JOURNAL OF BUSINESS AND SOCIAL SCIENCES
eISSN:2805-5187 | Vol.2025, Issue 3, No.3

Leveraging Generative AI for Sustainable Development: Opportunities, Risks and Ethical Pathways

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Abstract

Generative Artificial Intelligence (GenAI) is emerging as a transformative technology with great potential to advance the United Nations Sustainable Development Goals (SDGs). This paper presents a systematic review of recent research to examine how GenAI contributes to sustainable development in sectors such as education, healthcare, and governance. The study highlights the major opportunities offered by GenAI, including improved productivity, equitable access to information, and data-driven decision making that supports long-term sustainability. At the same time, it identifies critical risks such as high energy consumption, environmental impact, and ethical challenges related to fairness, transparency, and accountability. The review follows the PSALSAR framework to collect, evaluate, and synthesize existing evidence on the benefits and risks of GenAI. It also assesses emerging approaches to responsible AI governance that aim to create an inclusive and sustainable digital ecosystem. By balancing innovation with ethical responsibility, this study provides policy and research recommendations to guide the sustainable and equitable use of generative AI for global development.

Keywords

Generative Artificial Intelligence, Sustainable Development Goals, Ethical AI, Responsible AI Governance, Energy Efficiency in AI, Sustainable Growth, Digital Inclusion, Environmental Impact, Data-Driven Decision Making, Sustainable Innovation

Submission: 15 October 2025; **Acceptance:** 21 December 2025 **Available online:** December 2025

Introduction

Background and Motivation

The rapid and widespread diffusion of Artificial Intelligence (AI) into nearly all organizational and societal activities necessitates its ethical and responsible deployment. While AI adoption offers notable benefits, it also carries potential ramifications and unexpected negative outcomes. Consequently, establishing responsible principles and effective governance mechanisms has become a central point of discussion to ensure AI is fair, equitable, ethical, and generally beneficial for all affected stakeholders.

AI is widely considered a general-purpose technology with broad applicability, possessing the potential to vastly improve efficiency and help resolve humanity's greatest challenges, such as the United Nations Sustainable Development Goals (SDGs) [7]. The UN Department of Economic and Social Affairs highlights AI's potential to meaningfully enable 79% (134 of 169) of the SDG targets [7]. However, despite global efforts, progress toward the 2030 Agenda for Sustainable Development is severely off-track, with 80% of SDG targets having deviated, stalled, or regressed as of 2023 [6]. This urgency highlights the critical need for transformative solutions.

The emergence of powerful Generative AI (GenAI) models, particularly Large Language Models (LLMs) such as ChatGPT, has introduced a paradigm shift in human-machine interaction [1]. These models demonstrate unprecedented capabilities in generating human-like text, engaging in complex dialogue, and solving problems based on massive datasets [8]. This technological leap necessitates revisiting and expanding responsible practices, as LLMs pose novel dilemmas regarding human creativity and accountability [5].

GenAI's Global Relevance, UN SDGs Linkage

Generative AI, exemplified by ChatGPT, is recognized as a critical ally and a game-changer for sustainable development [1][8]. It can be leveraged to understand human requirements for delivering desirable solutions, adapt to different environmental conditions for comprehensive decision-making, and provide equal access to information, thereby mitigating inequality [6].

LLMs have roles across the three pillars of sustainability social, environmental, and economic [8]. For instance, LLMs promote Quality Education (SDG 4) by providing accessible and personalized learning experiences, acting as a personalized tutor delivering tailored explanations, quizzes, and engaging lessons [3][4]. In Good Health and Well-being (SDG 3), LLMs enable intelligent recommendations for personalized diets and exercise strategies [1]. LLMs can also contribute to Clean Energy (SDG 7) by optimizing systems, managing energy consumption, and maintaining supply-demand balance using big data analysis [8][9].

However, the pursuit of progress through GenAI is fraught with challenges, as the computational requirements for training large-scale models are substantial, leading to concerns regarding environmental impact (e.g., carbon release and resource exhaustion) [5][9]. Furthermore, integrating these technologies without addressing algorithmic bias, data privacy, and accountability risks worsening existing social disparities, potentially hindering progress toward goals like Gender Equality (SDG 5) and Reduced Inequalities (SDG 10) [2][5].

