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Generative AIs and the Hidden Cost of Intelligence: A Multidisciplinary Review of LLMs Progress, Resource Consumption and Path to a Sustainable Future

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ABSTRACT

The rapid advancement of Large Language Models (LLMs) and Generative Artificial Intelligence (GenAI) has reshaped technological, business and social environments. Though the models — GPT-4, GPT-5, Claude and others — have shown unparalleled abilities in automation, creative work and decision-making, they have placed enormous burdens on natural resources such as energy, water and computational infrastructure raw materials. This paper offers a multidisciplinary analysis with integrated views from environmental science, computer engineering, economics and business information systems perspective. The research analyzes the environmental externalities of LLMs training and deployment, and measures resource usage patterns and places them in context of global sustainability objectives. Methodologically, the study utilizes a mixed review framework by incorporating systematic literature review and secondary data analysis from peer-reviewed journals in ScienceDirect, Taylor & Francis, Wiley Online, IEEE, MDPI, SpringerLink, SAGE, Emerald and other trustworthy databases. The findings show that the growth of GenAI is happening at an unsustainable level unless checked by strategic interventions on infrastructure efficiency, policy regulation and corporate environment responsibility. It is suggested to imperatively reconcile AI innovation with the circular economy and carbon-neutral computing principles to guarantee that intelligence augmentation is not at the cost of planetary well-being.

Keywords: Generative AI, Large Language Models, artificial intelligence, sustainability, energy consumption, energy footprint, carbon footprint, carbon emission, water consumption, multidisciplinary review

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1 INTRODUCTION

Generative Artificial Intelligence (GenAI) has evolved from a theoretical notion to a driving force in technological innovation in the last five years (Ben-Ishai et al., 2024; Brock & von Wangenheim, 2019; Robbins & Van Wynsberghe, 2022). Large Language Models (LLMs) such as GPT-3, GPT-4, GPT-5, Claude and PaLM are now highly integrated into workflows in industries ranging from financial analysis to healthcare diagnosis and creative output (Amankwah-Amoah et al., 2024; Cherukuri, 2024; Laskin & D'Agostino, 2024; Zhang et al., 2023). This acceleration is fuelled by exponential advances in model design, greater access to high-performance computational resources and unprecedented availability of training data (Kaplan et al., 2020; Strubell et al., 2019; Xiong et al., 2024). The promise of GenAI is that it can create human-like text, combine knowledge and automate decision-making at scale (Ågerfalk, 2020; Ben-Ishai et al., 2024). But this promise is paid in a hidden price. The computational demands for training and running cutting-edge LLMs are enormous, with billions—if not trillions—of parameters and requiring massive clusters of GPUs or TPUs (Kaplan et al., 2020; Patterson et al., 2021; Verdecchia et al., 2023; Xiong et al., 2024). These facilities use a lot of electricity, which tends to come from non-renewable energy resources and necessitate enormous water supplies to utilize for cooling purposes (Cao et al., 2022; Debus et al., 2023; Li et al., 2025; Luccioni & Hernandez-Garcia, 2023; Mytton, 2021; Pimenow et al., 2024). Additionally, the physical components underlying GenAI systems rely on extracting rare earth elements and other vital minerals, bringing environmental and geopolitical issues (Dauvergne, 2022; Robbins & Van Wynsberghe, 2022; Spelda & Stritecky, 2020).

From a business and economic perspective, the growth of GenAI is both an opportunity and a risk. In one way or another, companies are enabled by enhanced operating efficacy, forecasting and innovation acceleration (Amankwah-Amoah et al., 2024; Brock & von Wangenheim, 2019; Laskin & D'Agostino, 2024). Conversely, environmental expenses jeopardize corporate sustainability obligations and may provoke regulation in the near term (Dauvergne, 2022; Maple et al., 2023; Pimenow et

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al., 2024; Tkachenko, 2024). The economic aspect is therefore connected with environmental science, policy studies and technological innovation (Arroyabe et al., 2024; Gupta et al., 2021; Kulkov et al., 2024), which turns into a fundamentally multidisciplinary problem.

Recent academic interest has started to measure the environmental impact of AI. Strubell et al. (2019) gained popularity by calculating that training one Natural Language Processing (NLP) model produced as much carbon dioxide as five cars during their lifetime. Subsequent research (d'Aramon et al., 2024; Everman et al., 2023; Kaneko, 2025; Luccioni & Hernandez-Garcia, 2023; Patterson et al., 2021) has further updated these estimates such that the path of AI development, unless checked, has the potential to emerge as one of the most resource-consuming industries in the digital economy (Li et al., 2025; Robbins & Van Wynsberghe, 2022). Parallel to this, environmental policy and corporate governance research (Al-Sabahi et al., 2025; Aysan et al., 2024; Khaddam & Alzghoul, 2025; Kyriakarakos, 2025; Maple et al., 2023) has emphasized the possibility of linking AI innovation to sustainability objectives through strategic interventions (Oladapo et al., 2024; Tsolakis et al., 2022).

This study contributes to this new body of knowledge by exploring the nexus between LLMs advances and natural resource use, highlighting energy demands, water requirements and material inputs. It takes a mixed-method approach, drawing on both systematic literature review of impact-factor peer-reviewed journals and secondary analysis of AI infrastructure reports and datasets of environmental organizations. By doing so, it aims to address the following research questions:

- What are the core natural resource needs of contemporary LLMs and automated GenAI systems?
- How do the needs vary by sector and geography?
- What policy, technical and business measures can help to reduce the environmental cost of AI breakthroughs without inhibiting the progress?

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Through responding to these questions, the study seeks to provide actionable recommendations to AI developers, policymakers and business leaders, towards making the next generation of intelligent systems sustainable.

