Policy Network on Artificial Intelligence (PNAI)
Sub-group on Environmental Sustainability within Generative AI Value Chain
DRAFT VERSION, October 2024

Environmental Sustainability and the Generative AI Value Chain

Discussion Paper

1. Introduction

Digital transformation is a global phenomenon that enhances productivity, disrupts traditional business models, and fosters a wide range of innovations with significant implications for humanity's future (UNIDO, 2024). Driven mainly by data-based systems (DS), the transformation of socioeconomic, political, and market activity holds tremendous potential to advance sustainability, alas the current global trajectory often perpetuates the use of frontier technologies to exacerbate unsustainable practices that harm natural ecosystems, worsen multidimensional inequality, and threaten human well-being (CODES, 2022, UNCTAD, 2024a).

Since their prolific explosion in 2022, the ubiquity and exponential expansion of generative artificial intelligence AI (Gen-AI) platforms has become a global phenomenon (Harlin et al., 2023). While Gen-AI models such as Open AI's Generative Pre-trained Transformer (GPT) models and other related foundation models (FM) present opportunities for innovation across industries, there is a growing realization that not every Gen-AI application will be inherently beneficial or realize its anticipated advantages (Bender et al. 2021). Beyond existential risks that could exacerbate longstanding ethical and socioeconomic issues, such as surveillance, privacy violations, multidimensional inequality, and discrimination, to name a few — DS such as Gen-AI also pose significant risks associated with global environmental sustainability concerns (Bashir et al. 2024; Ahmed & Kirchlager, 2024; Kalantzakos 2020).

Companies are incentivized to prioritize AI performance, efficiency, and scalability, often overlooking the environmental costs of Gen-AI innovations, at scale, while negating social and environmental impacts (Domínguez Hernández et al,. 2024; Varoquaux et al,.2024). At present, efforts to enhance computing sustainability are primarily centred on improving efficiency — such as boosting hardware energy efficiency, optimizing AI algorithms, and increasing the carbon efficiency of computing workloads through techniques like spatiotemporal workload shifting (Bashir et al., 2024).

However, the narrow focus on efficiency and scalability, driven by relentless demand fails to address the broader environmental challenges tied to Gen-AI (Bashir t al., 2024). To mitigate the existential risks associated with Gen-AI, concerted interventions to improve integrated thematic and topic modelling analysis (Raman, et al,.2024), robust global AI governance (Ahmed and Kirschlager, 2024) and ensure the widespread use of digital public goods (DPGs)[1], amongst other factors.

The Policy Network on AI (PNAI) is dedicated to integrating environmental considerations into the responsible global governance of Gen-AI, that aligns with best practices to support the global Majority (PNAI, 2023; WEF, 2024). PNAI's commitment aligns with ongoing broader sustainability goals, including the United Nations Sustainable Development Goals (SDGs), which encompass objectives broadly related to adaptation, mitigation, and loss and damage, including biodiversity loss, wildlife conservation, and the sustainable use of natural resources. By raising awareness of the governance dimensions needed to support sustainable practices throughout the Gen-AI value chain, PNAI aims to understand the environmental impact associated with the development, deployment, and disposal of Gen-AI technologies and prioritizes policy action for climate justice while simultaneously minimizing the overall negative environmental impact of Gen-AI.

Assessing and mitigating the environmental impact of Gen-AI technologies is particularly important for the global Majority, who may disproportionately bear the consequences of climate change linked to unsustainable digital economy practices (UNCTAD, 2024a). Communities in low-income and middle-income countries (LMICs)[2] often bear the brunt of environmental degradation and the extraction of labour and natural resources that are associated with technological transitions (UNCTAD, 2021). To achieve planetary health and human wellbeing, a shift in perspective and holistic approach to addressing grand challenges is needed, which requires analysis beyond the triple planetary crisis, to include other dimensions such as institutionalised inequality, decolonialisation, shifts in social and demographic dynamics, advancements in frontier technologies (FT), geopolitical tensions, governance issues, trust in multilateral social and institutional frameworks, as well as migration and conflict, among other factors (Ahmed and Kirschlager, 2024;UNDP, 2024).