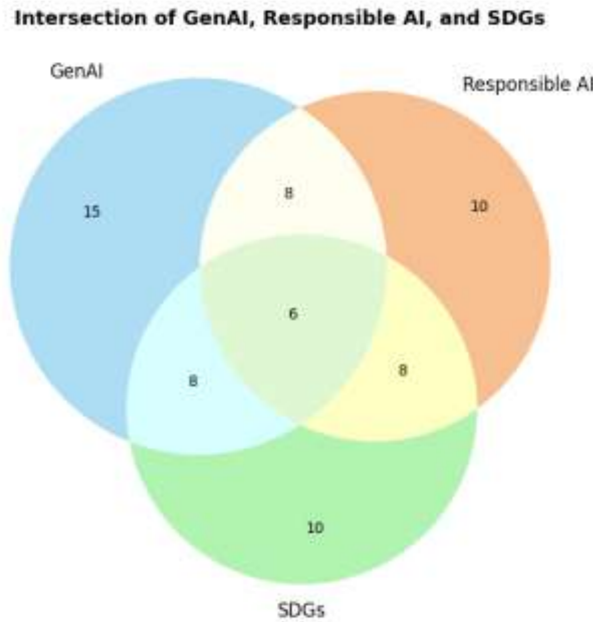

Figure 1: Venn Diagram

The Venn diagram provides a visual summary of how the fields of Generative AI, Responsible AI, and the Sustainable Development Goals (SDGs) both overlap and diverge within the context of sustainable digital transformation. The diagram underscores key synergies where all three domains intersect, representing initiatives, research, or policy that address AI innovation, ethical governance, and sustainability simultaneously. At the same time, it highlights noticeable gaps for example, innovations in GenAI that do not fully incorporate responsible frameworks or SDG priorities, and responsible AI efforts that may lack explicit connections to generative technologies or developmental outcomes. This framing sets the stage for a deeper exploration in this paper of the opportunities, risks, and governance challenges at these intersections, ultimately supporting the case for integrated, multi-disciplinary approaches to advancing sustainable and ethical AI deployment

The numbers shown within each region of the Venn diagram represent the count of initiatives, frameworks, or research items that are unique to a single domain, shared between two domains, or located at the intersection of all three. For example, elements in just one circle (e.g., GenAI only) are counted in the non-overlapping areas, while numbers in the overlapping sections indicate the extent to which GenAI, Responsible AI, and SDGs are meaningfully integrated in current practice or literature.

Objectives and Research Questions

The overarching objective of this review is to develop a coherent understanding of how responsible GenAI (LLMs/ChatGPT-like models) is currently contributing to the SDGs, analyzing the opportunities, foundational governance needs, and persistent challenges.

This review addresses the following research questions:

1. *Opportunities and Sectoral Roles:* How do Generative AI (LLMs/ChatGPT-like models) specifically contribute to and accelerate progress toward the economic, social, and environmental targets of the UN SDGs?
2. *Governance and Performance:* What core responsible AI principles and performance indicators are necessary for the ethical and reliable deployment of GenAI systems contributing to sustainability, and how do they compare with traditional AI solutions?
3. *Challenges and Limitations:* What are the major technical, ethical, social, and policy challenges associated with ensuring the responsible and sustainable implementation of GenAI for SDG attainment?

Literature Review

Review of Existing Work on GenAI, SDGs, and Sustainability

Research on the deployment of AI is extensive, noting several benefits of adoption, but research focused on the intersection of AI and sustainability, particularly within the SDG framework, remains characterized by key gaps [9]. The literature on AI and its applications to the SDGs has increased significantly, particularly since 2019 [9]. AI research output often focuses on technical areas such as water resource management, vegetation monitoring, and energy systems [9].

The existing body of work on Responsible AI (RAI) predominantly focuses on either theoretical RAI guidelines or technical aspects of traditional AI [2]. RAI frameworks are developed to address concerns such as fairness, bias mitigation, privacy protection, and security enhancement [2]. Responsible AI governance is defined as a set of practices ensuring the development, deployment, and monitoring of AI applications throughout their entire lifecycle in a safe, trustworthy, and ethical manner [2].

