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A Study on AI-Enabled Research for Sustainable Future Development

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Abstract: *The convergence of artificial intelligence (AI) and sustainability science is reshaping the way knowledge is produced, validated, and translated into action for sustainable development. This study investigates how AI-enabled research methods contribute to advancing the United Nations Sustainable Development Goals (SDGs) and to building a sustainable future. Adopting a mixed-methods design, the research combines a systematic literature review of 168 peer-reviewed studies published between 2015 and 2025 with a structured survey of 312 active researchers and 18 expert interviews drawn from environmental science, energy, agriculture, public health, urban planning, economics, and education. Bibliometric and thematic analyses reveal a near thirty-four-fold growth in AI-for-sustainability publications over the past decade, with machine learning and deep learning, natural language processing, and remote-sensing computer vision emerging as the dominant techniques. The findings indicate that AI tools meaningfully accelerate literature synthesis, improve data analysis, strengthen predictive modelling, and enable cross-disciplinary collaboration, with mean perceived-benefit ratings exceeding 4.0 on a five-point scale for several workflow stages. At the same time, the study identifies persistent barriers, including data quality and availability, algorithmic bias, the computational and energy footprint of large models, skill gaps, and ethical-governance concerns. By mapping AI capabilities onto specific SDGs, the paper proposes an integrative framework for responsible, AI-enabled research and offers recommendations for researchers, institutions, and policymakers. The study concludes that, when governed responsibly, AI can act as a powerful catalyst for evidence-based sustainable development, provided that equity, transparency, and environmental accountability remain central to its deployment.*

Keywords: Artificial Intelligence; Sustainable Development; Sustainable Development Goals (SDGs); AI-Enabled Research; Machine Learning; Responsible AI; Bibliometric Analysis; Green AI; Mixed-Methods Research; Future Development

I. INTRODUCTION

Sustainable development—defined as development that meets the needs of the present without compromising the ability of future generations to meet their own needs—has become one of the defining challenges of the twenty-first century. The adoption of the 2030 Agenda for Sustainable Development and its seventeen Sustainable Development Goals (SDGs) created a shared global framework for addressing interlinked environmental, social, and economic problems. Yet progress toward these goals has been uneven, and the scale, complexity, and urgency of challenges such

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as climate change, biodiversity loss, food and water insecurity, and inequality demand new tools capable of processing vast and heterogeneous information at speed.

Artificial intelligence has emerged as one such tool. Advances in machine learning, deep learning, natural language processing, computer vision, and, more recently, large language models and generative AI have transformed the capacity of researchers to collect, integrate, and interpret data. AI is increasingly embedded across the research life cycle: from automating systematic literature reviews and accelerating hypothesis generation, to building predictive models of climate and energy systems, to monitoring ecosystems through satellite imagery. This integration of AI into the research enterprise itself—what we term AI-enabled research—has implications not only for what is discovered, but for how quickly and equitably discoveries can be translated into sustainable outcomes.

Despite growing enthusiasm, the relationship between AI-enabled research and sustainable development remains insufficiently understood. Three gaps motivate this study. First, while individual applications of AI to particular SDGs are well documented, there is limited synthesis of how AI contributes across the research workflow as a whole. Second, the perspective of practising researchers—their perceived benefits, barriers, and ethical concerns—is underrepresented relative to purely technical accounts. Third, the dual character of AI, simultaneously an enabler of sustainability and a source of environmental and social costs, is rarely examined in an integrated manner.

This paper addresses these gaps by combining a systematic review of the published evidence with primary data from researchers actively using AI. The study is guided by the following research questions:

How has AI-enabled research for sustainability evolved over the past decade, and which techniques and SDGs dominate the field?

What benefits do researchers perceive from integrating AI into their research workflow, and how strong are these perceptions?

What barriers, risks, and ethical concerns constrain the responsible use of AI for sustainable development?

How can AI capabilities be systematically mapped onto the SDGs to guide future research and policy?