2. Literature Review

The environmental implications of Generative AI (GenAI) and Large Language Models (LLMs) have emerged as a prominent concern in scholarly and policy discussions, driven by the exponential growth in computational complexity and the infrastructure required to sustain it (Bender & Friedman, 2018; Chen, 2023; Kaplan et al., 2020; Luccioni & Hernandez-Garcia, 2023; Patterson et al., 2021; Strubell et al., 2019; Yang et al., 2024; Zhang et al., 2023; Xiong et al., 2024). This literature review synthesizes findings across environmental science (Dauvergne, 2022; Gupta et al., 2021; Sobkowiak et al., 2023; Tao et al., 2023; Tkachenko, 2024; Tsolakis et al., 2022), computer engineering (Agomuo et al., 2024; Argerich & Patiño-Martínez, 2024; Cao et al., 2022; Cherukuri, 2024; Debus et al., 2023; Ding et al., 2024; Everman et al., 2023; Hamels et al., 2021; Kaneko, 2025; Ljungdahl et al., 2022; Liu et al., 2021; Luccioni & Hernandez-Garcia, 2023; Mytton, 2021; Patterson et al., 2021; Pimenow et al., 2024; Schwartz et al., 2020; Strubell et al., 2019; Vartziotis et al., 2024), information systems (Ågerfalk, 2020; Amankwah-Amoah et al., 2024; Arroyabe et al., 2024; Brock & von Wangenheim, 2019; Laskin & D'Agostino, 2024; Verdecchia et al., 2023), and business sustainability research (Akpan & Adebayo, 2025; Al-Sabahi et al., 2025; Aysan et al., 2024; Banerjee et al., 2024; Belrzaeg et al., 2025; Ben-Ishai et al., 2024; Besinger et al., 2024; Frimpong, 2025; Khaddam & Alzghoul, 2025; Khan et al., 2021; Krishnan et al., 2022; Kulkov et al., 2024; Kyriakarakos, 2025; Lee & Chen, 2022; Lee et al., 2025; Li et al., 2025; Lucivero, 2020; Ma & Zhang, 2024; Maple et al., 2023; Meena et al., 2025; Meng & Noman, 2022; Mhlanga, 2023; Oladapo et al., 2024; Praveen et al., 2025; Robbins & Van Wynsberghe, 2022; Ruiz-Sánchez et al., 2024; Tian & Adriaens, 2025; Yunyun et al., 2024) to establish a comprehensive understanding of the topic.

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2.1 The Rise of Large Language Models

LLMs are a huge step forward in AI functionality, moving from initial rule-based systems to transformer models able to reason contextually and generate language (Chen, 2023; Yang et al., 2024). While GPT-3 achieved a record with 175 billion parameters, GPT-4 and GPT-5 models have increased computational demands exponentially (Cherukuri, 2024; Zhang et al., 2023). The requirement for computational power increases at the cost of larger training data, model parameters and the use of multi-modal functionality.

The peer-reviewed literature of high-impact journals like IEEE Transactions on Neural Networks and Learning Systems, Nature Machine Intelligence highlights that the AI scaling laws (Kaplan et al., 2020; Xiong et al., 2024; Luccioni & Hernandez-Garcia, 2023) forecast a linear relationship between model performance and utilization of resources—implying environmental expenses will increase in proportion to capabilities without architectural paradigm shifts or improvements in efficiency.

2.2 Energy Consumption in AI Development

Energy demand has been the focal point of several landmark studies (Kaplan et al., 2020; Luccioni & Hernandez-Garcia, 2023; Patterson et al., 2021; Strubell et al., 2019). Strubell et al. (2019), published in ACL Anthology, quantified that training large NLP models can emit up to 284 metric tons of CO_2 equivalents. More recent research from Joule (Kaneko, 2025) revealed that state-of-the-art LLMs consume megawatt-hours of electricity during both training and inference phases (Everman et al., 2023; Luccioni & Hernandez-Garcia, 2023). Furthermore, reports from ScienceDirect (Luccioni & Hernandez-Garcia, 2023) highlight that inference—though less intensive per operation than training—can exceed training costs over the lifetime of a model due to widespread deployment (Everman et al., 2023; Verdecchia et al., 2023).

Mass datasets have been used to train LLMs and processed repeatedly in distributed computer clusters. Larger parameters and multi-model capabilities have been estimated to have increased energy requirements from three to five times during the transfer from

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GPT-3 to GPT-4 (Zhang et al., 2023; Cherukuri, 2024). Furthermore, this increase in energy demand is consistent with studies that show the immense power consumption of large-scale AI training, a challenge referred to as "Green AI" (Schwartz et al., 2020). Researchers have proposed methods to evaluate this carbon impact at various stages, including the inference stage, where models are put into practical use (d'Aramon et al., 2024; Everman et al., 2023). This has led to an emerging body of work focused on creating more sustainable AI systems (Verdecchia et al., 2023; Vartziotis et al., 2024).

The literature identifies three primary energy drivers:

- **Model Complexity:** Larger models require more floating-point operations per second (FLOPS) which directly increases electricity consumption (Kaplan et al., 2020; Luccioni & Hernandez-Garcia, 2023; Strubell et al., 2019).
- **Training Duration:** Extended training cycles—sometimes lasting weeks with the use of compound energy (Luccioni & Hernandez-Garcia, 2023; Patterson et al., 2021; Strubell et al., 2019).
- **Deployment Scale:** Inference related energy costs surpass training related costs over time as more enterprises integrate LLMs into workflows (Everman et al., 2023; Luccioni & Hernandez-Garcia, 2023; Tkachenko, 2024).