Core responsible AI principles synthesized from concentrated efforts include accountability, diversity, non-discrimination and fairness, human agency and oversight, privacy and data governance, technical robustness and safety, transparency, and social and environmental well-being [2]. Specifically, trustworthiness in AI is based on components such as the system being lawful, ethical, and robust (encompassing both social and technical elements) [2][5].

Summary of Foundational Studies and Gaps

A critical gap exists in bridging theoretical RAI frameworks with practical implementations in real-world settings, and in transitioning from traditional RAI thinking to Responsible Generative AI (GenAI) [2]. While 74% of organizations have incorporated GenAI into their operations, only 26% have implemented a comprehensive, organization-wide RAI strategy [11].

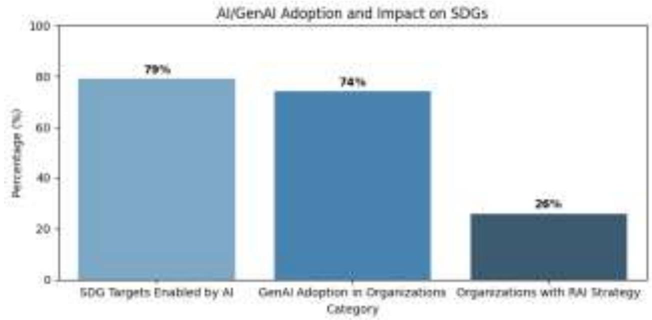

Figure 2:

A Comparative Analysis of AI's SDG Potential, GenAI Adoption, and RAI Strategy Prevalence

The UN Department of Economic and Social Affairs highlights AI's potential to enable 79% of the SDG targets [7]. However, despite global efforts, progress toward the 2030 Agenda is off-track, with only 26% of organizations having comprehensive Responsible AI strategies [11].

Gaps concerning GenAI and SDGs:

- *Social Sustainability:* Although AI is widely used in health (SDG 3), education (SDG 4), and environmental modeling, its application in core social sustainability goals is minimal. Goals like SDG 1 (No Poverty), SDG 5 (Gender Equality), and SDG 17 (Partnerships for the Goals) are severely underrepresented in current highly cited literature; for instance, only seven reviews and no empirical studies were found applying AI to poverty (SDG 1) in one major review [9].
- *Ethical and Normative Integration:* Ethical considerations related to AI are almost entirely absent from much of the scientific literature reviewed concerning AI and the SDGs. Most studies are limited to systems knowledge, often failing to address the normative or transformative dimensions central to sustainability science [9].
- *LLM-Specific Challenges:* The emergence of LLMs, such as ChatGPT, introduces a novel set of conditions that must be considered. GenAI models are often opaque "black boxes," hindering transparency, trust, and accountability. They are prone to hallucinations (generating inaccurate or fabricated content), and their non-deterministic outputs make developing consistent and repeatable explanations challenging. Addressing these model-related complexities requires XAI (Explainable AI) to evolve to meet the unique intricacies of GenAI [5].

Methodology

This section outlines the methodology for conducting the systematic review, adhering to a well-established framework to ensure rigor and comprehensive coverage of the scope (LLMs/ChatGPT-like models and SDGs).