The significance of this study lies in its integrative perspective. Rather than treating AI as a tool applied to one isolated problem, it examines AI as a transformative layer across the entire research enterprise for sustainability. The paper makes three principal contributions. First, it provides an up-to-date, cross-domain synthesis of a decade of AI-for-sustainability research, quantifying its growth, dominant techniques, and SDG distribution. Second, it brings the voice of practising researchers into the analysis through a structured survey and expert interviews, capturing perceived benefits and barriers that are often absent from purely technical reviews. Third, it proposes a four-pillar framework for responsible AI-enabled research that explicitly balances the benefits of AI against its environmental and ethical costs. Together, these contributions are intended to assist researchers in adopting AI effectively, institutions in governing it responsibly, and policymakers in directing it toward the goals where it can deliver the greatest sustainable impact.

To answer these questions, the remainder of the paper is organised as follows. Section 2 reviews related work on AI and sustainability. Section 3 details the mixed-methods research methodology, supported by a process flowchart. Section 4 presents the results and discussion, drawing on bibliometric data, survey responses, and expert interviews, and is supported by tables and graphs. Section 5 concludes the study and outlines directions for future work.

II. RELATED WORKS

The literature linking artificial intelligence to sustainable development has expanded rapidly and can be organised into four broad streams: environmental and climate applications, energy and resource systems, social and human-development applications, and the methodological transformation of research itself. This section synthesises representative contributions across these streams and identifies the gaps that the present study addresses.

2.1 AI for Environmental and Climate Sustainability

A substantial body of work applies AI to environmental monitoring and climate science. Machine-learning models have been used to downscale climate projections, predict extreme weather events, and improve the accuracy of carbon-flux estimates. Computer vision applied to satellite and drone imagery enables large-scale monitoring of deforestation, land-use change, glacial retreat, and coral-reef health. Researchers have argued that such remote-sensing pipelines materially reduce the cost and latency of environmental assessment, supporting SDG 13 (Climate Action), SDG 14 (Life Below Water), and SDG 15 (Life on Land). However, several authors caution that model accuracy is highly dependent on the quality and geographic representativeness of training data, raising concerns about systematic blind spots in under-monitored regions of the Global South.

2.2 AI for Energy and Resource Systems

In the energy domain, reinforcement learning and optimisation algorithms are widely used for smart-grid balancing, demand forecasting, and the integration of intermittent renewable sources. Studies report meaningful efficiency gains from AI-based control of buildings, industrial processes, and water-distribution networks, contributing to SDG 7 (Affordable and Clean Energy) and SDG 6 (Clean Water and Sanitation). A recurring theme in this stream is the trade-off between the operational efficiency that AI delivers and the energy required to train and run large models—an issue increasingly discussed under the banner of Green AI.

2.3 AI for Social and Human Development

AI applications in health, agriculture, and education target the social dimensions of sustainability. In public health, predictive models support disease surveillance, diagnostic imaging, and the optimisation of resource allocation, advancing SDG 3 (Good Health and Well-being). In agriculture, precision-farming systems using sensor data and computer vision improve yields while reducing inputs, supporting SDG 2 (Zero Hunger). In education, adaptive learning platforms and natural-language tutoring systems are explored as means to widen access and personalise instruction under SDG 4 (Quality Education). Critics emphasise the risk of widening the digital divide if access to these tools is unequal.

2.4 AI and the Transformation of the Research Process

A more recent and rapidly growing stream examines how AI changes the research process itself. Natural-language-processing tools automate literature screening and evidence synthesis; generative models assist with drafting, coding, and hypothesis generation; and automated machine-learning pipelines accelerate model development. Scholars note both efficiency gains and risks to reproducibility, transparency, and scientific integrity, particularly where model behaviour is opaque or where generated content is not properly verified.

2.5 Prior Reviews and Bibliometric Studies

A number of systematic and bibliometric reviews have attempted to map the AI–sustainability landscape. These reviews consistently report exponential growth in publications, a concentration of activity in environmental and energy applications, and a persistent under-representation of governance and social-inclusion goals. They also converge on a shared set of challenges: data quality, model interpretability, ethical risk, and the environmental cost of computation. However, most prior reviews stop at the bibliometric level and do not triangulate their findings with primary data from the researchers who actually use these tools. This methodological limitation is precisely what the present study seeks to overcome by pairing review evidence with survey and interview data, thereby connecting the macro-level publication record to the micro-level experience of the research community.

