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The Role of Artificial Intelligence in Promoting the Sustainable Development Goals

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دور الذكاء الاصطناعي في تعزيز أهداف التنمية المستدامة (*SDGs*)

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Abstract:
This paper explores the transformative role of artificial intelligence (AI) as a strategic tool for achieving the United Nations Sustainable Development Goals (SDGs). It highlights the immense potential of machine learning and big data analytics across vital sectors—including healthcare, education, smart agriculture, and sustainable cities—to optimize resources and combat climate change. However, the study also critically examines the significant challenges of this digital transformation, such as algorithmic bias, privacy violations, the massive carbon footprint of data centers, and the risk of widening the digital divide between the Global North and South. The paper concludes that robust international governance frameworks and ethical legislation are essential to ensure a responsible technological revolution, recommending substantial investment in "green AI" and global cooperation for inclusive knowledge transfer.

Keywords: Artificial Intelligence (AI), Sustainable Development Goals (Sdgs), Machine Learning, Big Data, Resource Efficiency, Climate Change, Ethical Challenges, Carbon Footprint, Digital Governance, Environmental Sustainability.

الملخص
تستكشف هذه الورقة الدور التحويلي للذكاء الاصطناعي (AI) كأداة استراتيجية لتحقيق أهداف التنمية المستدامة للأمم المتحدة، حيث تحلل الدراسة كيف يمكن لخوارزميات التعلم الآلي وتحليل البيانات الضخمة تحسين كفاءة الموارد، ومكافحة التغير المناخي، وتعزيز العدالة الاجتماعية والاقتصادية، مع الإشارة إلى التحديات الأخلاقية والتقنية المرتبطة بذلك. وفي هذا السياق، تسلط الدراسة الضوء على الإمكانات الهائلة التي توفرها التقنيات الذكية في مجالات حيوية متعددة، مثل تطوير منظومات الرعاية الصحية عبر التشخيص المبكر للأمراض وتوقع الأوبئة، ودعم قطاع التعليم من خلال توفير منصات تعليمية مرنة تتكيف مع احتياجات الطلاب الفردية وتساهم في تقليص الفجوات المعرفية. كما تبحث الورقة في كيفية تمكين الزراعة الذكية لزيادة إنتاجية المحاصيل وتقليل استهلاك المياه والأسمدة، إلى جانب دور الذكاء الاصطناعي في بناء المدن المستدامة عن طريق الإدارة الذكية لشبكات المرور وتوفير الطاقة في المباني السكنية والصناعية. وعلى الجانب الآخر، يطرح البحث تحليلاً نقدياً للتحديات والتهديدات المصاحبة لهذا التحول الرقمي، وفي مقدمتها معضلة الانحياز الخوارزمي وغياب الشفافية في بعض الأنظمة المعقدة، بالإضافة إلى المخاطر المتعلقة بانتهاك الخصوصية وأمن البيانات. ولا تغفل الورقة مناقشة الأثر البيئي المباشر للتكنولوجيا نفسها، والمتمثل في البصمة الكربونية الضخمة لمراكز البيانات نتيجة استهلاكها الهائل للطاقة والمياه لتشغيل النماذج الذكاء الاصطناعي العملاقة. وتحذر الدراسة من أن غياب التوزيع العادل لهذه التقنيات قد يؤدي إلى اتساع الفجوة الرقمية بين دول الشمال والجنوب العالمي، مما قد يعمق أوجه عدم المساواة القائمة

بدلاً من علاجها. وبناءً على هذه المعطيات، تخلص الورقة إلى ضرورة صياغة أطر حوكمة دولية صارمة وتشريعات أخلاقية تضمن توجيه هذه الطفرة التكنولوجية لخدمة الإنسانية بشكل مسؤول، مع التوصية بالاستثمار المكثف في تطوير "الذكاء الاصطناعي الأخضر" الصديق للبيئة وتفعيل قنوات التعاون الدولي لنقل المعرفة لضمان مستقبل مستدام وشامل للجميع.