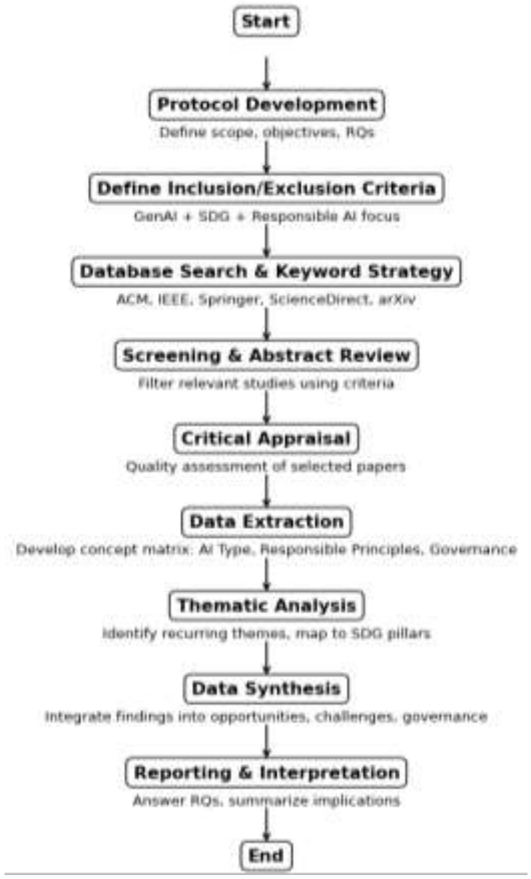

Figure 3: Workflow

Systematic Review Framework (e.g., PSALSAR or SLR steps)

The systematic literature review was based on well-established procedures to ensure the inclusion of relevant publications. The sources themselves outline methodologies consistent with a scoping review or systematic literature review approach. The process generally follows sequential steps, including protocol development, defining criteria, searching data sources, quality checks, data extraction, and synthesis.

Specifically, the systematic review process utilized in related foundational literature involved five key steps:

1. Gathering Information: Initial identification of documents (e.g., 1,080 documents identified in one source).
2. Reviewing Abstracts: Filtering based on relevance to inclusion/exclusion criteria.
3. Critically Viewing the Approach: Detailed examination of the study's relevance and methodology.
4. Data Extraction: Organizing extracted data into a concept matrix based on distinct themes (e.g., AI Types, Responsible Principles, AI Governance).
5. Data Synthesis: Systematically combining and summarizing data to draw meaningful conclusions.

Inclusion/Exclusion Criteria, Data Sources, Analysis Approach

- Inclusion Criteria (Aligned with Post-ChatGPT Era Focus):
  - Studies focusing explicitly on Generative AI (GenAI), including Large Language Models (LLMs) such as ChatGPT, GPT-4, or Bard.
  - Literature connecting GenAI/LLMs directly to one or more of the UN Sustainable Development Goals (SDGs) or overall sustainability and social impact.
  - Content covering Responsible AI (RAI), AI ethics, fairness, bias mitigation, and regulatory frameworks as applied to GenAI.
  - Studies published in English.
  - Papers from recognized academic journals, conference proceedings, or influential governance reports.
- Exclusion Criteria:
  - Studies focused solely on traditional, narrow AI techniques without mentioning Generative AI or LLMs.
  - Studies lacking empirical evidence or theoretical grounding.
  - Studies with a primary technical focus, such as architectural infrastructure or model benchmarking, unless directly addressing responsible deployment aspects (e.g., bias detection, safety benchmarks)
- Data Sources and Search Strategy:
  - The search strategy in foundational GenAI literature included keywords related to responsible AI, Generative AI, LLMs, and associated ethical concepts like “Ethical AI,” “Bias Mitigation,” and “Accountability”. The target databases generally include major academic repositories (e.g., ACM Digital Library, IEEE Xplore, SpringerLink, ScienceDirect, and arXiv).
- Analysis Approach:
  - The synthesis utilizes qualitative thematic analysis to identify recurring themes, gaps, and intersections among the findings regarding GenAI, responsibility, and the SDGs. It relies on synthesizing findings based on extracted themes such as Responsible Principles (e.g., Accountability, Transparency) and AI Capabilities. The analysis specifically maps LLM contributions and challenges across the three pillars of sustainability: social, environmental, and economic.

Results and Findings

The analysis of GenAI's role in the SDGs reveals a complex landscape of opportunities concentrated primarily in high-resource sectors, alongside significant technical and ethical governance requirements.

Opportunities and Sectoral Roles (Education, Healthcare, Governance)

GenAI technologies, particularly LLMs, accelerate progress across various SDGs, especially where data is organized and available, or where challenges are suitable for AI-driven solutions involving pattern recognition, optimization, and prediction.