Communities who have been and continue to be marginalised need to be empowered to move beyond narratives as mere 'victims' and should be considered as holders of valuable and legitimate knowledge in times of Gen-AI and triple planetary crisis to ensure that the potential benefits of AI are not realized at the cost of LMIC's ecological

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[1] Digital public goods refer to open-source software, open AI models, open standards, open content, and open data that adhere to privacy and other applicable international and domestic laws, standards, best practices, and do no harm. The concept of DPGs stems from the economic term "public good" referring to resources and services individuals cannot (or should not) be excluded from. https://digitalpublicgoods.net/PublicGoodDataReport.pdf

[2] Designations such as "global Majority", "low-income and middle-income countries", "high-income countries" or "developing" are intended for statistical convenience and do not necessarily express a judgement about the stage reached by a particular country or area in the economic development process

ecosystems, livelihoods, and natural resources (Lehuedé 2024) and perpetuate historical and ongoing patterns of inequity (Elia 2023; Guerrero 2023), where wealthier nations and their corporations may benefit from the efficiencies generated by Gen-AI, while poorer regions bear the environmental costs without reaping similar rewards (UNCTAD, 2024a).

Decisions regarding the deployment and regulation of Gen-AI technologies are often made by high-income countries and large corporations, sidelining voices from marginalized communities that are most affected by these choices (WEF, 2024). This lack of representation in climate governance frameworks further entrenches inequalities and diminishes the ability of these communities to advocate for their needs (Ren & Wierman, 2023).

While the field of sustainable AI has developed and has been put forward as a way of addressing the environmental justice issues associated with AI throughout its lifecycle (Luccioni et al., 2024; Robbins and van Wynsberghe 2022; Strubell, et.al.,2020), there is limited literature focused on the Gen-AI value chain or a value chain assessment (VCA) of the environmental toll of Gen-AI.

This discussion paper was created to facilitate much needed multistakeholder dialogue, providing insights into the opportunities and environmental externalities underpinning the infrastructure and the value chain of Gen-AI. The aim is to highlight the importance of sustainable practices through showcasing case studies. The development of this discussion paper is based on insights from multidisciplinary stakeholders from diverse regions, ensuring a holistic perspective on environmental sustainability and the Gen-AI value chain[3].

2. Environmental Sustainability and the Generative AI Value Chain

2.1. State of Global Gen-AI Governance

The current global governance of AI in general, faces several critical issues that reflect the complexities and rapid advancements of the technology such as, structural limitations, global imbalances and navigating a complex geopolitical landscape characterized by rapid technological advancements, cross-border impacts, ethical considerations, and the need for balance between innovation and regulation (Ahmed et al., 2023; WEF, 2024).

Furthermore, current practices of safety and risk mitigation for governing AI often focus narrowly on improving energy efficiency without adequately addressing the broader sustainability and sociotechnical challenges, leading to an incomplete

[3] See Annex 1 for motivation for a Gen-AI value chain analysis vs life cycle assessment

understanding of the environmental costs associated with Gen-AI development and deployment (Domínguez Hernández et al. 2024). The development of larger and more complex models is often prioritized for competitive reasons, without fully accounting for the carbon cost of training and deploying these models at scale (Bashir et al. 2024; Varoquaux et al,.2024). As investment in the development and application of Gen-AI technologies continues to grow, it becomes increasingly crucial to understand their impact on the environment.

Furthermore, discussions regarding the balance between the potential benefits of Gen-AI systems and their environmental costs must be based on concrete data and evidence (Bashir, et al.,2024). Unfortunately, most developers and operators of these systems are not currently providing the necessary data. The lack of publicly available information hinders the formulation and implementation of effective evidence-based policies (PNAI, 2023).

In addition, as models optimise datasets and computational power to produce outputs that lack richness and variety, the solutions created may be inadequate for the global Majority. Analysing the Gen-AI value chain emphasises that innovation must emerge from a robust local digital ecosystem, where businesses, entrepreneurs, and academic institutions play a pivotal role. Multistakeholder collaboration will be crucial in co-creating coordinated agile and adaptive governance that facilitate the creation of green digital jobs and sustainable livelihoods that support both economic growth and environmental resilience (Bashir et al., 2024).

2.2. Exploring the Generative AI Value Chain

The Gen-AI value chain outlines the various stages and components that comprise in the development, deployment, and utilization of Gen-AI technologies (Harlin, et al., 2023).

