption and Production). AI models, such as YOLOv5 and Mask R-CNN, can be utilized to automate recycling, achieving high accuracy in material sorting. Blockchain-integrated ML enhances supply-chain transparency, while generative models design sustainable materials (Noman et al., 2022).

In the context of SDG 13 (Climate Action), the contribution of AI to support climate modeling, emission estimation, and disaster prediction has been one of the most remarkable. NASA's "Climate AI," for instance, integrates GNNs and PINNs (Physics-Informed Neural Networks) for forecasting sea-level rise and glacial melt. Similarly, Transformer-based models can predict extreme weather and thus can be used to foster resilience to climate change (Reichstein et al., 2019).

As it pertains to AI within the framework of DG 14 (Life Below Water), it has proven a powerful ally in marine ecosystem monitoring, supporting efforts to conserve ocean health and biodiversity. Computer vision and deep learning techniques enable automated identification and classification of marine species and habitats. Platforms such as CoralNet, which utilize deep Convolutional Neural Networks (CNNs), analyze underwater imagery to monitor species composition, detect coral bleaching, and assess reef health (Beijbom et al., 2015; Wäldchen and Mäder, 2018). Characteristically, AI-driven remote sensing models identify sources of ocean pollution and track zones of plastic accumulation by processing satellite imagery and sonar data. Autonomous underwater vehicles equipped with AI-powered sensors enhance real-time marine surveillance, mapping of seafloor ecosystems, and detection of illegal fishing. With these tools, AI significantly reduces the cost and time required for marine biodiversity assessments.

In relation to SDG 15 (Life on Land), AI technologies have revolutionized terrestrial ecosystem management and biodiversity protection. Machine learning models analyze satellite and drone imagery to monitor deforestation, illegal mining, and land-use change with near-real-time precision. Platforms such as Google's "GFW" (Global Forest Watch) use CNN-based algorithms to detect deforestation patterns and alert authorities before irreversible damage occurs. In parallel, AI-enabled acoustic monitoring systems use RNNs (Recurrent Neural Networks) and Transformer-based audio classifiers (e.g., YAMNet) to recognize animal (i.e., bird) vocalizations, providing useful data on species presence/absence and/or migration. These approaches facilitate large-scale, continuous biodiversity assessments across remote regions (Hansen et al. 2013). Furthermore, predictive models identify areas in risk of desertification or undergoing significant habitat loss, therefore being extremely useful to support targeted conservation policies.

In connection with SDG 16 (Peace, Justice, and Strong Institutions), AI contributes to building peaceful and just societies by strengthening transparency, accountability, and conflict monitoring. NLP models, such as BERT and XLNet, analyze news articles, reports, and social media to detect signs of political unrest, hate speech, or misinformation in real-time. The "Global Database of Events, Language, and Tone" (GDELT) leverages machine learning to track and categorize global events, offering actionable insights for peacekeeping and crisis prevention. Additionally, AI-powered anomaly detection systems flag irregularities in public procurement or financial transactions, helping uncover corruption and fraud. These innovations support governments and international organizations in monitoring SDG 16 indicators, such as the rule of law, institutional trust, and public safety. However, ethical safeguards and explainable AI frameworks are crucial in preventing misuse and ensuring fairness in algorithmic governance (Dasandi and Mikhaylov, 2019).

Regarding the influence of AI over SDG 17 (Partnerships for the Goals), AI plays a strategic role in strengthening global partnerships for sustainable development by facilitating data integration, capacity building, and cross-sector collaboration. Advanced ML methods harmonize heterogeneous datasets from national statistics, remote sensing, and social media to enhance the comparability of SDG indicators across countries. Cloud-based AI platforms, such as Google Earth Engine, enable shared access to analytical tools and training resources for governments and NGOs. Moreover, AI supports knowledge transfer through collaborative initiatives, such as the "Partnership on AI" and "AI for Good" programs, which unite academia, industry, and policymakers. By fostering open data ecosystems and equitable access to AI technology, SDG 17 ensures that innovation benefits all nations and accelerates collective progress toward the 2030 Agenda (Vinuesa et al., 2020), strengthening global cooperation (Truby, 2020).

Evidently, there is a wide range of AI methods and models that can be used to aid in the monitoring and achievement of each SDG, so a comprehensive tabulation of the potential of different AI models and methods for each SDG may aid in navigating the very complex set of appurtenances of AI and SDG (Fig. 1).