Table 1: GenAI Applications for Sustainable Development Goals

SDG Focus Area	GenAI / LLM Role and Application
SDG 4: Quality Education	Personalized Learning: LLMs act as personalized tutors, delivering tailored content, quizzes, and real-time feedback, supporting inclusive and equitable education. Teacher Support: LLMs free faculty from routine administrative tasks (e.g., grading, generating materials) to focus on higher-order teaching (mentorship, critical thinking). Accessibility and Literacy: LLMs assist disabled learners (e.g., dysphasia) to express thoughts more precisely, and help students from low-income families improve essential skills such as writing.
SDG 3: Good Health & Well-being	Diagnostics and Treatment: AI supports disease diagnosis, personalized treatment planning, drug discovery (e.g., AlphaFold), and epidemiology. LLMs specifically enable personalized diet and exercise strategies based on individual health records.
SDG 7 & 13: Affordable Clean Energy & Climate Action	System Optimization: LLMs optimize complex energy systems by analyzing large-scale data (e.g., weather, load demand) to support strategic decision-making and maintain supply-demand balance. Environmental Monitoring: AI assists in monitoring pollution levels and optimizing water infrastructure management

	(SDG 6).
SDG 8 & 9: Decent Work & Economic Growth / Industry, Innovation & Infrastructure	Vocational Training: LLMs support vocational training by delivering up-to-date knowledge and helping individuals displaced from jobs transition to new, high-salary roles. Productivity: Human–AI collaboration enhances efficiency, innovation, and resilience, promoting sustainable economic growth.
SDG 16: Peace, Justice & Strong Institutions	Legal & Advocacy Support: NLP algorithms in LLMs extract relevant information from legal texts, laws, and testimonies, empowering lawyers, policymakers, and human rights advocates in decision-making and justice efforts.

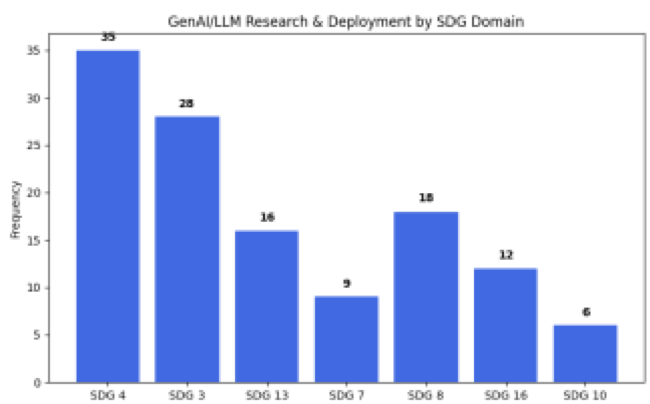

Figure 3: Frequency of GenAI/LLM Research by SDG Domain

GenAI and Large Language Model (LLM) applications are not evenly distributed across the Sustainable Development Goals (SDGs), reflecting sectoral and research priorities within the global AI for sustainability ecosystem. The following figure quantifies the current focus of GenAI/LLM research and deployment by SDG domain, providing a comparative view of which goals are most actively addressed by cutting-edge AI technologies in both research and applied contexts.

The observed distribution in the chart clearly shows that educational initiatives (SDG 4) and health and well-being (SDG 3) are the leading domains for GenAI/LLM research and deployment, significantly outpacing other SDGs. There is moderate activity in climate action (SDG 13), economic growth (SDG 8), and justice and institutions (SDG 16), while social equity and industry innovation (such as SDG 10 and SDG 7) remain less represented. This pattern highlights both the opportunities and the current gaps in leveraging GenAI for comprehensive SDG progress.

Performance Metrics (Social, Environmental, Economic Impacts of GenAI)

Performance and evaluation in the context of responsible GenAI require moving beyond traditional metrics (e.g., accuracy) to encompass ethical and societal impact.