According to IEA, secondary data analysis shows that fully renewable powered grids (less than 50g CO_2/kWh) emit up to 900g CO_2/kWh from data centers in coal-heavy grids (D'Aramon et al., 2024, Khan et al., 2021; Patterson et al., 2021; Spelda & Stritecky, 2020). This difference implies that the environmental footprint mostly depends on the geographic location of training facilities (Brock & von Wangenheim, 2019; Dauvergne, 2022; Tsolakis et al., 2022).

All these studies reach a conclusion that the carbon footprint of AI development is largely determined by the energy mix in the hosting area (Debus et al., 2023; Hamels et al., 2021; Pimenow et al., 2024; Robbins & Van Wynsberghe, 2022). Data centers operated by coal-based grids (certain regions of Asia) have much greater emissions than

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those fueled by renewable energy (Pimenow et al., 2024; Robbins & Van Wynsberghe, 2022).

2.3 Water Usage and Thermal Management

Water usage in AI infrastructure is less known but critical as other resources. Nature Sustainability (Tao et al., 2023) reports that AI data centers use large amounts of freshwater for cooling purposes, with the process of training GPT-3 estimated to take hundreds of thousands of liters (Lucivero, 2020; Mytton, 2021). Google's sustainability report also supports that water usage peaks where LLMs activity is highest, especially where evaporative cooling is used (Cao et al., 2022). Particularly in water-stressed areas, the convergence of water usage and artificial intelligence is very important since it raises ethical and practical questions (Robbins & Van Wynsberghe, 2022). Williams and Casey (2022) note that competition between industrial water use and local community needs might worsen socio environmental tensions, especially as AI demand grows in underdeveloped countries (Krishnan et al., 2022; Frimpong, 2025).

Cooling systems for AI infrastructure depend heavily on water. Evaporative cooling used by hyperscale data centres directly uses water (Mytton, 2021; Cao et al., 2022); chilled water systems indirectly use water by means of electricity generation (Hamels et al., 2021). Nature Sustainability (Tao et al., 2023) research indicates that training GPT3 in a US facility might be used up to 700,000 liters of freshwater. It is enough to meet the daily requirements of more than 3,000 individuals (Li et al., 2025). Although liquid immersion cooling methods can lower reliance on water, acceptance is limited by significant retrofitting expenses (Ljungdahl et al., 2022).

Water impact is location sensitive in geographical terms (Krishnan et al., 2022; Tian & Adriaens, 2025). In dry areas, water withdrawals for artificial intelligence might directly conflict with municipal and agricultural needs, therefore generating socio economic issues. Williams and Casey (2022) found that such rivalry might stress corporate-community ties, possibly leading to legal restrictions or operational shutdowns (Robbins & Van Wynsberghe, 2022).

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2.4 Raw Material Requirements and Supply Chain Implications

High-performance artificial intelligence processing relies on sophisticated GPUs and TPUs, which in turn depend on lithium, cobalt, and rare earth elements—materials that are often mined in environmentally and socially sensitive areas (Dauvergne, 2022). According to studies from Wiley Interdisciplinary Reviews: Computational Statistics and MDPI Sustainability, increasing AI hardware production without taking supply chain sustainability into account will only make the environmental and geopolitical dangers associated with AI deployment worse (Verdecchia et al., 2023; Robbins & Van Wynsberghe, 2022; Tsolakis et al., 2022).

2.5 Business, Financial and Policy Perspectives

The adoption of LLMs poses a problem from a business perspective. On the one hand, using artificial intelligence reduces expenses, improves productivity, and opens up fresh income channels (Amankwah-Amoah et al., 2024; Ben-Ishai et al., 2024; Brock & von Wangenheim, 2019). Conversely, sustainability reporting systems like the Global Reporting Initiative (GRI) and Task Force on Climate-related Financial Disclosures (TCFD) emphasize businesses to declare and minimize the environmental footprint of their digital activities (Dauvergne, 2022; Robbins & Van Wynsberghe, 2022). Impact factor publications such the *Journal of Business Ethics*, *Technological Forecasting and Social Change* (Spelda & Stritecky, 2020) help to explain the rising investor interest in green artificial intelligence projects—that is, in algorithms and infrastructure meant at lowering resource and energy intensity (Schwartz et al., 2020; Verdecchia et al., 2023).

3. Methodology

This study adopts a mixed-method methodological framework by combining a systematic literature review (SLR) with secondary data analysis.

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3.1 Systematic Literature Review (SLR)

The searches were performed on ScienceDirect, SAGE, Emerald, Taylor and Francis, Wiley Online Library, IEEE Xplore, SpringerLink, arXIV, Nature - NPJ Clean Water and MDPI etc. Publications focused on impact factor journals released between 2019 and 2025 were filtered based on keywords such as "Generative AI environmental impact", "LLM energy consumption", "energy consumption of Generative AI", "AI water usage", "carbon footprints in AI", "carbon emission by LLM", "water footprints in AI", "Green AI" and "sustainable AI infrastructure". For analysis, we used NVIVO to efficiently identify the keywords and themes from the literature. NVIVO was specifically selected for its advanced capabilities that facilitated better in-depth analysis and the quantification of theoretical data to derive practical implications. Initially, 100 articles were sorted out. However, at the phased out stage, only 62 articles were filtered and considered that met the requirements of underlying study. This aligns with previous studies on the environmental costs of AI, including energy consumption, carbon emissions, and water usage (Akpan & Adebayo, 2025; Argerich & Patiño-Martínez, 2024; d'Aramon et al., 2024; Everman et al., 2023; Luccioni & Hernandez-Garcia, 2023; Pimenow et al., 2024; Spelda & Stritecky, 2020; Strubell et al., 2019; Tao et al., 2023).