الكلمات المفتاحية: الذكاء الاصطناعي (AI)، أهداف التنمية المستدامة (SDGs)، التعلم الآلي، البيانات الضخمة، كفاءة الموارد، التغير المناخي، التحديات الأخلاقية، البصمة الكربونية، الحوكمة الرقمية، الاستدامة البيئية.

Introduction

The 2030 Agenda for Sustainable Development established seventeen interlinked Sustainable Development Goals (SDGs) intended to balance economic growth, social inclusion, and environmental protection (United Nations General Assembly, 2015). Progress remains uneven — the UN's own 2024 assessment found only 17% of targets on track globally, with over a third stalled or reversing (United Nations, 2024) — motivating interest in AI as a strategic accelerator. Using expert elicitation, Vinuesa et al. found AI could enable 134 of 169 SDG targets while simultaneously inhibiting 59, with the environmental pillar showing the least clear net benefit (Vinuesa et al., 2020). This dual finding anchors the paper: AI's contribution to sustainability is neither uniformly positive nor negative, and a credible assessment must hold both sides of the ledger together.

2. Research Problem, Question, and Methodology

The problem addressed here is the absence of an integrated governance framework that lets AI's potential to accelerate the SDGs be realised without deepening the inequalities and environmental pressures sustainability policy is meant to reduce. The guiding question: how can AI be deployed as a strategic enabler of the SDGs while mitigating its environmental costs, ethical risks, and contribution to the digital divide? This paper adopts a narrative (non-systematic) literature review: sources were drawn from leading peer-reviewed journals spanning AI, sustainability science, information systems, and applied ethics, plus official regulatory texts and sector reports, prioritising work published 2018–2024 that directly addresses AI's relationship to the SDGs, its environmental footprint, its governance, or the digital divide. Deliberate effort was made to include research groups beyond the frequently cited SDG-mapping cluster. Every source was cross-checked against publisher records (DOI resolution), and every in-text citation was verified against the reference list and vice versa; the review does not claim exhaustive coverage and should be read as a synthesis and governance proposal rather than a systematic mapping of the field.

3. Literature Review

This section moves from the optimistic case for AI, through its environmental and ethical costs, to the geopolitical and sector-specific evidence that ties the two together.

3.1 Technological optimism. Vinuesa et al.'s expert panel found AI could support progress on nearly 80% of assessed SDG targets, most strongly for poverty, health, and education (Vinuesa et al., 2020), extended by the same group to indicator-level assessment (Gupta et al., 2021), model interpretability (Vinuesa & Sirmacek, 2021), and regulatory design (Goh & Vinuesa, 2021). Sector evidence corroborates this: machine learning is central to smart-grid forecasting and renewable integration, though evaluations remain concentrated in North America and Europe (Kiasari et al., 2024), and deep learning now detects deforestation from satellite imagery at over 90% accuracy (Jelas et al., 2024)—strong performance, but with limited evidence yet from the Global South.

3.2 Environmental and technical critique. Strubell et al. showed that training a large Transformer model can emit as much CO2 as five cars over their lifetimes (Strubell et al., 2019; Strubell et al., 2020), prompting Schwartz et al.'s “Green AI” proposal to treat efficiency as a first-class research objective (Schwartz et al., 2020). The footprint extends beyond carbon: training GPT-3 evaporated roughly 700,000 litres of freshwater, with global AI water withdrawal projected at 4.2–6.6 billion m^3 by 2027 (Li et al., 2023), and generative AI could generate 1.2–5.0 million tonnes of e-waste by 2030, though circular-economy strategies could cut this by up to 86% (Wang et al., 2024). No single-footprint assessment of AI's environmental cost is complete.