Key Performance Indicators (KPIs) for evaluating Responsible AI, necessary for GenAI:

- Bias Detection and Fairness: Promoting equitable performance across diverse demographics. Fairness is quantified through metrics like disparate impact. LLMs exhibit biases based on training datasets, such as reinforcing stereotypes about poverty being region-specific.
- Explainability (Transparency): Enhancing stakeholders' understanding of model decisions, often addressed through Explainable AI (XAI) techniques like feature relevance analysis and local explanation methods (LIME, SHAP). GenAI's black-box nature necessitates sophisticated post-hoc explainability methods to ensure auditability.
- Accountability: Ensuring clear responsibility for AI outcomes. This is challenging in LLMs, as determining who is responsible for decisions made by AI systems is often multilayered and difficult to resolve.
- Data Privacy Compliance: Guaranteeing adherence to regulations (like GDPR) and safeguarding sensitive data, which is critical since GenAI often relies on massive datasets. Techniques like differential privacy are relevant.
- Sustainability (Environmental Well-being): Tracking energy consumption to minimize environmental impact. This includes evaluating the high energy demands of training large-scale GenAI models, which can be mitigated via techniques like model compression and parameter-efficient fine-tuning (PEFT).
- Robustness and Safety: Measuring performance under varying conditions and mitigating security risks, such as deepfakes, synthetic identity fraud, and the generation of toxic or biased content. Safety benchmarks (e.g., HarmBench, DecodingTrust) address critical issues but often show limited coverage of security, misinformation, and privacy.

Comparison with Existing Approaches

Benchmark GenAI against Traditional/Other AI Solutions for SDGs

While earlier narrow AI techniques largely focused on specific optimizations (e.g., water management, energy grid optimization), GenAI (LLMs) offers a distinctive advantage through human-like interaction and content generation across disciplines.

Feature	Traditional / Narrow AI	Generative AI (LLMs / ChatGPT)
Scope of Impact	Focused problem-solving (e.g., single process optimization, image detection).	Broad, cross-cutting impact (content generation, personalized interaction, complex planning, and reasoning assistance).
SDG Focus	Strong bias toward technical/environmental systems (SDGs 6, 7, 13).	Strong impact on social systems (SDGs 3, 4, 8, 16) through personalized assistance and information dissemination.
Learning / Education	Intelligent Tutoring Systems (ITS) existed, but often required extensive domain-specific rules.	Provides personalized learning pathways, 24/7 support, instant feedback, and tailored content, mimicking a tutor's role.
Governance Complexity	Challenges focused on explainability and bias in structured data / deterministic models.	Challenges amplified by non-deterministic outputs, hallucinations, and copyright disputes over training data, requiring continuous regulatory adaptation.

Highlight Innovations and Areas of Improvement

Innovations:

- Multilingual Access: LLMs accelerate translation capabilities for lesser-known languages (e.g., Google's 1000 Languages Initiative), bridging language barriers and making global communication more accessible (SDG 10).
- Enhanced Research Synthesis: NLP algorithms can be integrated into collaborative platforms to analyze and synthesize large volumes of scientific literature, patents, and technical documents (SDG 17) [10].
- Risk Mitigation Tools: GenAI drives the development of specialized safety benchmarks (e.g., HarmBench, TrustLLM) and tools for toxicity detection and bias evaluation across different contexts.

Areas for Improvement:

- Deepening Sustainability Expertise: GenAI applications remain characterized by an opportunistic starting point with limited integration across disciplines. There is a critical gap where AI methodologies are not effectively bridging with deep sustainability expertise.
- Focus on Neglected SDGs: Research needs to expand GenAI use in neglected areas, particularly SDG 1 (No Poverty), SDG 5 (Gender Equality), and SDG 17 (Partnerships).
- Balancing Performance and Interpretability: The inherent complexity of advanced GenAI models makes interpretability challenging, creating a tension with regulatory mandates for explainability (e.g., EU AI Act).

Challenges and Limitations

The utilization of GenAI for sustainable development is severely impacted by intertwined technical and socio-political challenges.

Technical Limitations (model size, training cost, data bias, etc.)

- Data Bias and Quality: GenAI heavily relies on extensive datasets. However, limited or biased datasets can skew AI-generated outcomes, leading to inaccurate or unjust recommendations, particularly impeding progress toward social goals like SDG 10 (Reduced Inequality). For example, training on biased historical data led Amazon’s AI recruitment tool to discriminate against women.
- Model Complexity (Black Box): Advanced LLMs are often opaque "black boxes," making transparency, trust, and accountability difficult to achieve, especially in high-stakes applications. This challenge is amplified by GenAI’s propensity for generating non-deterministic outputs.
- Hallucination and Misinformation: GenAI is prone to generating fabricated or factually wrong results (hallucinations), which undermines user trust and safety. This requires continuous updates to regulatory standards, especially concerning deepfakes during elections.
- Computational Cost: The massive computational requirements for training large-scale GenAI models lead to significant energy consumption, raising concerns about environmental impact and potentially worsening climate change (SDG 13).