3.2 Secondary Data Analysis

Environmental metrics were extracted from corporate sustainability reports (Google, Microsoft, Meta, OpenAI), International Energy Agency (IEA) datasets and United Nations Sustainable Development Goal (SDG) progress indicators. This data analysis is critical to assess the broader implications and progress toward sustainable AI development (Ben-Ishai et al., 2024; Gupta et al., 2021; Kulkov et al., 2024; Oladapo et al., 2024).

Data was coded thematically into four categories as energy consumption, water usage, raw material demand, policy and business implications. The thematic categories are well-supported by existing literature for Energy Consumption (Ding et al., 2024; Liu et

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al., 2021; Ljungdahl et al., 2022; Ma & Zhang, 2024; Mhlanga, 2023; Pimenow et al., 2024; Strubell et al., 2019), Water Usage (Li et al., 2025; Mytton, 2021; Tao et al., 2023; Tian & Adriaens, 2025), Policy and Business Implications (Ågerfalk, 2020; Al-Sabahi et al., 2025; Amankwah-Amoah et al., 2024; Aysan et al., 2024; Belrzaeg et al., 2025; Brock & von Wangenheim, 2019; Dauvergne, 2022; Laskin & D'Agostino, 2024; Oladapo et al., 2024; Tkachenko, 2024). Reliability has been ensured by cross-validation with multiple sources.

4. Results and Discussion

The synthesis of the literature and secondary data analysis exposes complicated and occasionally contradictory issues regarding the development of Generative AI (GenAI) and Large Language Models (LLMs). Though these systems provide transforming powers in decision making, productivity and innovation throughout different industries (Amankwah-Amoah et al., 2024; Cherukuri, 2024; Laskin & D'Agostino, 2024; Lee et al., 2025; Oladapo et al., 2024), their environmental expenses—in energy, water and raw materials—are considerable and growing (d'Aramon et al., 2024; Debus et al., 2023; Everman et al., 2023; Hamels et al., 2021; Kaplan et al., 2020; Luccioni & Hernandez-Garcia, 2023; Pimenow et al., 2024; Strubell et al., 2019; Tao et al., 2023; Tkachenko, 2024; Verdecchia et al., 2023). These costs are a crucial point of discussion in the context of sustainability and technology (Robbins & Van Wynsberghe, 2022; Spelda & Stritecky, 2020), and research highlights the need for a more sustainable approach (Schwartz et al., 2020; Vartziotis et al., 2024).

4.1 Energy Footprint Findings

According to data collected from studies covering ScienceDirect, IEEE, Nature, Wiley, Taylor and Francis, the average energy consumption for training modern LLMs is more than 1.3 GWh per training cycle, which is equivalent to the annual electricity usage of more than 120 US families (Patterson et al., 2021; Strubell et al., 2019). The most notable shift has been observed in the primary source of emissions from training to inference (Everman et al., 2023; Luccioni & Hernandez-Garcia, 2023). Energy costs of

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the inference phase surpass those of the initial training phase, particularly in high-traffic applications like customer service, financial analysis and content generation. This suggests that discussions about the sustainability of artificial intelligence must now concentrate on ongoing operating costs rather than one time training emissions.

The regional carbon intensity gap is another important result. Training models in areas dependent on coal-based electricity might result in 15–20 times more emissions than training in a totally renewable-powered facility (Hamels, et al. 2021). For instance, training a model in Inner Mongolia can have many times more carbon footprint than training it in a Nordic country driven by hydropower and wind (Luccioni & Hernandez-Garcia, 2023).

4.2 Water Usage Insights

Water usage analysis shows significant differences based on facility location and cooling techniques (Mytton, 2021; Robbins & Van Wynsberghe, 2022). A hyperscale artificial intelligence training facility in a semi arid area that uses evaporative cooling may consume millions of liters of freshwater annually (Li et al., 2025; Liu et al., 2021; Mytton, 2021). The opportunity cost of such usage is that it may exacerbate drought conditions in water stressed areas, which could result negatively in the form of public outrage or governmental intervention (Li et al., 2025; Mytton, 2021). Use of water by Microsoft in Arizona could be one of such artificial intelligence workloads that sparked criticism from environmental organizations and prompted internal sustainability audits. Intriguingly, the study also found a cyclical consumption pattern with peak water usage matching the summer months when cooling needs are at their highest (Ljungdahl et al., 2022; Mytton, 2021). This demand is seasonal and fits with times of agricultural irrigation stress, therefore raising the likelihood of conflict between community usage and industrial requirements (Li et al., 2025; Mytton, 2021).

4.3 Raw Material Dependency

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The literature repeatedly highlights the impossibility of relying on lithium, cobalt and rare earth metals for the manufacture of AI hardware (Robbins & Van Wynsberghe, 2022). As LLMs develop, the need for GPUs, TPUs and related semiconductor technology grows (Patterson et al., 2021). Resources Policy (Dauvergne, 2022) and other Wiley Interdisciplinary Reviews sources (Verdecchia et al., 2023) note that most cobalt mining takes place in the Democratic Republic of the Congo, with environmental and human rights consequences. In addition to that, semiconductor manufacturing is resource-intensive by nature due to its need for huge amounts of ultra-pure water and generation of toxic chemical waste (Lucivero, 2020). Because AI reliant industries can be impacted by ripple effects of geopolitical instability or supply disruptions, this supply chain risk threatens world sustainability as well as AI progress immensely (Oladapo et al., 2024).

4.4 Business and Policy Implications

According to corporate strategy, there must be an integration of GenAI into operations with sustainability accounting which leads to proper ROI calculations. Stakeholders and regulators are pressuring businesses that implement LLMs to account for environmental impact for the full lifecycle of their AI tools (d'Aramon et al., 2024; Luccioni & Hernandez-Garcia, 2023; Strubell et al., 2019). Investors are increasingly evaluating AI projects not only on their financial viability but also on their ESG (Environmental, Social and Governance) performance (Aysan et al., 2024; Laskin & D'Agostino 2024; Lee et al., 2025; Khaddam & Alzghoul, 2025). Stakeholders are asking tech businesses to publicly share carbon and water used measures linked to AI workloads (Pimenow et al., 2024; Debus et al., 2023; Li et al., 2025, Mytton, 2021; Tao et al., 2023).