AI Techniques / Models	SDG 1 Poverty	SDG 2 Hunger	SDG 3 Health	SDG 4 Education	SDG 5 Gender	SDG 6 Water	SDG 7 Energy	SDG 8 Work	SDG 9 Innovation	SDG 10 Inequality	SDG 11 Cities	SDG 12 Consumption	SDG 13 Climate	SDG 14 Ocean	SDG 15 Land	SDG 16 Justice	SDG 17 Partnership
Convolutional Neural Networks (CNNs)	•••	•••	•••	•••	••	•••	••	•••	•••	•••	•••	••	•••	•••	•••	••	•
Recurrent Neural Networks (RNNs/LSTMs)	••	•••	•••	•••	••	•••	•••	•••	•••	••	•••	••	•••	••	••	••	•
Transformer Models (BERT, GPT)	••	••	•••	•••	•••	••	••	•••	•••	••	••	•••	•••	••	••	•••	•••
Vision Transformers (ViT)	•••	•••	•••	••	•	••	••	•••	•••	•••	•••	••	•••	•••	•••	•	•
Graph Neural Networks (GNNs)	••	••	••	••	••	••	••	•••	•••	•••	•••	••	•••	••	••	••	•••
Reinforcement Learning (RL)	•	••	•••	••	•	••	•••	•••	•••	••	•••	••	••	••	••	•	•
Physics-Informed Neural Networks (PINNs)	•	••	••	•	—	•••	•••	•	••	•	••	•	•••	•••	••	—	•
Generative Models (GANs, VAEs)	••	••	••	••	•	••	••	••	•••	••	••	•••	•••	••	••	•	••
Random Forests & Gradient Boosting	•••	•••	•••	•••	••	•••	•••	•••	•••	•••	•••	••	•••	••	•••	••	••
Anomaly Detection (Autoencoders, Isolation Forests)	••	••	••	••	•	•••	••	•••	•••	••	••	•••	••	••	••	•••	••
Computer Vision (YOLO, Mask R-CNN)	•••	•••	•••	••	•••	••	••	•••	•••	•••	•••	•••	•••	•••	•••	••	•
Natural Language Processing (NLP)	••	••	•••	•••	•••	••	••	•••	•••	•••	••	•••	••	••	••	•••	•••
Deep Q-Networks (DQN)	—	•	••	•	—	••	•••	••	•••	•	•••	••	••	•	•	—	•
Time-Series Forecasting Models	••	•••	•••	••	••	•••	•••	•••	•••	••	•••	••	•••	•••	••	••	••
Federated Learning	••	••	•••	•••	••	••	••	••	••	••	••	••	••	••	••	••	•••
Transfer Learning	•••	•••	•••	•••	••	•••	•••	•••	•••	•••	•••	••	•••	•••	•••	••	••
Bayesian Networks	••	•••	•••	••	••	•••	••	•••	••	••	••	••	•••	••	••	••	••
Agent-Based Models (ABMs)	••	••	••	••	••	••	••	•••	••	•••	•••	••	•••	•	••	••	••
Explainable AI (XAI - SHAP, LIME)	•••	••	•••	•••	•••	••	••	•••	•••	•••	•••	•••	•••	••	••	•••	•••
Fairness-Aware Machine Learning	•••	••	•••	•••	•••	••	••	•••	•••	•••	•••	•••	••	••	••	•••	•••

High Relevance (•••) Medium Relevance (••) Low Relevance (•) Minimal/No Application (—)

Fig. 1 Assessing the potential of some key AI methods, techniques, and models in monitoring and achieving each one of the 17 SDGs (authors' own elaboration)