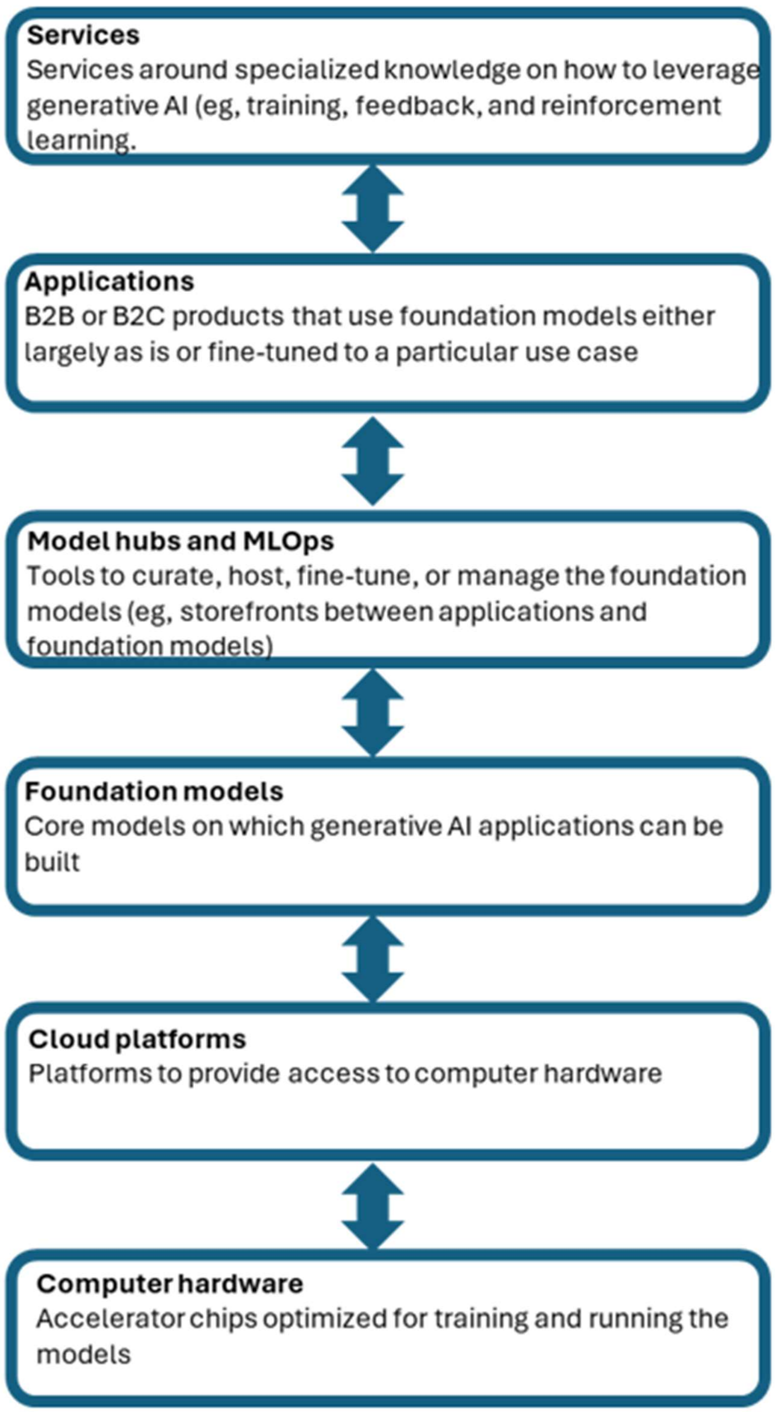
The Gen-AI value chain involves hardware in the form of devices and sensors to capture the data and data centres to store them, cloud platforms and networks for communicating data, foundation models, model hubs that act as repositories for storing and accessing foundation models, applications such as end-user interfaces, and existing AI service providers and new niche players that specialize in Gen-AI applications (Harlin et al.,2023).

The Gen-AI value chain reflects a complex ecosystem that supports the creation and deployment of innovative AI solutions. As Gen-AI continues to evolve, understanding the value chain is essential for identifying investment opportunities, anticipatory governance, and assessing the potential impact of these technologies to enhance environmental stewardship.

As shown in Figure 1, the Gen-AI value chain consists of several non-linear and dynamic key elements that contribute to the overall functionality and effectiveness of

Gen-AI systems, including natural resources and energy to build and transport the devices and products, which emit greenhouse gases throughout the value chain (Bashir et al. 2024).

Figure 1: The Generative AI Value Chain



Source: Harlin et al.,2023

2.3. Key Differences Between Gen-AI and Traditional AI Applications

Gen-AI and traditional (weak or narrow) AI applications differ primarily in their goals and methods of operation, traditional AI typically focuses on recognizing patterns, making predictions, or automating tasks based on pre-existing data (Bond-Taylor et al., 2022).