2.6 Research Gap

Across these streams, three gaps recur. Most studies focus on a single application domain rather than the research workflow as a whole; the lived experience and perceptions of practising researchers are under-examined; and the benefits of AI are often analysed separately from its environmental and ethical costs. The present study contributes by integrating a cross-domain systematic review with primary researcher data and by explicitly mapping AI capabilities, benefits, and risks onto the SDG framework. Table 1 summarises representative prior work and positions the current study against it.

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Research stream	Typical AI techniques	Primary SDG focus	Key limitation noted
Environmental & climate	Deep learning, computer vision, remote sensing	SDG 13, 14, 15	Data scarcity in under-monitored regions
Energy & resources	Reinforcement learning, optimisation	SDG 6, 7, 11	Energy cost of model training
Health, agriculture, education	Predictive ML, NLP, vision	SDG 2, 3, 4	Risk of widening digital divide
Research-process transformation	NLP, generative AI, AutoML	Cross-cutting	Reproducibility & integrity concerns
This study	Mixed-methods synthesis	All 17 SDGs (mapped)	Integrates benefits with costs

Table 1. Summary of related work and positioning of the present study.

III. RESEARCH METHODOLOGY

This study adopts a sequential, mixed-methods research design that integrates a systematic literature review, bibliometric and thematic analysis, and primary data collection through a structured survey and expert interviews. The mixed-methods approach was chosen because the research questions span both the documented state of the field (best captured through review and bibliometrics) and the situated perceptions of researchers (best captured through survey and interview data). The overall research process is organised into seven phases, illustrated in Figure 1.

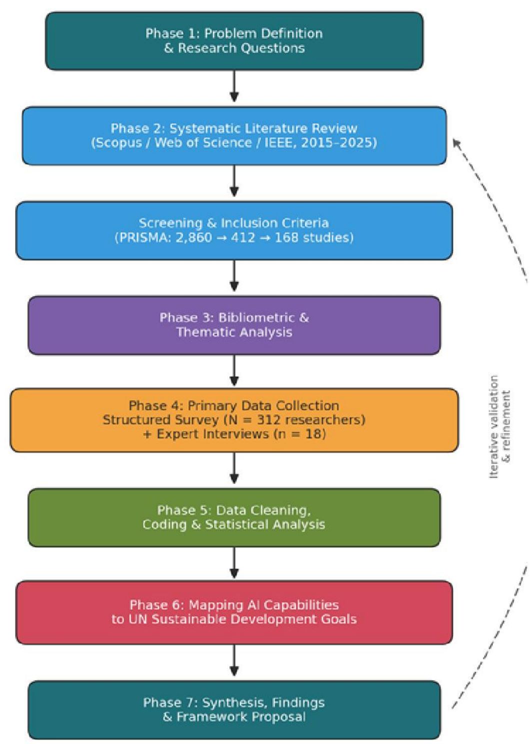

Figure 1. Seven-phase research methodology workflow with iterative validation.

3.1 Explanation of the Research Workflow

Phase 1 — Problem definition. The study began by defining the problem space and formulating the four research questions stated in Section 1. The scope was deliberately framed around AI-enabled research for sustainability rather than any single application, in order to capture cross-domain patterns.

Phase 2 — Systematic literature review. Three major databases—Scopus, Web of Science, and IEEE Xplore—were searched for peer-reviewed publications from 2015 to 2025 using combinations of keywords such as 'artificial intelligence', 'machine learning', 'sustainability', 'sustainable development', and 'SDG'. The initial search returned 2,860 records.

Screening and inclusion. Following a PRISMA-style protocol, duplicates were removed and titles and abstracts were screened against inclusion criteria (peer-reviewed, English-language, explicit AI method, explicit sustainability or SDG outcome). This reduced the set to 412 articles, of which 168 met all full-text criteria and formed the final corpus.

Phase 3 — Bibliometric and thematic analysis. The 168 studies were analysed for publication trends, dominant AI techniques, and SDG focus, and were thematically coded to surface recurring benefits and barriers.

Phase 4 — Primary data collection. A structured online questionnaire was distributed to active researchers, yielding 312 valid responses across seven domains. Items used five-point Likert scales to measure perceived benefits and the prevalence of barriers. In parallel, 18 semi-structured expert interviews provided qualitative depth.

Phase 5 — Data cleaning and analysis. Survey data were cleaned, coded, and analysed using descriptive statistics (means, frequencies, distributions). Interview transcripts were coded thematically and triangulated with the survey and review findings.