2. AI-powered Environmental Research: The case of Ae4ria

Ae4ria utilizes AI-powered text analysis to connect human security with the SDGs, as part of a broader effort to track progress on sustainability using AI. In addition, the Ae4ria AI Skills Tool takes things a step further by examining how AI can identify the skills, jobs, and learning paths associated with sustainability-focused documents. This helps us see how digital changes can shape a workforce that's ready for a greener future. All these efforts matter because human security—which covers not just economic well-being, but also food, health, environment, personal safety, community, and politics—is at the heart of lasting development. The real challenge is not just having better technology, but ensuring that we have the right institutions and incentives to make economic growth and environmental care go hand in hand, while also protecting those who are most at risk. Economically, utilizing AI for environmental benefits should be viewed as part of a broader perspective that encompasses market failures, hidden costs, and the need for informed policies that address both today's pressing needs and our long-term objectives for a safer, more sustainable world (Dasgupta 2021). The seven pillars of human security—economic, food, health, environmental, personal, community, and political security—are intrinsically linked to environmental sustainability and the achievement of the SDGs. Our recent empirical work demonstrates that AI-powered text analytics and machine learning can systematically map these connections, revealing critical intersections and gaps in current policy frameworks (Koundouri et al., 2025). For instance, environmental security directly connects to SDGs 13, 14, and 15 (climate action, life below water, and life on land), while economic security aligns with SDGs 1, 8, and 10 (poverty reduction, decent work, and reduced inequalities). These mappings are not merely academic exercises but provide actionable insights for policymakers. By employing machine learning algorithms to analyze policy documents, we can identify where human-security interventions can simultaneously advance multiple SDGs, creating synergistic effects that maximize both economic efficiency and social impact. The development of the Ae4ria SDG Tracker[1] exemplifies how AI tools can democratize access to complex policy analysis. This web-based application utilizes natural-language processing to assess the relevance of documents to the SDGs, enabling policymakers to quickly evaluate whether their strategies adequately address the multidimensional aspects of human security and sustainability. Complementing this, the Ae4ria AI Skills Tool[2] expands the analytical scope from policy relevance to workforce transformation. By mapping the skills, occupations, and learning opportunities embedded in sustainability-related texts, the tool helps connect environmental and digital strategies with human-capital development. Its integrated SDG alignment offers a practical framework for identifying how digital transformation supports both environmental objectives and the evolving competencies required for a green, resilient economy.

Traditional economic approaches to environmental management have relied on static instruments such as carbon taxes, emissions trading schemes, and regulatory standards. However, the complexity of modern environmental challenges requires dynamic, adaptive mechanisms that can respond to rapidly changing conditions and emerging threats to human security. AI technologies fundamentally transform our capacity to address these challenges in several key ways. First, they enable more accurate pricing of environmental externalities (Nordhaus 2019) through machine learning models that can process vast datasets, including satellite imagery, sensor networks, and transaction data, thereby contributing to more precise estimations of environmental impacts. Preliminary research suggests that AI can improve the representation of complex system dynamics in environmental-economic modeling, potentially leading to more accurate pricing mechanisms. Second, AI technologies optimize resource allocation across multiple objectives, which is essential given that the multi-criteria nature of sustainable development requires balancing economic growth, environmental protection, and social equity. AI algorithms can identify Pareto-optimal solutions that maximize welfare across these dimensions while considering the interconnections between different aspects of human security. For example, investments in renewable energy infrastructure that address environmental security can simultaneously create employment opportunities, enhance economic security, and reduce air pollution, thereby improving health security. Third, AI enables adaptive management strategies that offer significant advantages over traditional policy instruments, which often require lengthy legislative processes to modify. AI-powered systems can continuously adjust interventions based on real-time data, and this adaptability is crucial for maintaining human security in the face of climate change, where conditions can shift rapidly and unpredictably.

The successful integration of AI into environmental governance requires addressing fundamental questions about equity, accountability, and democratic participation. Our preliminary analysis of human security reports suggests that while AI applications show strong connections to certain SDGs, significant gaps may remain in addressing inequality (SDG 10) and institutional quality (SDG 16). As shown in related empirical analyses (see the contributions of the co-authors in this volume), these patterns warrant further investigation. Several key policy considerations demand attention in this context. First, algorithmic justice and environmental equity must be prioritized, as AI systems trained on historical data may perpetuate existing environmental injustices. For instance, predictive models for climate adaptation investments might systematically undervalue vulnerable communities that have been historically underserved. Policy frameworks must ensure that AI applications actively correct for these biases through techniques such as fairness-aware machine learning and inclusive data collection practices. Second, transparency and explainability represent critical governance challenges, as environmental decisions impact entire communities and ecosystems. The "black box" nature of some AI algorithms poses challenges to democratic accountability; yet, recent advances in explainable AI offer pathways to maintain both model performance and interpretability, enabling stakeholders to understand and contest algorithmic decisions that affect their environment and livelihoods. Third, data sovereignty and privacy concerns arise because environmental monitoring often requires extensive data collection about individuals and communities. Balancing the need for comprehensive data with privacy rights requires innovative approaches such as federated learning, where AI models are trained on distributed data without centralizing sensitive information.

Preliminary applications of ML-enhanced integrated assessment models indicate promising potential for improving our understanding of climate-economy interactions. By applying Random Forest algorithms and advanced NLP techniques to policy documents, initial findings suggest previously overlooked connections between human security dimensions and climate action (Koundouri et al. 2025). For example, preliminary analysis of post-conflict recovery reports suggests that community security interventions may be correlated with environmental restoration efforts (SDGs 13, 14, 15), indicating that peacebuilding and ecological rehabilitation could benefit from integrated rather than separate policy approaches. This insight, subject to further empirical validation in related sections of this volume, has potential implications for the design of climate finance mechanisms and the allocation of adaptation funds.