While traditional AI applications emphasize accuracy and efficiency in task completion, Gen-AI prioritizes creativity and the ability to produce novel outputs that didn't exist before. For instance, chatbots powered by traditional AI may provide factual responses, while those using generative AI can engage in more human-like, creative conversations (WEF, 2024). Gen-AI represents a paradigm shift by enabling the autonomous creation of novel content and adapting to complex scenarios. However, both traditional AI and Gen-AI are complementary, with traditional AI methods still holding immense value for many applications (Harlin et al.,2023).

The differences between Gen-AI and traditional AI applications require distinct governance approaches because of the inherent risks and implications each type of AI presents (Bender et al. 2021; Brundage et al. 2020).

However, a coordinated, collaborative, and inclusive approach is vital to create meaningful and effective governance structures that reflect the needs of the global Majority and address the complexities of Gen-AI's negative environmental implications. As the demand for AI continues to rise, these environmental costs will only escalate, underscoring the urgent need to address the sustainability challenges associated with the Gen-AI value chain.

2.4. The Gen-AI Value Chain and the Environment

2.4.1. Mapping the Environmental toll of the Gen-AI Value Chain

Each stage of this value chain contributes to the overall carbon footprint and resource depletion. The following summaries the environment toll at each stage of the suggested Gen-AI value chain model:

i. Computer Hardware

Computer hardware provides the foundational layer which includes semiconductors, and specialized processors, such as Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs) that provide the necessary computational power to handle the extensive data processing and complex algorithms required by Gen-AI models (Harlin et al.,2023). The production of computer hardware involves substantial energy consumption, contributing to carbon emissions. For instance, manufacturing a single high-performance GPU can emit over 200 kg of $CO2$, highlighting the energy-intensive nature of the process (Bashir et al. 2024).

While Gen-AI dominates global technological discussions, it cannot be viewed in isolation, as the raw materials and components driving its progress are controlled by a few, globally dispersed chip manufacturers. The dependency on these semiconductor companies underscores the interconnectedness of AI with the broader technological and supply chain ecosystem (Burkacky et al., 2024). Many governments have designated semiconductors as 'critical technologies,' due their foundational role at the base of the technology stack makes them essential to the advancement of nearly every emerging technology, since semiconductors enable the processing of large amounts of data and the rapid execution of complex calculations that form the foundation of AI systems, including Gen-AI (Janjeva et al.,2024).

Left unchecked, the semiconductor boom could exacerbate huge levels of toxic waste in the form of air pollutants and groundwater contamination, due to certain chemicals and gases used in semiconductor manufacturing (Perkins 2024). As far back as the 1980s, the use of chemicals in semiconductor operations has long been a challenge, the updated F-gas regulation and the proposed ban on per- and polyfluoroalkyl substances (PFAS) reflects growing regulatory efforts to mitigate the environmental impacts associated with semiconductor production (Hess, 2024).

However, the increased integration of Gen-AI systems into various sectors creates new complexities and risks that require coordinated international efforts to ensure their safe and responsible use (WEF, 2024). In the context of growing concerns over climate change and biodiversity loss, addressing the environmental footprint of AI technologies is crucial. As Gen-AI applications evolve and proliferate, it becomes essential to address their ecological footprint to ensure sustainable digital development and a just green digital twin transition (Bashir et al.,2024).

In addition, the computational power to train Gen-AI models requires significant energy that contributes to the overall carbon footprint of AI technologies and water use (Ren and Wierman, 2023). There are projections that the current computationally intensive training process for models Gen-AI like GPT-3 and the demand for high-performance semiconductor components, including logic chips (CPUs, GPUs, AI accelerators), memory chips (HBM, DDR), and data storage chips (NAND) will skyrocket to unprecedented levels by 2030 contributing to a significant carbon footprint, which poses challenges in achieving net-zero greenhouse gas emissions and accelerates depletion of natural resources (Bashir et al.,2024; Burkacky,et al.2024).

The data centres housing the hardware necessary for training and running Gen-AI models require significant cooling to maintain optimal operating temperatures. This cooling process often involves substantial water usage and consume large amounts of electricity, with estimates indicating that data centres account for approximately 20 percent of electricity consumption in some regions and raising concerns about water scarcity in regions where these data centres are located (Bashir et al. 2024; Ren, 2023).