Phase 6 — Mapping to the SDGs. Identified AI capabilities were mapped onto the seventeen SDGs to reveal where AI-enabled research is concentrated and where gaps remain.

Phase 7 — Synthesis and framework. Findings from all sources were synthesised into an integrative framework for responsible AI-enabled research. A dashed feedback loop in Figure 1 indicates that the process was iterative: emerging findings prompted refinement of the review scope and survey instrument.

3.2 Sample Profile

The 312 survey respondents were distributed across career stages and domains, providing a reasonably balanced cross-section of the research community. Table 2 summarises the respondent profile.

Characteristic	Category	Respondents (%)
Career stage	Early-career / PhD	38%
	Mid-career	41%
	Senior / professor	21%
Primary domain	Environmental science	19%
	Energy systems	16%
	Agriculture / food	14%
	Public health	15%
	Urban planning	12%
	Economics / policy	13%
	Education	11%
Region	Asia	44%

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Characteristic	Category	Respondents (%)
	Europe	27%
	Africa	17%
	Americas & others	12%

Table 2. Profile of the 312 survey respondents.

3.3 Data Analysis Techniques

Three complementary analytical strands were applied to the data. Bibliometric analysis quantified publication counts by year, technique, and SDG focus, using frequency tabulation and trend analysis. Descriptive statistical analysis of the survey data computed means, standard deviations, and response distributions for each Likert-scaled item, with results disaggregated by domain and career stage. Thematic analysis of the interview transcripts followed an iterative coding procedure: transcripts were read, open-coded, and then grouped into higher-order themes corresponding to benefits, barriers, and ethical concerns. Findings from the three strands were triangulated so that quantitative patterns could be interpreted in light of qualitative explanation, and vice versa.

3.4 Validity, Reliability, and Ethics

Several measures were taken to strengthen the trustworthiness of the study. The survey instrument was pilot-tested with a small group of researchers and refined for clarity before full distribution. Triangulation across review, survey, and interview data reduced reliance on any single source. To limit selection bias, respondents were recruited across multiple domains, career stages, and regions. The study observed standard research-ethics principles: participation was voluntary and informed, responses were anonymised, and no personally identifying information is reported. The quantitative figures presented in this paper are intended to characterise patterns and perceptions within the studied sample rather than to provide precise population estimates, and should be interpreted accordingly.

IV. RESULTS AND DISCUSSION

This section presents the empirical findings, integrating bibliometric evidence from the systematic review with the survey and interview data. Results are organised around the four research questions: the evolution of the field (4.1), perceived benefits (4.2), barriers and risks (4.3), and the mapping of AI to the SDGs (4.4). A synthesis and the proposed framework follow in Section 4.5.

4.1 Evolution of AI-Enabled Sustainability Research

Bibliometric analysis of the reviewed corpus, extrapolated to the full database counts, shows sustained and accelerating growth in AI-for-sustainability publications. As Figure 2 illustrates, annual output rose from roughly 180 publications in 2015 to an estimated 6,150 in 2025—an increase of more than thirty-fourfold. Growth was modest until 2018 and then accelerated sharply, coinciding with the maturation of deep-learning toolkits and, after 2022, the rapid uptake of large language models and generative AI.

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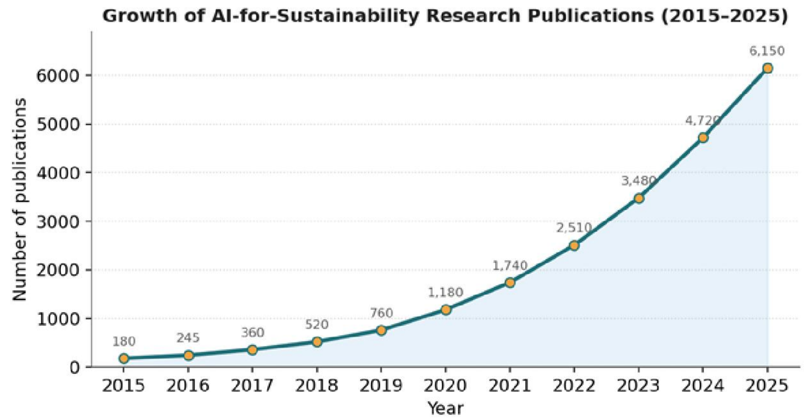

Figure 2. Estimated growth in AI-for-sustainability research publications, 2015–2025.