Another example illustrating how AI tools can be instrumental in exploring and implementing environmental policies is the research conducted in Ae4ria related to the European Green Deal, which presents a compelling case study of AI integration in environmental policy. Machine learning algorithms are being explored and piloted to monitor compliance with emissions reduction targets through satellite imagery analysis, support the allocation of Just Transition Fund resources to affected regions, model potential economic impacts of carbon border adjustment mechanisms, and identify opportunities for green innovation and industrial transformation. Beyond these environmental applications, AI also plays a growing role in aligning digital transformation with workforce adaptation under the Green Deal framework. The Ae4ria AI Skills Tool contributes to this effort by analyzing policy and strategy documents to identify the specific skills, occupations, and training pathways associated with Europe's green transition. Through its AI-enabled mapping of competencies and SDG linkages, the tool helps policymakers and educational institutions understand how the goals of the Green Deal intersect with labor-market evolution and lifelong learning strategies. Together, these applications demonstrate how AI can enhance both the efficiency and inclusiveness of environmental policies, ensuring that the transition to sustainability supports innovation while fostering equitable access to emerging green and digital opportunities (Koundouri et al. 2023). This outlines the economic and policy dimensions of this challenge, highlighting the need for continued collaboration across disciplines, sectors, and borders. Through such integrated approaches, we may be able to harness the transformative potential of AI to address environmental challenges while enabling sustainable development and equitable digital transition for all.

Considering these applications and the needs of an NGO, state, region, or other legal entity, the applicability of AI in achieving the SDGs varies accordingly. In the case of Ae4ria, for instance, the set of AI methods and models that can be used in monitoring, assessment, and implementation of the SDGs can be adjusted accordingly to satisfy the research priorities and objectives pursued by Ae4ria (Fig. 2).

AI Techniques / Models	Climate Change Mitigation & Adaptation	Water-Food-Energy Nexus	Sustainable Blue Growth & Fisheries	Circular Economy	Sustainable Finance & ESG/SDG Metrics	Smart Water Systems & Management	Education & Capacity Building	Policy Analysis & Stakeholder Engagement	Innovation Acceleration & Commercialization	Regional Climate Resilience
Convolutional Neural Networks (CNNs)	●●●	●●●	●●●	●●	●●	●●●	●●	●	●●	●●●
Recurrent Neural Networks (RNNs/LSTMs)	●●●	●●●	●●	●●	●●●	●●●	●●	●●	●●	●●●
Transformer Models (BERT, GPT)	●●	●●	●●	●●	●●●	●●	●●●	●●●	●●●	●●
Vision Transformers (ViT)	●●●	●●	●●●	●●	●	●●	●	●	●●	●●●
Graph Neural Networks (GNNs)	●●●	●●●	●●	●●	●●	●●●	●	●●	●●	●●●
Reinforcement Learning (RL)	●●●	●●●	●●	●●	●	●●●	●	●	●●	●●●
Physics-Informed Neural Networks (PINNs)	●●●	●●●	●●	●	—	●●●	●	—	●	●●●
Generative Models (GANs, VAEs)	●●●	●●	●	●●●	●●	●●	●●	●●	●●●	●●
Random Forests & Gradient Boosting	●●●	●●●	●●●	●●●	●●●	●●●	●●	●●	●●	●●●
Anomaly Detection (Autoencoders, Isolation Forests)	●●	●●	●●	●●●	●●●	●●●	●	●●	●●	●●
Computer Vision (YOLO, Mask R-CNN)	●●●	●●	●●●	●●●	●●	●●	●●	●	●●	●●●
Natural Language Processing (NLP)	●●	●●	●●	●●	●●●	●●	●●●	●●●	●●●	●●
Deep Q-Networks (DQN)	●●	●●	●	●	—	●●●	—	—	●	●●
Time-Series Forecasting Models	●●●	●●●	●●●	●●	●●●	●●●	●●	●●	●●	●●●
Federated Learning	●●	●●	●●	●●	●●	●●	●●●	●●●	●●	●●
Transfer Learning	●●●	●●●	●●●	●●	●●	●●●	●●●	●●	●●●	●●●
Bayesian Networks	●●●	●●●	●●	●●	●●●	●●●	●●	●●●	●●	●●●
Agent-Based Models (ABMs)	●●●	●●●	●●	●●	●●	●●	●●	●●●	●●	●●●
Explainable AI (XAI - SHAP, LIME)	●●●	●●●	●●	●●●	●●●	●●●	●●●	●●●	●●●	●●●
Fairness-Aware Machine Learning	●●●	●●●	●●	●●●	●●●	●●	●●●	●●●	●●	●●●

Critical / High Potential of AI (●●●) Significant / Medium Potential of AI (●●) Supportive / Low Potential of AI (●) Limited Application (—)

Fig. 2 Assessing the potential of different AI methods and models in the context of the research priorities of Ae4ria (authors' own elaboration)

3. Using AI-powered Research to tackle SDGs: The example of SDG7

The applications of AI methods in energy research have grown significantly since 2020, whereas the fields of economics, political science, law, and business have claimed ever higher portions of the research publications (Fig. 3).