Social/Policy Limitations (access, environmental cost, ethics)

- Ethical Alignment and Governance: There is a significant challenge in translating abstract, high-level ethical principles (like fairness, transparency, and accountability) into deployable practices throughout the GenAI project lifecycle. Failure to address ethical concerns could worsen social disparities.

- Digital Divide and Access: Resource constraints, particularly in terms of funding and technical expertise, hinder the widespread adoption and scalability of GenAI solutions in underserved regions. This lack of equitable access exacerbates the digital divide.
- Job Displacement: The threat of job displacement across various fields due to GenAI-driven automation could worsen economic inequalities and hinder progress toward decent work (SDG 8).
- Copyright and IP Disputes: The use of copyrighted material to train GenAI models raises significant legal and ethical questions about ownership and necessitates evolving legal frameworks.
- Accountability Gaps: Determining responsibility whether it lies with developers, data sources, regulators, or end-users for GenAI's biased outcomes and privacy concerns remains contentious.

Discussion

Analysis of Results in Context (tradeoffs, productivity vs. environmental cost)

GenAI presents a transformative capability for the SDGs, particularly in the social domain (education, health) and economic productivity, yet this promise is conditional on rigorous responsible governance.

Trade-offs in Responsibility and Performance: Organizations often face trade-offs in seeking the right equilibrium between performance, transparency, and ethical conduct. For instance, improving the explainability (transparency) of an AI system may come at the expense of its accuracy. Similarly, the drive for higher performance in LLMs (e.g., scaling from GPT-3 to GPT-4) typically increases model complexity, which directly hinders interpretability.

Productivity vs. Environmental Cost: GenAI promises massive improvements in efficiency, supporting sustainable economic growth (SDG 8) and optimizing complex systems (SDG 7, 9). However, this productivity gain comes at a cost. The enormous energy consumption and carbon release associated with training and operating large AI models risk worsening climate change (SDG 13), directly undermining sustainability goals. Resolving this tension requires proactive strategies, such as developing energy-efficient AI models, reducing computational needs, and utilizing renewable energy sources.

The Importance of Governance and Stakeholder Alignment: Effective governance, defined through structural, procedural, and relational practices, is essential for translating high-level ethical principles into actionable deployment methods throughout the AI lifecycle. Structural practices involve assigning roles (e.g., AI governance committees) and responsibilities. Relational practices focus on fostering collaboration, AI literacy training, and engaging external stakeholders, including end-users, to ensure solutions are ethically aligned and contextualized.

Recommendations for Ethical and Responsible AI Deployment

To maximize GenAI benefits while mitigating risks, organizations should focus on the following core areas:

1. Prioritize Ethical Infrastructure: Establish clear governance practices that include assigning roles for decision-making (structural practices) and developing standardized procedures for data management and human-AI interaction (procedural practices). This must include developing robust incident response and crisis management procedures to address AI-related issues promptly.
2. Ensure Data Integrity and Fairness: Mandate the use of inclusive datasets and conduct regular audits to detect and mitigate algorithmic biases, ensuring compliance with fairness guidelines and accountability frameworks. For GenAI, this means addressing stereotypes perpetuated by training data (e.g., racial or gender biases in image generators).
3. Invest in Explainable AI (XAI): Develop XAI tools tailored for the complexities of LLMs to illuminate processes, identify biases, and enhance user trust, ensuring compliance with transparency regulations.
4. Promote AI Literacy: Organizations must invest in training and education to equip employees and stakeholders with the knowledge and competencies necessary to understand and utilize GenAI responsibly, focusing on ethical literacy and critical thinking.
5. Adopt a Risk-Based Approach: Regulatory frameworks should take a risk-based approach to GenAI governance (similar to the EU AI Act), classifying systems based on potential harm and mandating transparency and accountability accordingly.