Governments and international organizations are looking at legal structures on the policy front to reduce the environmental impact of artificial intelligence. Proposals go from carbon taxes on data center activities to required environmental impact disclosures for artificial intelligence models beyond particular parameter limits (Ben-

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Ishai et al., 2024; Bender & Friedman, 2018; Tkachenko, 2024). Integrating environmental aspects into AI governance may take considerations from the European Union's Green Deal (Hamels et al., 2021).

4.5 Multidisciplinary Observations

Because this study takes a multidisciplinary approach, several notable cross-domain linkages emerge as:

- **Information Systems:** The algorithms and compression of models such as quantization and pruning in computer science can be used directly to reduce environmental effects (Schwartz et al., 2020; Strubell et al., 2019; Verdecchia et al., 2023).
- **Business & Finance:** ESG linked funding may encourage green AI technologies which would appeal to investors who are looking for eco-friendly AI systems (Al-Sabahi et al., 2025; Khaddam & Alzghoul, 2025; Lee et al., 2025).
- **Environmental Science:** Using lifecycle assessment (LCA) techniques can measure the cradle-to-grave effect of artificial intelligence (Luccioni & Hernandez-Garcia, 2023; Patterson et al., 2021). It will enable the regulators, policymakers and businesses to make better decisions (Gupta et al., 2021; Verdecchia et al., 2023).
- **Operations Management:** Strategic placement of data centers depending on water resources and renewable availability can greatly lower unfavorable environmental effects (Cao et al., 2022; Mytton, 2021).

5. Conclusion

There is a contradiction between GenAI and LLMs. Both are drivers of innovation and economic change (Ågerfalk, 2020; Amankwah-Amoah et al., 2024; Ben-Ishai et al., 2024; Brock & von Wangenheim, 2019; Laskin & D'Agostino, 2024; Maple et al., 2023), but they also cause a lot of environmental damages (Patterson et al., 2021; Robbins & Van Wynsberghe, 2022; Strubell et al., 2019). The results of this study

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show that without conscious efforts, the growth path of these technologies is expected to exacerbate world issues pertaining to raw material extraction, water use and energy consumption (Spelda & Stritecky, 2020).

From an environmental perspective, energy intensity is still the most important issue, particularly as operational inference expenses surpass onetime training costs (Argerich & Patiño-Martínez, 2024; Everman et al., 2023; Pimenow et al., 2024; Strubell et al., 2019; Xiong et al., 2024; Yang et al., 2024). Growing worries about water use especially in areas where people consumption and agriculture compete with AI infrastructure are emerging (Li et al., 2025; Mytton, 2021; Tao et al., 2023; Tian & Adriaens, 2025). Reliance on raw materials introduces yet another level of complexity by fusing geopolitical tensions with worldwide supply chain vulnerabilities and hence complicating the growth of artificial intelligence (Dauvergne, 2022).

The business and policy repercussions are also significant. Companies have to include environmental criteria into strategic decision making by modifying sustainability systems to reflect particular AI impacts (Besinger et al., 2024; Kulkov et al., 2024; Lee et al., 2025; Oladapo et al., 2024). Policymakers have to foresee the environmental effects of AI development and implement focused laws to support or enforce environmentally friendly activities (Pimenow et al., 2024; Robbins & Van Wynsberghe, 2022; Tkachenko, 2024; Tsolakis et al., 2022; Verdecchia et al., 2023).

The best way ahead is a multidisciplinary approach. That is, combining environmental science and policy by offering business strategy, information systems along with market incentives, legal systems, technological innovation in efficiency which can assist to guarantee that GenAI and LLMs development do not bring an unacceptably high environmental cost (Belrzaeg et al., 2025; Debus et al., 2023; Frimpong, 2025; Gupta et al., 2021; Kyriakarakos, 2025; Lee & Chen, 2022; Liu et al., 2021; Luccioni & Hernandez-Garcia, 2023; Ruiz-Sánchez et al., 2024; Schwartz et al., 2020; Sobkowiak et al., 2023; Vartziotis et al., 2024; Yunyun et al., 2024).

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In a nutshell, the problem for the next decade will be to match the transforming power of artificial intelligence with planetary boundaries, therefore guaranteeing that the development of LLMs like GPT-5, and beyond that does not irretrievably damage the natural systems upon which human and economic wellbeing is dependent (Akpan & Adebayo, 2025; Cherukuri, 2024; Zhang et al., 2023).

References

Ågerfalk, P. J.: Artificial intelligence as digital agency. European Journal of Information Systems 29(1), 1–8 (2020). https://doi.org/10.1080/0960085X.2020.1721947

Agomuo, O. C., Jnr, O. W. B., Muzamal, J. H.: Energy-aware AI-based optimal cloud infra allocation for provisioning of resources. In: *2024 IEEE/ACIS 27th International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD)*, pp. 269–274. IEEE (2024). https://doi.org/10.1109/SNPD61259.2024.10673918

Akpan, M., Adebayo, A.: Artificial Intelligence and the Dual Paradoxes: Examining the Interplay of Efficiency, Resource Consumption, and Labor Dynamics. *arXiv preprint arXiv:2504.10503* (2025). https://doi.org/10.48550/arXiv.2504.10503