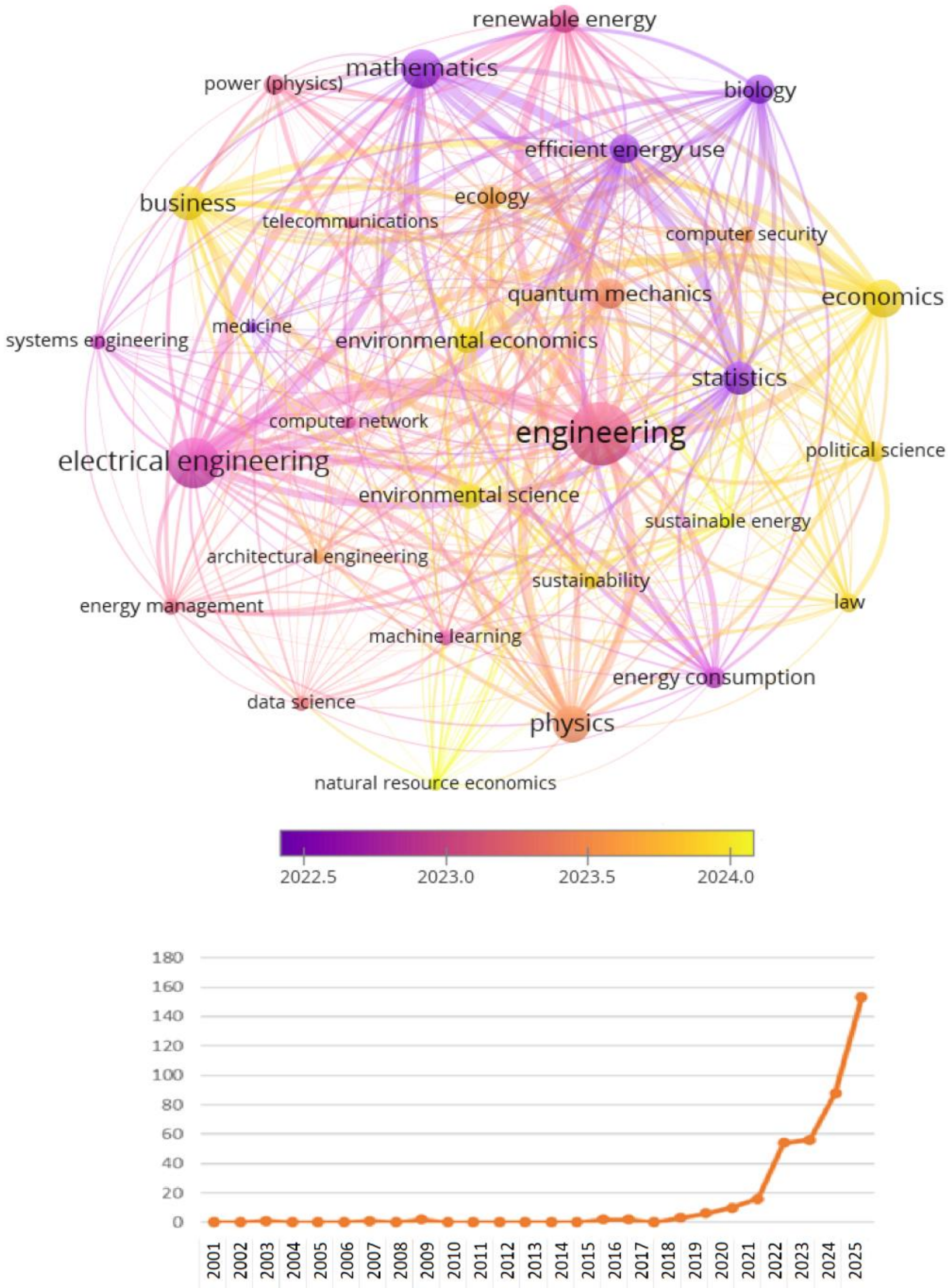

Fig. 3 The main concepts in the literature of AI and energy (top): the larger the node, the more sizeable the literature that concerns the corresponding concept, and the thicker the link between two nodes, the more the publications that relate to them both. The annual growth of this literature by the number of publications (bottom). Source of data: Openalex database; 1/1/2000-15/11/2025)

Indeed, there is a wide range of potential applications of AI techniques and models in tackling each of the seven targets of SDG7, "Sustainable and clean energy" (Fig. 4). Next, it is described how some such AI methods can be useful in analysis and problem-solving related to SDG7.