As the world transitions to low-carbon technologies, such as electric vehicles and renewable energy systems, the demand for critical minerals like lithium, cobalt, and nickel is surging (Kalantzakos, 2020). These minerals are essential for batteries and other components of so-called green technologies, leading to intensified mining activities. The rising demand for low-carbon technologies escalates the need for critical minerals, as the production of computer hardware involves the extraction of various natural resources, including silicon and rare earth metals (EPA, 2012). The processing of raw rare earth minerals can lead to environmental degradation, habitat destruction, and increased carbon emissions associated with mining and manufacturing, mainly for the global Majority, where there are higher geographic concentration of reserves and processing for five critical minerals: cobalt, copper, lithium, nickel, and rare earth elements (UNCTAD, 2024b).

The environmental costs associated with extracting resources for AI infrastructure are significant and multifaceted (UNCTAD, 2024b). Additionally, the rapid obsolescence of hardware technology leads to the discarding of outdated equipment, contributing to the growing problem of electronic waste (e-waste). The Global E-waste Monitor 2024 report indicates that e-waste generation in 2022 reached a record 62 million metric tonnes, with only 22 percent being officially collected and recycled, the annual generation of e-waste is rising by 2.6 million tonnes annually, on track to reach 82 million tonnes by 2030 (UNITAR, 2024). Sustainable disposal and recycling practices are essential to mitigate the environmental impact of outdated equipment.

ii. Cloud Platforms

Gen-AI is revolutionizing industries by empowering machines to produce content, tackle complex challenges, and fuel innovations once thought impossible, from generating human-like text to creating realistic images, the capabilities of generative AI are vast and transformative (Intel, 2024).

Gen-AI requires substantial computational power to process and generate data, reliable cloud environments offer the scalability needed to handle these demands (Harlin et al.,2023). Cloud platforms facilitate flexibility so that resources can be scaled up or down based on the workload, ensuring that Gen-AI models run efficiently without hardware limitations. This is particularly beneficial for training large models, which may require varying levels of resources at different stages of the value chain (Harlin et al.,2023).

Major cloud service providers, such as Amazon (AWS), Microsoft Azure, and Google Cloud, are increasingly offering scalable infrastructure that enables the deployment of Gen-AI applications and models, facilitating access to vast computational resources and new database capabilities for storing and rapidly retrieving the unstructured and semi-structured data used in Gen-AI systems (Accenture, 2023).

However, cloud platforms that host Gen-AI applications consume substantial energy for both processing and cooling, data centres must maintain optimal temperatures to ensure efficient operation, leading to increased electricity and water usage (Bashir et al. 2024) and the ongoing maintenance of cloud infrastructure, including hardware upgrades and system monitoring, can contribute to resource depletion and environmental impact. A 2019 study estimated that training a large natural language model like GPT-3 on cloud platforms could result in carbon emissions equivalent to the lifetime emissions of five cars (Strubell, et.al.,2019). While there are efforts to stem the ecological externalities from increased energy use, there remains a lot more to do given the world's increasing need for computing power (Bashir et al. 2024).

The operational costs associated with running Gen-AI systems—particularly regarding cloud computing and energy consumption—are significant. Smaller organizations or those in developing regions may not have the financial capacity to sustain such expenses. This economic barrier leads to increased reliance on established providers who can absorb these costs, thereby limiting the ability of local entities to pursue independent innovation (Lynn et al., 2023).

iii. Foundation Models

Gen-AI models rely on extensive datasets to learn patterns and generate realistic outputs. For instance, during the training phase, Gen-AI models absorb petabytes of data—from diverse sources like books, websites, and other machine-readable digital content. The quality and diversity of the training data directly impact the performance of the AI (Wu & Higgins, 2023)

Foundation Models (FM) are large pre-trained models, such as BERT, OpenAI's GPT-4, and DALL-E, which serve as the core building blocks for various Gen-AI applications, (also called large language models or LLMs) and are meant for general use (Harlin et al.,2023).

FMs require extensive computational power and training periods, once FM are trained, they require continuous energy for inference and processing tasks, the ongoing energy demand can significantly add to the carbon footprint of AI applications, particularly as their usage scales (Patterson et al. 2021). Once AI models are deployed, they require ongoing operational energy for inference and processing tasks. The exact environmental cost of Gen-AI activity is not known, since the developers of the latest models do not provide detailed emissions figures. A thorough assessment of the environmental costs involved in maintaining Gen-AI technologies is urgently required (Bashir et al. 2024).

While there are efforts being made towards enhance algorithm efficiency and reduce computational requirements to meet the growing demand for Gen-AI applications such as the development of more innovative efficient transformer models, which aim to decrease the number of operations and memory demand needed during training

(Burkacky, et al., 2024) and mitigate hallucinations (IBM, 2023), there is not enough global governance considerations on the categories of risks and harms related to environmental sustainability and natural resource management externalities associated with the most urgent negative impacts of FM and their downstream applications (Domínguez Hernández et al., 2024).