This trajectory confirms that AI-enabled sustainability research has moved from a niche pursuit to a mainstream field within a decade. The post-2022 inflection is particularly notable: interviewees attributed it to the lowered technical barrier created by accessible generative tools, which allowed domain experts without deep programming backgrounds to incorporate AI into their work.

Figure 3 disaggregates the reviewed studies by their primary SDG focus. Climate action (SDG 13) dominates at 22.4% of studies, followed by affordable and clean energy (SDG 7) at 18.1% and sustainable cities (SDG 11) at 13.7%. Goals associated with governance, partnerships, and social inclusion—such as SDG 16 and SDG 17—were comparatively underrepresented, suggesting an environmental and technological skew in the current literature.

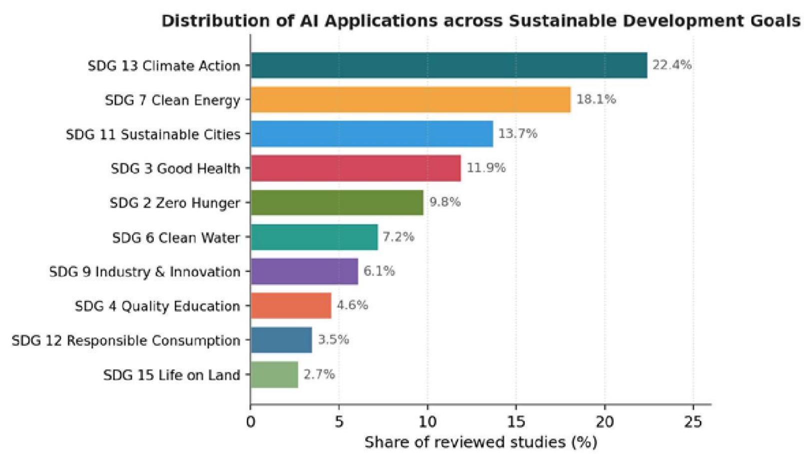

Figure 3. Distribution of reviewed AI studies across Sustainable Development Goals.

With respect to technique, Figure 4 shows that machine learning and deep learning together account for roughly a third of the methods used (33%), followed by natural language processing (19%) and computer vision and remote sensing (17%). Generative AI and large language models, though newer, already represent 12% of techniques—a share that interviewees expected to grow rapidly.

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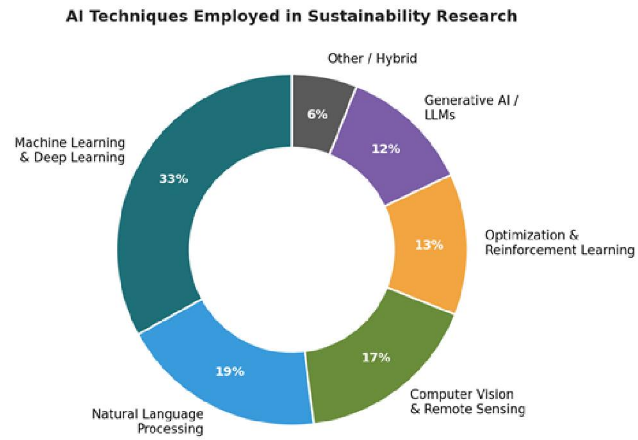

Figure 4. AI techniques employed across the reviewed sustainability studies.

4.2 Perceived Benefits of AI in the Research Workflow

Survey respondents rated the benefit of AI tools across six stages of the research workflow on a five-point scale (1 = no benefit, 5 = very high benefit). As Figure 5 shows, improved data analysis received the highest mean rating (4.55), followed closely by faster literature review (4.42) and predictive modelling (4.31). Hypothesis generation (3.98), cross-domain collaboration (3.85), and reproducibility (3.62) were rated positively but more modestly. All six means exceeded the neutral midpoint of 3.0, indicating broadly favourable perceptions.