AI Techniques / Models	7.1.1 Access to Electricity	7.1.2 Clean Cooking Fuels & Tech	7.2.1 Renewable Energy Share	7.3.1 Energy Intensity	7.a.1 Financial Flows	7.b.1 Renewable Capacity
Convolutional Neural Networks (CNNs)	●●●	●●	●●●	●●	●	●●●
Recurrent Neural Networks (RNNs/LSTMs)	●●	●	●●●	●●●	●●	●●●
Transformer Models (BERT, GPT)	●●	●●	●●	●●	●●●	●●
Vision Transformers (ViT)	●●●	●●	●●●	●	●	●●●
Graph Neural Networks (GNNs)	●●●	●	●●●	●●●	●	●●
Reinforcement Learning (RL)	●●●	●	●●●	●●●	●	●●●
Physics-Informed Neural Networks (PINNs)	●	—	●●●	●●●	—	●●
Generative Models (GANs, VAEs)	●●	●	●●●	●●	●	●●
Random Forests & Gradient Boosting	●●●	●●●	●●●	●●●	●●	●●●
Anomaly Detection (Autoencoders, Isolation Forests)	●●	●	●●	●●●	●●	●●
Computer Vision (YOLO, Mask R-CNN)	●●●	●●	●●●	●●	●	●●●
Natural Language Processing (NLP)	●●	●●	●●	●●	●●●	●●
Deep Q-Networks (DQN)	●●	—	●●●	●●●	—	●●
Time-Series Forecasting Models	●●●	●●●	●●●	●●●	●●●	●●●
Federated Learning	●●	●●	●●	●●	●●●	●●
Transfer Learning	●●●	●●	●●●	●●●	●●	●●●
Bayesian Networks	●●●	●●	●●●	●●●	●●	●●
Agent-Based Models (ABMs)	●●●	●●●	●●	●●	●	●●
Explainable AI (XAI - SHAP, LIME)	●●●	●●	●●●	●●●	●●●	●●
Fairness-Aware Machine Learning	●●●	●●●	●●	●●	●●●	●●

High Potential of AI (●●●) Medium Potential of AI (●●) Low Potential of AI (●) Minimal Application (—)

Fig. 4 The potential of some AI techniques and models to tackle each one of the six targets of SDG7 "Sustainable and Clean Energy" (authors' own elaboration)

Here, we review several initiatives that exemplify the application of artificial intelligence in the context of power system operations and electricity market design. These applications are largely driven by the confluence of two factors: the rapid improvement of machine learning technology as well as the increasing need for uncertainty management in the electric power sector, where renewable resources introduce novel technological challenges. The specific areas of application include: (i) dynamic dimensioning of reserves, (ii) optimization of continuous trading in intraday markets, (iii) computation of equilibria in balancing markets, and (iv) hydrothermal planning. We also discuss challenges that are emerging as a result of the widespread deployment of data centers required to support artificial intelligence infrastructure.

