TecnoLógicas

Editorial

Towards Conscious AI: The Role of Computer Sciences in the Energy, Social, and Ethical Sustainability of Artificial Intelligence

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The emergence of artificial intelligence (AI) in the past decade has profoundly transformed multiple areas of knowledge and industry. However, this transformative potential presents two sides of the same coin: on the one hand, the promise of smarter, more efficient, and fairer development; on the other hand, an increasing impact on energy, environmental, social, and ethical terms. In this context, computer science play an essential role in ensuring that the development and use of AI are sustainable—not only energetic, but also social and ethical. This editorial explores how recent advances open promising paths and what challenges remain.

For AI to become a true engine of sustainable development, the computer science community must adopt a holistic approach combining technical optimization (efficiency, hardware, software), computational ethics (fairness, explainability, values), and social governance (inclusion, access, impact). We will develop these aspects in two main dimensions: energy sustainability and social/ethical sustainability.

Energy sustainability: Computational efficiency

The exponential growth of AI models, particularly large-scale generative models and the so-called Large Language Models (LLMs), has generated an energy and carbon footprint that can no longer be considered marginal. A recent review shows that the so-called “Green AI” has become a cornerstone of the sustainability of the AI ecosystem [1].

Computer sciences contribute techniques such as pruning (removing unnecessary parameters), quantization (reducing weight precision), and knowledge distillation (transferring knowledge to smaller models). A comprehensive framework [2] highlights pruning and quantization among the main techniques to reduce model energy consumption. Complementarily, [3] analyzes how these tactics improve the energy efficiency of machine learning models.

A landmark study [4] proposes the SPROUT framework for LLM inference, reducing the carbon footprint by more than 40% through guided generation. Moreover, the integration of AI techniques into renewable energy management is another key vector of technological sustainability. An analysis of variables influencing solar and wind energy forecasting using ensemble methods is presented in [5], demonstrating how AI can optimize renewable energy integration and thus reduce the overall energy footprint of intelligent systems. This type of work shows how computer sciences not only improve model efficiency but also contribute directly to the sustainable energy transition. The need for carbon footprint reduction strategies in AI is also emphasized in [6], highlighting that large models must be designed with environmental awareness.

Beyond the models themselves, the supporting infrastructure must also be revised. In [2] was proposed a “Green AI” framework that includes efficient hardware, sustainable data centers, and scalability for less privileged environments. A data center report indicates that electricity use could increase by approximately 4% of national consumption to 8–11% in the United States by 2030, underscoring the urgency of efficiency [7].

An emerging technique for efficiency is federated learning, which reduces the need for centralized data transmission and storage. Cost and emission reductions when applying federated reinforcement learning in buildings are shown in [8]. Likewise, survey on “Green Federated Learning” explores how to make FL more environmentally friendly [9].

Together, computer sciences promote AI’s energy sustainability through three key vectors: algorithmic optimization, greener infrastructures, and decentralized deployment models. However, efficiency alone is not enough; we must also consider social and ethical impact.

Social and ethical sustainability

The sustainability of AI is not limited to its energy footprint; it also concerns social justice, fairness, explainability, and alignment with human values. Computer sciences play a crucial role in designing frameworks, algorithms, and tools that operate responsibly. A computational framework of human values aimed at incorporating ethical principles into AI systems is presented in [10]. A comprehensive ethical framework integrating transparency, fairness, and privacy into AI technologies is developed in [11].

The relationship between explainable AI (XAI) and fairness is critically reviewed in [12], concluding that explainability alone is insufficient and emphasize the need for more precise context-dependent metrics. Another emerging line proposed by [13] introduces inequality-based metrics (Gini, Atkinson) to learn user preferences and incorporate the notion of “epistemic fairness” in machine learning.

AI deployment must account for community inclusion, equitable access, and transparency in its impact. A recent sociotechnical approach published in 2025 addresses the intersection of bias and social justice in AI systems [14]. Additionally, the study in [15] examines large language model supply chains, warning that sustainability must also consider training, hardware, renewable energy, and developing-country contexts.

Computer science provides tools and frameworks capable of addressing bias, transparency, auditing, and human values in AI. Integrating these aspects with technical efficiency is the key to achieving truly sustainable AI.

This editorial argues that sustainable AI development requires a dual perspective: energy efficiency through technical optimization and renewable infrastructures, and social and ethical sustainability through value-based frameworks, fairness, and transparency. Computer sciences are central to designing algorithms and systems that make AI both powerful and responsible.

Future research priorities include the development of social metrics integrable into algorithms, auditing tools combining energy efficiency and data fairness, infrastructure aligned with renewable energy and resource traceability, participatory governance models including communities and developing countries, and longitudinal studies linking technical results with human development indicators.

For AI to become a true engine of sustainable development, it is not enough to advance in capabilities; we must design with awareness, measure with rigor, and govern with fairness.

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