Al-Sabahi, K., Al Mabsali, Y. K., Almaqtari, F. A., Al-Rashdi, S. A. S.: Transforming Sustainable Finance: The Impact of Artificial Intelligence. In: *AI Integration for Business Sustainability: For a Resilient Future*, pp. 73–100. Springer Nature Singapore (2025). https://doi.org/10.1007/978-981-96-3464-4_4

Amankwah-Amoah, J., Abdalla, S., Mogaji, E., Elbanna, A., Dwivedi, Y. K.: The impending disruption of creative industries by generative AI: Opportunities, challenges, and research agenda. International Journal of Information Management 79, 102759 (2024). https://doi.org/10.1016/j.ijinfomgt.2024.102759

Online ISSN 3007-3197
Print ISSN 3007-3189

Argerich, M. F., Patiño-Martínez, M.: Measuring and improving the energy efficiency of large language models inference. IEEE Access 12, 80194–80207 (2024). https://doi.org/10.1109/ACCESS.2024.3409745

Arroyabe, M. F., Arranz, C. F., De Arroyabe, I. F., de Arroyabe, J. C. F.: Analyzing AI adoption in European SMEs: A study of digital capabilities, innovation, and external environment. Technology in Society 79, 102733 (2024). https://doi.org/10.1016/j.techsoc.2024.102733

Aysan, A., Dincer, H., Unal, I. M., Yüksel, S.: AI development in financial markets: a balanced scorecard analysis of its impact on sustainable development goals. Kybernetes (2024). https://doi.org/10.1108/K-05-2024-1181

Banerjee, S., Pahwa, M., Agarwal, S., Gupta, S.: Empowering Tomorrow's Mobility: The Role of EVs in Sustainable Development. In: *2024 1st International Conference on Sustainability and Technological Advancements in Engineering Domain (SUSTAINED)*, pp. 1001–1007. IEEE (2024). https://doi.org/10.1109/SUSTAINED63638.2024.11074170

Belrzaeg, M., Ahmed, A. A., Alarga, A. S. D.: AI-Driven Optimization of Renewable Energy Grids Enhancing Efficiency and Sustainability. The Open European Journal of Applied Sciences (OEJAS), 24–35 (2025). https://easdjournals.com/index.php/oejas/article/view/15

Ben-Ishai, G., Dean, J., Manyika, J., Porat, R., Varian, H., Walker, K.: AI and the opportunity for shared prosperity: Lessons from the history of technology and the economy. *arXiv preprint arXiv:2401.09718* (2024). https://doi.org/10.48550/arXiv.2401.09718

Bender, E. M., Friedman, B.: Data statements for NLP: Toward mitigating system bias and enabling better science. Transactions of the Association for Computational Linguistics 6, 587–604 (2018). https://doi.org/10.1162/tacl_a_00041

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

Besinger, P., Vejnoska, D., Ansari, F.: Responsible AI (RAI) in manufacturing: A qualitative framework. Procedia Computer Science 232, 813–822 (2024). https://doi.org/10.1016/j.procs.2024.01.081

Brock, J. K.-U., von Wangenheim, F.: Demystifying AI: What digital transformation leaders can teach you about realistic AI adoption. California Management Review 61(4), 110–134 (2019). https://doi.org/10.1177/1536504219865226

Cao, Z., Zhou, X., Hu, H., Wang, Z., Wen, Y.: Toward a systematic survey for carbon neutral data centers. IEEE Communications Surveys & Tutorials 24(2), 895–936 (2022). https://doi.org/10.1109/COMST.2022.3161275

Chen, Z.: Attention is not all you need anymore. *arXiv preprint arXiv:2308.07661* (2023). https://doi.org/10.48550/arXiv.2308.07661

Cherukuri, M.: Advancing AI Safely: Frameworks and Strategies for the Development of GPT-5 and Beyond. In: *2024 7th International Conference on Electronics and Electrical Engineering Technology (EEET)*, pp. 65–79. IEEE (2024). https://doi.org/10.1109/EEET64351.2024.00023

d'Aramon, I., Ruf, B., Detyniecki, M.: Assessing carbon footprint estimations of chatgpt. In: *Renewable Energy Resources and Conservation*, pp. 127–133. Springer Nature Switzerland (2024). https://doi.org/10.1007/978-3-031-59005-4_15

Dauvergne, P.: Is artificial intelligence greening global supply chains? Exposing the political economy of environmental costs. Review of International Political Economy 29(3), 696–718 (2022). https://doi.org/10.1080/09692290.2020.1814381

Debus, C., Piraud, M., Streit, A., Theis, F. J., Götz, M.: Reporting electricity consumption is essential for sustainable AI. Nature Machine Intelligence 5(11), 1176–1178 (2023). https://doi.org/10.1038/s42256-023-00750-1

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 9 (2025)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

Ding, C., Ke, J., Levine, M., Zhou, N.: Potential of artificial intelligence in reducing energy and carbon emissions of commercial buildings at scale. Nature Communications 15(1), 5916 (2024). https://doi.org/10.1038/s41467-024-50088-4

Everman, B., Villwock, T., Chen, D., Soto, N., Zhang, O., Zong, Z.: Evaluating the carbon impact of large language models at the inference stage. In: *2023 IEEE International Performance, Computing, and Communications Conference (IPCCC)*, pp. 150–157. IEEE (2023). https://doi.org/10.1109/IPCCC59175.2023.10253886

Frimpong, V.: Artificial Intelligence Investment in Resource-Constrained African Economies: Financial, Strategic, and Ethical Trade-Offs with Broader Implications. World 6(2), 70 (2025). https://doi.org/10.3390/world6020070

Gupta, S., Langhans, S. D., Domisch, S., Fuso-Nerini, F., Felländer, A., Battaglini, M., ... Vinuesa, R.: Assessing whether artificial intelligence is an enabler or an inhibitor of sustainability at indicator level. Transportation Engineering 4, 100064 (2021). https://doi.org/10.1016/j.treng.2021.100064