A major challenge in electric power systems is the instantaneous balancing of electric power supply and demand. Even short-lived imbalances can induce cascading outages, which can bring the entire system to a halt. The dramatic effects of such cascading phenomena were experienced in the recent blackout in the Iberian Peninsula in April 2025. For this purpose, systems carry reserves. This is the headroom in power generation units that is left available to allow for certain flexible generation or demand technologies to adjust their setpoint of energy production/consumption in real time, thereby balancing any instantaneous and unanticipated disturbances in power balance. Reserves are costly to secure because the generation headroom that is made available to the system operator foregoes opportunities for profitable trades in the energy market. An important challenge, therefore, is to secure as much of this headroom as necessary in order to achieve certain reliability goals, but not more, since excess reserve capacity is economically wasteful. Reliability goals are expressed through probabilistic criteria that each European Member State needs to adhere to. For instance, the European Commission Regulation 1485/2017 (the so-called System Operation Guideline) stipulates that a reliability target of at least 99% should be respected. Traditionally, this reliability level is achieved through static dimensioning methods, where a single annual reserve target is set for the entire year to ensure that the 99.x% reliability target is met. From a methodological standpoint, this amounts to a problem of quantile estimation. Concretely, given a historical record of system imbalances, one can estimate a probability distribution for imbalances. The minimum number of static reserves required to achieve this reliability goal is then the 99.x% quantile of this distribution. Static dimensioning has been challenged in recent years as possibly inadequate for the needs of modern power systems. This is due to the fact that system conditions vary significantly on a daily basis, owing largely to the large-scale integration of renewable resources. For instance, a day-ahead forecast of high wind output for the following day entails a significant risk of energy shortfall, and a low risk of energy surplus, since actual wind generation can only be less than the forecast. This then raises the challenge of attempting to adapt the dimensioning of reserve to observable day-ahead conditions, so as to ensure a level of reserve requirements that adapts daily to the conditional distribution of imbalances given observable day-ahead conditions (e.g., temperature forecasts, electric power demand forecasts, solar irradiation forecasts, import forecasts, generation commitment forecasts, and so on). This practice is referred to as dynamic dimensioning, and it has been shown (de Vos et al., 2019) that this methodology was successfully adopted in the electric power system of Belgium. The estimation of quantiles for the conditional distributions of imbalances was prototyped and compared across three alternative machine learning methods: *k*-means, k-nearest neighbors, and artificial neural networks. The idea is to use these methods in order to create a mapping from observable day-ahead conditions to estimates for the 99.x% of the conditional distribution of imbalances, which now becomes the dynamic dimensioning decision. Prototyping, which subsequently led to adoption, demonstrated lower reserve requirements on average without compromising system reliability, as well as a more stable risk exposure for the system operator to system imbalances. The latter attribute was arguably the major advantage of the method, and an important driver in its adoption in Belgium (de Vos et al., 2019). Aside from these, intraday markets are markets for trading electric power, which commence one day in advance of electric power delivery and conclude a few minutes before real-time operations begin. They enable traders to adjust the conditions of their portfolios in response to new information that becomes available in real-time. Intraday markets have experienced a surge in liquidity and profit opportunities in recent years, largely due to the large-scale integration of renewable energy resources. This results in significant price spreads. Such spreads enable flexible asset owners, such as batteries, to procure energy at low prices in the intraday market and sell it back at periods of high prices, thereby leveling the marginal cost of the system and enhancing economic efficiency. The continuous intraday market is a pan-European trading platform where such trades take place on a continuous basis. In such a setting, it becomes important for traders to be able to rapidly lock in favorable trades from a continuous order book. A policy function approximation approach based on reinforcement learning can be used to define a price threshold for determining when an offer in the order book is favorable, allowing it to be locked in immediately (Bertrand and Papavasiliou, 2020). The trading algorithm developed by these authors is shown to outperform the "rolling intrinsic" trading strategy employed by a multinational energy utility. The superior performance of the developed trading algorithm is driven by its ability to avoid greedy trades and is reported to produce performance gains of 17.8% relative to rolling intrinsic. Balancing markets are the markets used for balancing the real-time delivery of electric power. In fact, there is an ongoing effort to integrate the design of these markets at the pan-European level, enabling Member States to support one another in the real-time balancing of the system. The design of balancing markets is crucial, since real-time prices drive all forward markets due to financial arbitrage. For this reason, Papavasiliou and Bertrand (2021) employed multi-agent reinforcement learning to simulate economic equilibria that emerge from various market design proposals. Multi-agent learning confirms equilibria that are computed analytically. This informs policy debate, and specifically highlights market design pitfalls that should be avoided, thereby offering prescriptive policy guidance. Interesting challenges remain, particularly regarding the convergence guarantees and what these multi-agent learning algorithms can reveal about settings where analytical characterizations of equilibria are not available. Furthermore, in systems with significant amounts of hydro, coordinating water storage is a challenging planning process due to the uncertainty of monthly rainfall. For instance, batch learning can be used in order to develop a stochastic dynamic programming algorithm that is shown to outperform PSR-SDDP, the best-in-kind commercial algorithm that is available for optimizing water levels in hydrothermal systems (Ávila and Papavasiliou 2024), since batch learning allows for dynamic programming algorithms to rapidly focus their search on relevant parts of the state space, and improve approximations of exact dynamic programming functions in the neighborhood of exactly those relevant parts of the space.

4. AI, Energy and Environment: The Data Centers Paradox

Artificial intelligence places significant demands on electric power consumption in the form of data centers. It remains to be seen whether these new loads can also exploit their temporal and spatial flexibility in power consumption to offer certain balancing services to the system. Such data centers are deployed in conjunction with renewable energy projects to offset both increased emissions resulting from power production requirements and potential increases in electricity prices due to system loading. A notable example in the case of Greece is Amazon, which has entered into eight power purchase agreements for a total installed capacity of 657 MW, with renewable investments planned for Thessaly, Macedonia, and the Peloponnese.