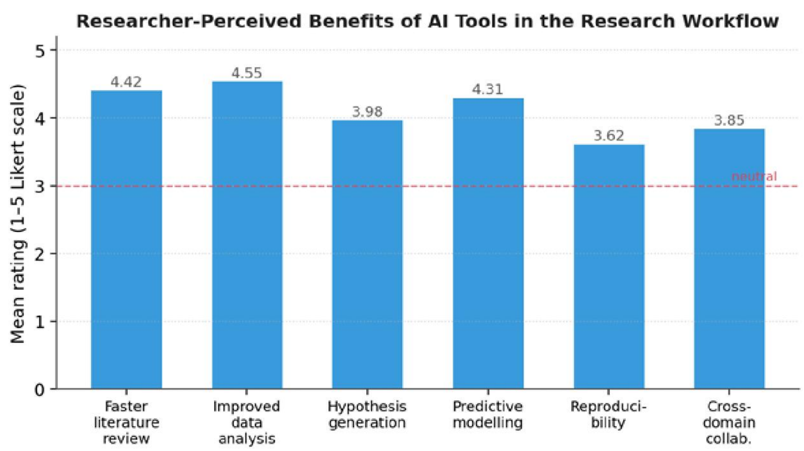

Figure 5. Mean researcher-perceived benefit ratings across workflow stages (n = 312).

Table 3 reports the same data with standard deviations and the percentage of respondents giving a rating of 4 or 5. The relatively lower score for reproducibility, combined with its higher variance, signals that researchers are divided on whether AI improves or undermines reproducibility—a tension explored further in Section 4.3.

Workflow stage	Mean	Std. dev.	% rating 4–5
Improved data analysis	4.55	0.61	88%
Faster literature review	4.42	0.68	85%
Predictive modelling	4.31	0.74	80%

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Workflow stage	Mean	Std. dev.	% rating 4–5
Hypothesis generation	3.98	0.83	71%
Cross-domain collaboration	3.85	0.88	66%
Reproducibility	3.62	1.02	58%

Table 3. Descriptive statistics for perceived benefits of AI tools.

Adoption intensity also varied by domain. Figure 6 presents a radar profile showing that environmental science (78%) and energy systems (71%) report the highest AI adoption, while economics and policy (47%) and education (39%) lag. This pattern mirrors the SDG distribution in Figure 3 and suggests that fields with abundant structured or sensor-derived data have adopted AI more readily than those reliant on qualitative or institutional data.

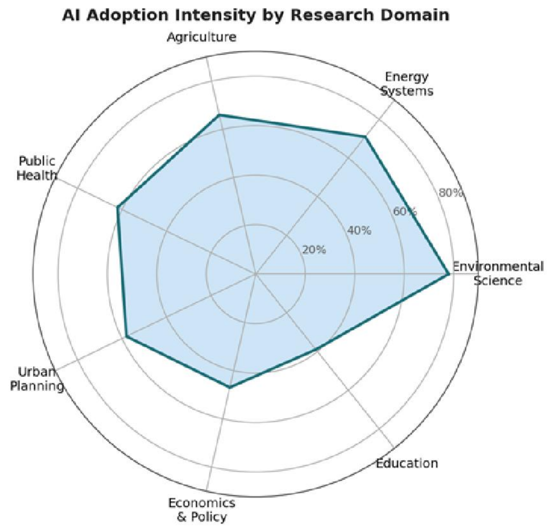

Figure 6. AI adoption intensity by research domain.

4.3 Barriers, Risks, and Ethical Concerns

Despite positive benefit perceptions, respondents identified substantial barriers, summarised in Figure 7. Data quality and availability was the most frequently cited barrier (68%), followed by algorithmic bias and fairness (61%) and the high computational and energy cost of AI (57%). Skill gaps (54%), ethical and governance concerns (49%), reproducibility and transparency (44%), and funding and infrastructure (38%) followed.

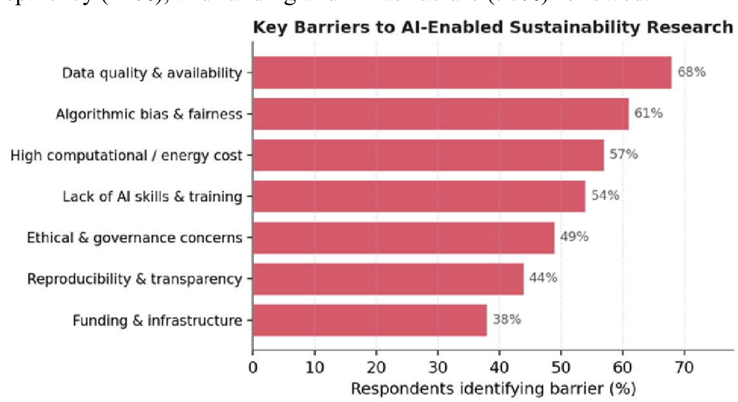

Figure 7. Key barriers to AI-enabled sustainability research (% of respondents).