3.3 Ethical dimension. Floridi et al.'s AI4People framework distilled five ethical principles into twenty governance recommendations (Floridi et al., 2018), a convergence corroborated by Jobin et al.'s mapping of 84 global AI ethics guidelines—though with substantial divergence in how signatories implemented them (Jobin et al., 2019). Explainable AI (XAI) operationalises these principles in practice, notably in healthcare (Sadeghi et al., 2024), building on Lundberg and Lee's SHAP framework (Lundberg & Lee, 2017). The stakes are concrete: Obermeyer et al.'s audit of a U.S. healthcare algorithm found Black patients had to be considerably sicker than white patients to receive the same risk score, because the model used cost as a proxy for need; correcting this raised the share of Black patients flagged for extra care from 17.7% to 46.5% (Obermeyer et al., 2019). Rafi et al.

add that privacy- and fairness-preserving objectives in federated learning are difficult to satisfy jointly (Rafi et al., 2024).

3.4 Geopolitical dimension. AI's benefits remain concentrated in the Global North (World Economic Forum, 2023): 2024 private investment reached $109.1 billion in the United States against $9.3 billion in China, alongside persistent African infrastructure gaps (Stanford HAI, 2025). Malatji's AI-readiness scores for sub-Saharan Africa ranged from 42.6 to 53.9 against a global-leader benchmark above 80 (Malatji, 2026), while Kong et al. found a similar Middle East–North Africa split (51.1 versus 38.6), with governance lagging adoption in both (Kong et al., 2024). The EU's AI Act, in force since August 2024, offers the clearest existing precedent for the binding governance this paper recommends (European Union, 2024).

3.5 Independent corroborating strands. Beyond the SDG-mapping tradition, Nishant et al. call for integrating institutional and design-thinking perspectives alongside technical ones (Nishant et al., 2020), while van Wynsberghe distinguishes “AI for sustainability” from the “sustainability of AI” itself—a distinction that structures the Discussion below (van Wynsberghe, 2021).

3.6 Economic and social pillar evidence. Robotic waste-sorting improves material recovery but struggles with visually similar materials (Satav et al., 2023). Logistics performance correlates strongly with overall SDG attainment ($r = 0.758$) yet negatively with SDG 12 and 13 (Chen et al., 2024)—AI advancing some goals while working against others. Adaptive learning platforms show consistent gains, though almost entirely in well-resourced institutions (Essa et al., 2023), precisely the kind of gap Section 4 flags.

4. Gaps Addressed by This Paper

[1] Sharp polarisation: much prior work is either optimistic about AI's developmental upside or focused on its environmental/ethical costs, rarely holding both in a single evaluative model.

[2] Fragmented climate accounting: studies praising AI's climate applications often omit AI's own energy and water footprint from the balance sheet.

[3] Thin governance detail: most literature describes what AI can theoretically do, with comparatively little operational guidance for regulators or institutions.

[4] Global South specificity: the bulk of the literature is anchored in developed-economy infrastructure and institutions, under-addressing the additional constraints facing developing countries.

5. Areas of Intersection: AI and the SDGs

Table 1 maps representative AI applications across the environmental, economic, and social pillars to their underlying mechanism and sustainability benefit, each entry tied to a verified source, including precision agriculture (Xing & Wang, 2024) and natural-disaster early warning (Jain et al., 2023) rather than presented as a general claim about the field.

Table 1. Representative AI Applications Across the Environmental, Economic, and Social Pillars

Pillar	Application	AI Mechanism	Sustainability Benefit
Environmental (Energy & Climate)	Smart grids	Predictive load-forecasting algorithms	Optimised renewable-energy distribution, reduced grid waste (Kiasari et al., 2024)
	Precision agriculture	Computer vision & remote sensing	Improved water/nutrient-use efficiency via sensor-guided irrigation and fertilisation (Xing & Wang, 2024)
	Climate monitoring	Deep learning on satellite imagery	Deforestation tracking at >90% accuracy (Jelas et al., 2024); natural-disaster early warning (Jain et al., 2023)
Economic (Innovation & Industry)	Circular economy	Robotic waste-sorting, computer vision	Higher material-recovery rates, waste-to-resource pipelines (Satav et al., 2023)
	Supply-chain optimisation	AI-driven logistics planning	Shorter routes, lower fuel consumption and emissions (Chen et al., 2024)
Social (Education & Health)	Personalised education	Adaptive learning platforms	Content tailored to student level, narrower knowledge gaps (Essa et al., 2023)
	Smart healthcare	AI-assisted diagnostics, XAI	Earlier disease detection, improved access in underserved areas