Indeed, the environmental footprint of AI itself presents a policy paradox that demands innovative economic instruments. Training large language models can generate substantial carbon emissions (Strubell et al., 2019), while data centers consume approximately 1.5% of the world's electricity, according to recent estimates from the IEA (IEA, 2025). Addressing this challenge requires a multifaceted approach that includes both incentive structures and systemic reforms. Governments can implement differential tax rates or subsidies based on the energy efficiency of AI systems and their contribution to environmental objectives, creating what might be termed "green AI incentives." For instance, AI applications that demonstrably reduce emissions in other sectors could receive preferential treatment, while purely commercial applications face higher computational taxes to reflect their environmental costs. Additionally, applying circular economy principles to digital infrastructure represents another crucial policy direction, given that the rapid obsolescence of hardware used in AI systems contributes to the growing problem of electronic waste. Policy frameworks should mandate extended producer responsibility for AI hardware, thereby ensuring that manufacturers bear responsibility for the entire lifecycle of their products. These frameworks should also incentivize the development of more durable and repairable systems that can extend the useful lifespan of hardware, and support research into energy-efficient algorithms and neuromorphic computing architectures that could fundamentally reduce the energy intensity of AI operations.

5. Future Directions and Research Priorities

The integration of AI, human security, and environmental sustainability requires continued innovation in both technology and governance. Preliminary research, including the development of the Ae4ria SDG Tracker[1], suggests that machine learning approaches can help reveal connections between different dimensions of sustainability, potentially enabling more effective and equitable policy design (Koundouri et al., 2025). Building on this foundation, the Ae4ria AI Skills Tool[2] extends the application of artificial intelligence toward workforce and educational dimensions of sustainability. By mapping the skills, occupations, and learning pathways most closely associated with sustainability-oriented policies, it bridges environmental objectives with the digital and green competencies required for a resilient economy. This complementary perspective underscores how AI can support not only data-driven policy formulation but also the broader transformation of human capital necessary to implement sustainable strategies.

Several priority areas demand attention in future research. First, there is a pressing need to develop context-aware AI systems that can adapt to the significant variations in environmental challenges across different geographic and socio-economic contexts. These future AI systems must be capable of responding to local conditions while simultaneously maintaining global coherence in addressing planetary boundaries. Second, while current research identifies important connections between human security and the Sustainable Development Goals, considerably more work is needed to quantify the magnitude of synergies and trade-offs between these dimensions. This will require developing new economic valuation methods that can capture the full spectrum of ecosystem services and human well-being indicators in ways that traditional approaches have not adequately addressed. Third, building institutional capacity represents another critical challenge, as the effective use of AI for environmental sustainability requires significant investment in human capital. Educational programs must bridge the gap between environmental science, economics, and data science, thereby creating a new generation of professionals who can navigate this complex interdisciplinary landscape. Ultimately, establishing international cooperation frameworks is crucial, as environmental challenges transcend national boundaries and necessitate coordinated governance of AI at the global level. This includes developing common standards for environmental AI applications, facilitating data sharing agreements across borders, and ensuring that the benefits of AI-driven sustainability solutions reach developing countries that might otherwise lack access to these transformative technologies.

6. Conclusion

Through machine learning (ML), deep learning (DL), natural language processing (NLP), and computer vision (CV), AI enables scalable, real-time insight across all dimensions of sustainability. Indeed, AI transforms how the world measures and advances sustainable development; from “AMP Robotics” sorting waste to “CityBrain” optimizing traffic and “IBM Fairness 360” promoting equity, AI offers unprecedented tools for global progress. The integration of AI into environmental sustainability efforts, viewed through the lens of human security and digital transformation, represents both an imperative and an opportunity. However, realizing the potential of AI requires careful attention to the economic, institutional, and ethical dimensions of AI deployment. The environmental footprint of AI itself must be addressed through innovative policy instruments, while governance frameworks must ensure that AI applications promote rather than undermine inclusiveness, transparency, and sustainability. As we advance, maintaining an integrated perspective that recognizes the interconnections between technology, economy, society, and environment will be essential.

[1] AE4RIA SDG Tracker. Available at: https://Ae4ria.org/Ae4ria-sdg-tracker/
[2] AE4RIA AI Skills Tool Available at: https://Ae4ria.org/Ae4ria-ai-skills-tool-quick-start-guide/

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