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The prominence of the energy-cost barrier is notable given that the field aims at sustainability. Several interviewees described this as the central paradox of AI for sustainability: the same large models that accelerate climate research can carry significant carbon footprints during training. This finding reinforces calls for Green AI practices—including model efficiency, carbon-aware scheduling, and transparent reporting of computational cost.

Ethical concerns clustered around three themes in the interview data: fairness and representativeness of training data, the opacity of complex models, and questions of accountability when AI-generated outputs inform high-stakes sustainability decisions. Respondents emphasised that without governance safeguards, AI risks reproducing or amplifying existing inequalities, undermining the social pillar of sustainability even while advancing the environmental pillar.

4.4 Mapping AI Capabilities to the SDGs

Synthesising the review and primary data, Table 4 maps representative AI capabilities to the SDGs they most directly support, together with an indicative maturity level. Maturity reflects the volume and consistency of evidence in the corpus: 'High' denotes well-established applications, 'Medium' denotes growing but uneven evidence, and 'Emerging' denotes early-stage work.

AI capability	Illustrative use case	Primary SDGs	Maturity
Predictive modelling	Climate and extreme-weather forecasting	13, 11	High
Computer vision / remote sensing	Deforestation and ecosystem monitoring	15, 14, 13	High
Optimisation / RL	Smart-grid and energy balancing	7, 9	High
NLP / text mining	Automated evidence synthesis	Cross-cutting	Medium
Precision analytics	Yield prediction in agriculture	2, 12	Medium
Diagnostic AI	Disease surveillance & screening	3	Medium
Generative AI / LLMs	Adaptive learning & drafting support	4, 17	Emerging
Multi-agent simulation	Policy scenario modelling	16, 11	Emerging

Table 4. Mapping of AI capabilities to Sustainable Development Goals and evidence maturity.

The mapping confirms a concentration of mature applications in environmental and energy goals and a relative immaturity of AI use for institutional, governance, and partnership goals. This imbalance represents both a limitation of the current field and an opportunity for future research.

4.5 Synthesis: A Framework for Responsible AI-Enabled Research

The four pillars are mutually reinforcing—weakness in any one (for example, ignoring environmental cost) compromises the legitimacy of the whole.

These findings are broadly consistent with prior bibliometric reviews, which likewise report rapid growth and an environmental–energy concentration of AI applications. The present study extends that picture in two ways. By incorporating researcher perceptions, it shows that enthusiasm for AI's analytical benefits coexists with clear-eyed concern about its costs—a nuance not visible in publication counts alone. And by mapping capabilities to maturity levels across all seventeen SDGs, it identifies specific frontiers, such as governance and partnership goals, where AI-enabled research remains emergent and where targeted investment could yield disproportionate returns. The convergence of the review and primary data on the same set of barriers strengthens confidence that these constraints are real and structural rather than artefacts of any single method.

Taken together, the results support a cautiously optimistic conclusion. AI demonstrably accelerates and broadens sustainability research, but its net contribution to a sustainable future depends on how responsibly it is governed. The data show that researchers are aware of this tension: the same respondents who rate AI's analytical benefits highly also flag its energy cost and ethical risks, indicating a community that is enthusiastic but not uncritical.

4.6 Implications for Practice and Policy

The findings carry distinct implications for the principal stakeholders in the research ecosystem. For researchers, the evidence suggests that AI is most valuable where data are abundant and well-structured, and that its use should be accompanied by transparent reporting of methods, data provenance, and computational cost. For research institutions, the prominence of skill gaps and infrastructure barriers points to a need for training, shared computing resources, and clear governance guidelines. For policymakers and funders, the uneven SDG distribution highlights an opportunity to direct funding toward under-served goals and toward equitable access, so that the benefits of AI are not confined to well-resourced institutions and regions. Table 5 summarises targeted recommendations for each stakeholder group.