6. Ethical Challenges and Risks

Sections 3.2 through 3.4 identified four recurring risks: the digital divide, energy and water consumption, algorithmic bias and opacity, and privacy and data-governance failures. Table 2 restates each in operational terms—what it consists of and which mitigation addresses it—carried forward directly into the governance framework in Section 7.

Table 2. Ethical and Technical Risks in AI Deployment, with Illustrative Mitigations

Challenge	Description	Illustrative Mitigation
Digital divide	Unequal access to AI infrastructure, data, and talent between developed and developing economies, risking a new "AI divide" layered on the pre-existing digital divide (World Economic Forum, 2023).	Technology-transfer agreements, subsidised cloud access, local capacity building
Energy & water consumption	Training and operating large models requires substantial electricity and, less visibly, freshwater for cooling; global AI water withdrawal is projected to reach 4.2–6.6 billion m^3 by 2027 (Li et al., 2023).	Renewable-powered data centres, lightweight/efficient model design ("Green AI"), mandatory water-use disclosure
Algorithmic bias & opacity	Models trained on unrepresentative or historically biased data can produce discriminatory outcomes; complex "black-box" models resist scrutiny (Floridi et al., 2018; Obermeyer et al., 2019).	Regular algorithmic audits, explainable AI (XAI) standards for high-stakes decisions
Privacy & data governance	Large-scale data collection required for AI raises risks of surveillance, unauthorised commercial use, and erosion of data sovereignty; privacy- and fairness-preserving objectives are difficult to satisfy jointly (Rafi et al., 2024).	Binding data-protection law, informed consent, data localisation where appropriate (European Union, 2024)

7. Proposed Governance Framework

Each pillar below draws on an existing framework (Green AI, AI4People, technology-transfer policy, SDG 17 partnership models); the contribution here is their explicit integration into a single accountability structure in which each pillar names the specific harm identified in Table 2 that it is meant to close, rather than standing as a generic best-practice list. Section 8 returns to the tensions this integration surfaces rather than treating the four pillars as independently sufficient.

Pillar 1 — Green AI governance. Energy-efficiency standards, funding for lightweight model architectures (Schwartz et al., 2020), and mandatory water-use disclosure alongside carbon disclosure, given AI's comparably large water and carbon footprints (Li et al., 2023).

Pillar 2 — Ethical and explainable AI. Regular algorithmic audits, mandatory explainability for high-stakes decisions (Sadeghi et al., 2024), and enforceable data-protection standards (Floridi et al., 2018). The EU AI Act shows such obligations are workable at scale, though extending them to resource-constrained jurisdictions requires the support described under Pillar 3 (European Union, 2024).

Pillar 3 — Bridging the digital divide. Technology-transfer agreements, subsidised cloud infrastructure, and local capacity-building to counter the concentration of AI benefits in the Global North (World Economic Forum, 2023).

Pillar 4 — Multi-stakeholder partnerships. Coordinating councils linking governments, technology firms, and academic institutions, aligned with SDG 17, plus co-financing instruments for AI applications targeting food security, pandemic response, and disaster management.