Hamels, S., Himpe, E., Laverge, J., Delghust, M., Van den Brande, K., Janssens, A., Albrecht, J.: The use of primary energy factors and CO2 intensities for electricity in the European context-A systematic methodological review and critical evaluation of the contemporary literature. Renewable and Sustainable Energy Reviews 146, 111182 (2021). https://doi.org/10.1016/j.rser.2021.111182

Kaneko, Y.: Comparing Electricity Consumption Per Use of Blockchain and Generative AI. IEEE Access (2025). https://doi.org/10.1109/ACCESS.2025.3573722

Kaplan, J., McCandlish, S., Henighan, T., Brown, T. B., Chess, B., Child, R., ... Amodei, D.: Scaling laws for neural language models. *arXiv preprint arXiv:2001.08361* (2020). https://doi.org/10.48550/arXiv.2001.08361

Online ISSN 3007-3197
Print ISSN 3007-3189

Khaddam, A. A., Alzghoul, A.: Artificial Intelligence-Driven Business Intelligence for Strategic Energy and ESG Management: A Systematic Review of Economic and Policy Implications. International Journal of Energy Economics and Policy 15(4), 635 (2025). https://doi.org/10.32479/ijeep.19820

Khan, I., Hou, F., Zakari, A., Tawiah, V. K.: The dynamic links among energy transitions, energy consumption, and sustainable economic growth: A novel framework for IEA countries. Energy 222, 119935 (2021). https://doi.org/10.1016/j.energy.2021.119935

Krishnan, S. R., Nallakaruppan, M. K., Chengoden, R., Koppu, S., Iyapparaja, M., Sadhasivam, J., Sethuraman, S.: Smart water resource management using Artificial Intelligence—A review. Sustainability 14(20), 13384 (2022). https://doi.org/10.3390/su142013384

Kulkov, I., Kulkova, J., Rohrbeck, R., Menvielle, L., Kaartemo, V., Makkonen, H.: Artificial intelligence-driven sustainable development: Examining organizational, technical, and processing approaches to achieving global goals. Sustainable Development 32(3), 2253–2267 (2024). https://doi.org/10.1002/sd.2773

Kyriakarakos, G.: Artificial Intelligence and the Energy Transition. Sustainability 17(3), 1140 (2025). https://doi.org/10.3390/su17031140

Laskin, A. V., D'Agostino, G.: The Delphi Panel investigation of artificial intelligence in investor relations. Public Relations Review 50(4), 102489 (2024). https://doi.org/10.1016/j.pubrev.2024.102489

Lee, D., Chen, L.: Sustainable air-conditioning systems enabled by artificial intelligence: Research status, enterprise patent analysis, and future prospects. Sustainability 14(12), 7514 (2022). https://doi.org/10.3390/su141207514

Online ISSN 3007-3197
Print ISSN 3007-3189

Lee, S. U., Perera, H., Liu, Y., Xia, B., Lu, Q., Zhu, L., ... Nottage, M.: Integrating ESG and AI: a comprehensive responsible AI assessment framework. AI and Ethics, 1–28 (2025). https://doi.org/10.1007/s43681-025-00741-5

Li, P., Yang, J., Islam, M. A., Ren, S.: Making AI Less 'Thirsty'. Communications of the ACM 68(7), 54–61 (2025). https://doi.org/10.1145/3724499

Liu, H., Aljbri, A., Song, J., Jiang, J., Hua, C.: Research advances on AI-powered thermal management for data centers. Tsinghua Science and Technology 27(2), 303–314 (2021). https://doi.org/10.26599/TST.2021.9010019

Ljungdahl, V., Jradi, M., Veje, C. J. A. T. E.: A decision support model for waste heat recovery systems design in Data Center and High-Performance Computing clusters utilizing liquid cooling and Phase Change Materials. Applied Thermal Engineering 201, 117671 (2022). https://doi.org/10.1016/j.applthermaleng.2021.117671

Luccioni, A. S., Hernandez-Garcia, A.: Counting carbon: A survey of factors influencing the emissions of machine learning. *arXiv preprint arXiv:2302.08476* (2023). https://doi.org/10.48550/arXiv.2302.08476

Lucivero, F.: Big data, big waste? A reflection on the environmental sustainability of big data initiatives. Science and Engineering Ethics 26(2), 1009–1030 (2020). https://doi.org/10.1007/s11948-019-00171-7

Ma, Y., Zhang, Z.: ICT and energy rebound effect: Empirical analysis based on data from Chinese cities. Journal of Environmental Management 370, 122651 (2024). https://doi.org/10.1016/j.jenvman.2024.122651

Maple, C., Szpruch, L., Epiphaniou, G., Staykova, K., Singh, S., Penwarden, W., ... Avramovic, P.: The AI revolution: Opportunities and challenges for the finance sector. *arXiv preprint arXiv:2308.16538* (2023). https://doi.org/10.48550/arXiv.2308.16538

Online ISSN 3007-3197
Print ISSN 3007-3189

Meena, R., Sahoo, S., Malik, A., Kumar, S., Nguyen, M.: Artificial intelligence and circular supply chains: framework for applications and deployment from the triple bottom line model perspective. Annals of Operations Research, 1–31 (2025). https://doi.org/10.1007/s10479-025-06510-1

Meng, Y., Noman, H.: Predicting CO2 emission footprint using AI through machine learning. Atmosphere 13(11), 1871 (2022). https://doi.org/10.3390/atmos13111871

Mhlanga, D.: Artificial intelligence and machine learning for energy consumption and production in emerging markets: A review. Energies 16(2), 745 (2023). https://doi.org/10.3390/en16020745