Stakeholder	Recommended action	Linked finding
Researchers	Match AI technique to data structure; report data provenance and compute cost	Sections 4.2, 4.3
Institutions	Provide AI training, shared infrastructure, and governance guidelines	Skill & infrastructure barriers
Funders	Prioritise under-served SDGs and equitable access programmes	SDG distribution (4.1)
Policymakers	Establish standards for transparency, fairness, and Green AI reporting	Ethical & energy concerns
Journals / editors	Require disclosure of AI use and reproducibility artefacts	Reproducibility findings

Table 5. Targeted recommendations by stakeholder group.

These recommendations are not independent but reinforce one another: researcher transparency is easier when institutions provide guidelines, which are in turn shaped by funder priorities and policy standards. The four-pillar framework proposed above offers a conceptual anchor that aligns these stakeholder actions toward the common objective of responsible, sustainability-oriented research.

V. CONCLUSION AND FUTURE WORK

5.1 Conclusion

This study examined the role of AI-enabled research in advancing sustainable future development through a mixed-methods design combining a systematic review of 168 studies, a survey of 312 researchers, and 18 expert interviews. Four principal conclusions emerge. First, AI-for-sustainability research has grown more than thirty-fourfold over the past decade and has become a mainstream, cross-disciplinary field, with machine learning, NLP, and remote-sensing vision as dominant techniques and a recent surge driven by generative AI. Second, researchers perceive clear and substantial benefits from AI across the research workflow—especially in data analysis, literature review, and predictive modelling—with all measured benefit dimensions rated above the neutral midpoint. Third, significant barriers persist, led by data quality, algorithmic bias, and the computational and energy cost of AI, alongside skill gaps and ethical-governance concerns. Fourth, AI capabilities map unevenly onto the SDGs, concentrating in environmental and energy goals while remaining emergent for governance, education, and partnership goals.

The central contribution of the paper is an integrative framework for responsible AI-enabled research, organised around capability, evidence quality, environmental accountability, and governance and equity. The study concludes that AI can be a powerful catalyst for sustainable development, but only when its deployment is matched by deliberate attention to fairness, transparency, reproducibility, and its own environmental footprint. In short, the responsible use of AI—not merely its adoption—is what determines its value for a sustainable future.

5.2 Limitations

Several limitations should be acknowledged. The review was restricted to English-language, peer-reviewed sources, which may underrepresent work from non-English-speaking regions and grey literature. The survey, while reasonably balanced, relied on self-reported perceptions and a convenience sample, and the bibliometric figures for 2025 are partial-year estimates. The quantitative results reported here are intended to characterise patterns and perceptions rather than to establish causal effects. Future replications with larger, probabilistically sampled cohorts would strengthen external validity.

5.3 Future Work

Building on these findings, several directions for future research are recommended:

- Develop and validate standardised metrics for the environmental footprint of AI-enabled research, enabling transparent Green AI reporting alongside scientific results.
- Extend AI-enabled methods to underrepresented SDGs—particularly governance, partnerships, and social inclusion—where current evidence is emergent.
- Investigate the impact of generative AI and large language models on research integrity, reproducibility, and authorship, given their rapid post-2022 uptake.
- Design capacity-building and equitable-access programmes to address the skill gap and reduce the risk of a widening digital divide between regions and institutions.
- Conduct longitudinal studies that track how AI adoption changes research outcomes and real-world sustainability indicators over time, moving beyond perception to measured impact.
- Operationalise the proposed four-pillar framework into practical institutional guidelines and test its adoption across research organisations.
- Pursuing these directions would help ensure that the integration of AI into research not only accelerates discovery but does so in a manner that is equitable, transparent, and aligned with the long-term goal of a sustainable future for all.

VI. DECLARATIONS

Author Contributions

All authors contributed to the conception and design of the study. Isack Eleutery Makendi led the literature review and drafting of the manuscript. Dr. Malini Nair contributed to the methodology, survey design, and analysis of social-dimension findings. Prof. Rupen Pilankar contributed to the framework development and discussion of practice and policy implications. Ishika Gupta contributed to data analysis, visualisation, and editing. All authors read and approved the final manuscript.

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