Future Work

Emerging Trends, Open Research Areas

Future research must focus on bridging the gaps between technical capabilities and deep sustainability expertise. Key emerging trends and open areas include:

- Longitudinal Impact and Temporal Dynamics: Most empirical studies focus on the present and use quantitative approaches; future work should prioritize transformative, longitudinal research on GenAI's sustained impact on sustainable development and social systems.
- Refining Governance Structures: Research is needed to identify the optimal vertical and horizontal structures for assigning rights and responsibilities for responsible GenAI governance within and across organizations.
- Empirical Validation of Governance Frameworks: While conceptual frameworks (like the AI Academic Convergence Framework for education) exist, empirical validation and real-world case studies are needed to evaluate their scalability and effectiveness.
- GenAI in Social Systems: Further exploration is required for applying LLMs to currently underrepresented social goals, such as poverty eradication (SDG 1), gender equality (SDG 5), and understanding how GenAI can facilitate partnerships (SDG 17).
- Defining Ethical KPIs: Research should continue to redefine benchmarks to prioritize ethical metrics (fairness, safety, transparency) alongside traditional performance metrics (accuracy, efficiency).

Suggestions for Stakeholders and Policy Improvements

Stakeholder Group	Policy Improvement Suggestions
Policymakers / Governments	• Develop comprehensive data privacy and security frameworks, including clear guidelines for data collection, storage, and anonymization in GAI applications. • Implement algorithmic bias audits and mitigation strategies across all high-risk GAI systems. • Prioritize investment in digital infrastructure in underserved communities to ensure equitable access to GAI tools (SDG 10).
Researchers / Academia	• Foster interdisciplinary collaboration (AI researchers, social scientists, ethicists) to integrate AI methods with social and normative sustainability concepts. • Focus research funding on creating new, energy-efficient algorithms and advancing Responsible AI standards.
Organizations / Developers	• Adopt co-creation approaches, involving end-users and external stakeholders in the development of GAI solutions to ensure cultural sensitivity and trust. • Establish clear guidelines for responsible GenAI use cases, including robust testing procedures and defining acceptable use in academic or professional environments.

Conclusion

This systematic review confirms the transformative potential of Generative AI, specifically Large Language Models (LLMs) such as ChatGPT, in accelerating progress toward the UN Sustainable Development Goals (SDGs). LLMs provide significant opportunities, particularly in advancing Quality Education (SDG 4) through personalized learning and aiding Good Health (SDG 3) via individualized health recommendations. They also contribute to economic productivity and industrial innovation (SDGs 8, 9) through optimization and human-AI cooperation.

Nevertheless, the path toward a sustainable and inclusive GenAI future is hindered by critical challenges. These include the technical limitations of black-box models and hallucinations, the significant environmental cost of training massive models, and severe social risks related to algorithmic bias, data privacy, and the exacerbation of the digital divide.

Emphasize Pathways to Sustainable and Inclusive GenAI

Achieving the full promise of GenAI requires a collective, multi-stakeholder effort. Pathways to sustainable and inclusive GenAI deployment must emphasize:

- Robust Governance: Implementing comprehensive governance frameworks (structural, procedural, and relational practices) that operationalize ethical principles throughout the entire AI lifecycle.
- Ethical Priority: Prioritizing ethical metrics (fairness, transparency, accountability, and environmental well-being) alongside technical performance in model design and evaluation.
- Inclusive Access: Strategic investment in infrastructure and AI literacy programs, especially in developing countries and underserved communities, to ensure the benefits of GenAI are equitably shared (SDG 4, SDG 10).
  - Interdisciplinary Research: Fostering deeper collaboration among AI researchers, ethicists, policymakers, and domain experts to integrate technological advancement with the normative and transformative aspects of sustainability science.

By carefully managing risks and aligning LLM capabilities with the principles of the SDGs, AI can act as a powerful force for positive transformation, paving the way for a more inclusive, equitable, and sustainable world for all.

Acknowledgement

There is no grant or funding bodies to be acknowledged for preparing this paper.

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