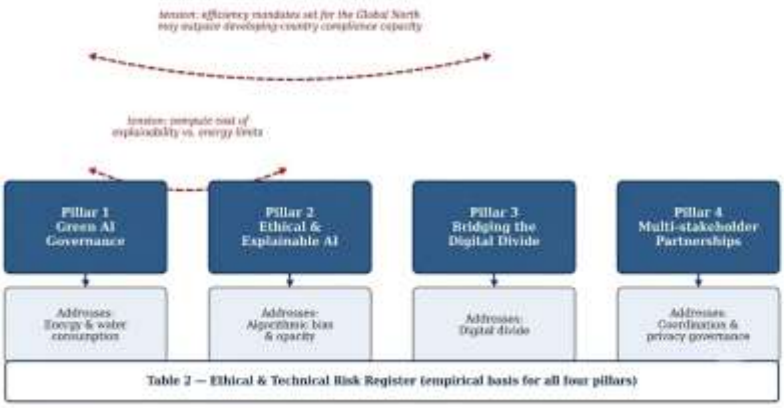

Figure 1. Proposed four-pillar AI governance framework, showing the specific harm each pillar is designed to close (Table 2) and the two principal cross-pillar tensions discussed in Section 8.

8. Discussion

The literature splits along a line van Wynsberghe makes explicit: "AI for sustainability" versus the "sustainability of AI" itself (van Wynsberghe, 2021) (Figure 2). The framework in Section 7 only holds if both are addressed together: Pillar 2's explainability mandate can itself raise compute, energy, and water use, so Pillar 1's disclosure requirements make that trade-off visible rather than treating explainability as costless. A second tension sits between Pillar 3 and Pillar 1: efficiency mandates calibrated to Global-North infrastructure may outpace developing-country compliance capacity, so capacity-building under Pillar 3 should be sequenced ahead of, not after, compliance deadlines (Nishant et al., 2020). Read together, the four pillars function as jointly binding constraints rather than an independent checklist, and future empirical work—ideally case studies from the Global South, where this literature remains thin—would test whether such joint constraints are workable in practice.

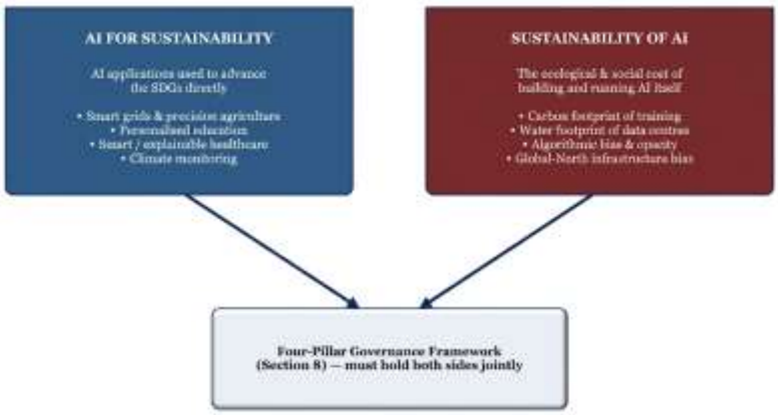

Figure 2. The organising distinction of this Discussion, after van Wynsberghe (2021): AI for Sustainability and the Sustainability of AI are treated as jointly binding constraints on the governance framework in Section 7, not as independent tracks.

9. Limitations

This is a narrative, not systematic, review: source selection was purposive rather than protocol-driven, though every claim was checked directly against its original source rather than a third party's citation of it. The reference base spans 31 sources across more than one research group, but empirical work from outside North America and Europe remains comparatively scarce, and the proposed framework is a synthesis of principles rather than a tested policy instrument whose feasibility will vary by national context.

10. Conclusion

AI is best understood neither as an unqualified accelerator nor an unqualified threat to sustainable development, but as a technology whose net effect depends on the governance choices made around it (Vinuesa et al., 2020). Binding, verifiable governance is needed across four interacting areas: AI's own footprint, the fairness of its decisions, the equity of its global distribution, and the partnerships needed to sustain all three. Future work should prioritise empirical, context-specific studies from the Global South, where the literature remains comparatively thin.

Declarations

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