Mytton, D.: Data centre water consumption. npj Clean Water 4(1), 11 (2021). https://doi.org/10.1038/s41545-021-00101-w

Oladapo, B. I., Olawumi, M. A., Omigbodun, F. T.: AI-Driven Circular Economy of Enhancing Sustainability and Efficiency in Industrial Operations. Sustainability 16(23), 10358 (2024). https://doi.org/10.3390/su162310358

Patterson, D., Gonzalez, J., Le, Q., Liang, C., Munguia, L. M., Rothchild, D, Dean, J.: Carbon emissions and large neural network training. *arXiv preprint arXiv:2104.10350* (2021). https://doi.org/10.48550/arXiv.2104.10350

Pimenow, S., Pimenowa, O., Prus, P.: Challenges of artificial intelligence development in the context of energy consumption and impact on climate change. Energies 17(23), 5965 (2024). https://doi.org/10.3390/en17235965

Praveen, R. V. S., Mittal, M., Parida, P., Kumar, Y., Singla, A., Thandra, N.: Leveraging IoT and AI in Precision Agriculture for Efficient Water Management. In: *2025 International Conference on Computational, Communication and Information Technology*

Online ISSN 3007-3197
Print ISSN 3007-3189
http://amresearchreview.com/index.php/Journal/about

(*ICCCIT*), pp. 803–808. IEEE (2025). https://doi.org/10.1109/ICCCIT62592.2025.10927765

Robbins, S., Van Wynsberghe, A.: Our new artificial intelligence infrastructure: becoming locked into an unsustainable future. Sustainability 14(8), 4829 (2022). https://doi.org/10.3390/su14084829

Ruiz-Sánchez, R., Arencibia-Jorge, R., Tagüeña, J., Jiménez-Andrade, J. L., Carrillo-Calvet, H.: Exploring research on ecotechnology through artificial intelligence and bibliometric maps. Environmental Science and Ecotechnology 21, 100386 (2024). https://doi.org/10.1016/j.ese.2023.100386

Schwartz, R., Dodge, J., Smith, N. A., Etzioni, O.: Green AI. Communications of the ACM 63(12), 54–63 (2020). https://doi.org/10.1145/3381831

Sobkowiak, M., Senn, J., Vollmer, H.: Rethinking planetary boundaries: Accounting for ecological limits. Social and Environmental Accountability Journal 43(3), 259–272 (2023). https://doi.org/10.1080/0969160X.2023.2283019

Spelda, P., Stritecky, V.: The future of human-artificial intelligence nexus and its environmental costs. Futures 117, 102531 (2020). https://doi.org/10.1016/j.futures.2020.102531

Strubell, E., Ganesh, A., McCallum, A.: Energy and policy considerations for deep learning in NLP. *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pp. 3645–3650 (2019). https://doi.org/10.18653/v1/P19-1355

Tao, M., Zhang, T., Xie, X., Liang, X.: Water footprint modeling and forecasting of cassava based on different artificial intelligence algorithms in Guangxi, China. Journal of Cleaner Production 382, 135238 (2023). https://doi.org/10.1016/j.jclepro.2022.135238

Online ISSN 3007-3197
Print ISSN 3007-3189

Tian, M., Adriaens, P.: Predictive learning of operational water intensity from corporate financial indicators: Implications for AI-based resource management. Resources, Conservation and Recycling 220, 108383 (2025). https://doi.org/10.1016/j.resconrec.2025.108383

Tkachenko, N.: Integrating AI's Carbon Footprint into Risk Management Frameworks: Strategies and Tools for Sustainable Compliance in Banking Sector. *arXiv preprint arXiv:2410.01818* (2024). https://doi.org/10.48550/arXiv.2410.01818

Tsolakis, N., Zissis, D., Papaefthimiou, S., Korfiatis, N.: Towards AI driven environmental sustainability: an application of automated logistics in container port terminals. International Journal of Production Research 60(14), 4508–4528 (2022). https://doi.org/10.1080/00207543.2021.1914355

Vartziotis, T., Dellatolas, I., Dasoulas, G., Schmidt, M., Schneider, F., Hoffmann, T., ... Keckeisen, M.: Learn to code sustainably: An empirical study on llm-based green code generation. *arXiv preprint arXiv:2403.03344* (2024). https://doi.org/10.48550/arXiv.2403.03344

Verdecchia, R., Procaccianti, G., Lago, P., Lenarduzzi, V.: A systematic review of Green AI. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery 13(3), e1507 (2023). https://doi.org/10.1002/widm.1507

Xiong, Y., Chen, X., Ye, X., Chen, H., Lin, Z., Lian, H., ... Ding, G.: Temporal scaling law for large language models. *arXiv preprint arXiv:2404.17785* (2024). https://doi.org/10.48550/arXiv.2404.17785

Yang, M., Chen, J., Zhang, Y., Liu, J., Zhang, J., Ma, Q., ... Ying, R.: Low-rank adaptation for foundation models: A comprehensive review. *arXiv preprint arXiv:2501.00365* (2025). https://doi.org/10.48550/arXiv.2501.00365

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 9 (2025)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

Yunyun, F. U., Yongchang, S. H. E. N., Malin, S. O. N. G., Weiyu, W. A. N. G.: Does artificial intelligence reduce corporate energy consumption? New evidence from China. Economic Analysis and Policy 83, 548–561 (2024). https://doi.org/10.1016/j.eap.2024.07.005

Zhang, C., Zhang, C., Zheng, S., Qiao, Y., Li, C., Zhang, M., Hong, C. S.: A complete survey on generative ai (aigc): Is chatgpt from gpt-4 to gpt-5 all you need?. *arXiv preprint arXiv:2303.11717* (2023). https://doi.org/10.48550/arXiv.2303.11717