Effective governance of Gen-AI requires robust data governance frameworks to ensure interoperability, transparency, and accountability. However, the lack of clear guidelines on data usage, unequal access to high quality datasets, and the potential for misuse complicate the establishment of reliable indicators for sustainability (PNAI, 2023).

iv. Model Hubs and Machine Learning Operations

Model hubs act as repositories for storing and accessing FMs, and machine learning operations (MLOps) encompass the tools and practices used for managing and deploying FM in real-world applications this stage is crucial for ensuring that models are effectively integrated into user-facing applications (Harlin et al.,2023).

Beyond the products themselves, energy consumption for storing, managing, and deploying models is also required for model hubs and MLOps. For example, regular updates and versioning of models can lead to increased resource consumption and waste generation, necessitating sustainable practices in the lifecycle management of AI models (Patterson et al., 2021).

The reliance on substantial computational resources for MLOps not only contributes to higher energy consumption but also raises concerns about the environmental impact of these technologies. The operational emissions linked to running Gen-AI systems can exacerbate climate change, necessitating thorough assessments of their environmental costs. Moreover, as model hubs and MLOps become more prevalent, the potential for monopolistic behaviour by a few dominant Gen-AI service providers increases, which can limit access for smaller players and marginalize communities in the Global Majority. This dependency on established providers can stifle innovation and exacerbate inequalities, as local developers may lack the resources to compete effectively in a landscape dominated by major tech companies.

v. Applications

The applications layer includes the end-user interfaces and solutions, such as chatbots, content generators, and creative tools, that utilize Gen-AI models to perform specific tasks. The application layer is expected to see rapid growth and innovation, offering significant value-creation opportunities due to the demand from both business-to-consumer (B2C) and business-to-business(B2B) applications (Harlin et al.,2023). Gen-AI applications have created a hyper-competitive tech ecosystem that requires Gen-AI platforms to develop constant improvements to the quality of their Gen-AI algorithms, this demand presents a wide range of issues such as high resource-intensity, which often requires vast amounts of quality data and computational power, aided as much by big data as it is by software and hardware (Bashir et al. 2024).

The use of Gen-AI applications, such as chatbots and content generators, requires significant computational resources and energy for real-time processing (Bashir et al. 2024). The environmental implications of these applications span from the depletion of natural resources to the contribution of carbon emissions (Crawford 2024; Strubell et.al., 2019).

vi. Services

The services component involves existing AI service providers and new niche players that specialize in generative AI applications geared to help organizations navigate the complexities of implementing Gen-AI technologies and often provide tailored solutions for specific industries or functionalities (Harlin et al.,2023). The provision of Gen-AI services, including consulting and support, often relies on substantial computational resources, contributing to energy consumption and environmental impact. The operational emissions associated with running Gen-AI systems can exacerbate climate change, necessitating a thorough assessment of the environmental costs involved in maintaining these technologies (Bashir et al. 2024).

The data required to train effective AI models is often controlled by these dominant firms, which hoard vast datasets that are crucial for innovation. This concentration restricts access for emerging players from the global Majority, who may lack the means to acquire or generate comparable datasets. Consequently, this reinforces a cycle of dependency where local innovators cannot compete effectively, further entrenching the power of established multinational “Big Tech” corporation.

Overall, the Gen-AI value-chain is dominated by a few large tech companies that control substantial computational resources, data, and infrastructure necessary for developing and deploying AI technologies. These companies leverage their existing market power to dictate terms for access to essential services, creating barriers for smaller players and startups. As a result, organizations in the global Majority often find themselves reliant on these monopolistic entities for critical resources, stifling their ability to develop independent solutions and innovations (Lynn et al., 2023).

3. Need for Gen-AI Environmental Impact Metrics and Indicators[4]

With the increased demand and use of Gen-AI so do the significant environmental costs associated with the development, training, and deployment of large-scale AI models (Strubell et.al., 2019). As Gen-AI becomes more widespread in applications

[4] In the context of assessing the environmental impact of the Gen-AI value chain, it is essential to distinguish between metrics and indicators, as both play critical roles but serve different purpose.

such as content generation, virtual assistants, and creative tools, its energy consumption, resource use, and carbon footprint grow (Bashir, et al.,2024). Training state-of-the-art models such as GPT-3 or image-generating generative adversarial network (GAN) involves processing massive datasets across large clusters of GPUs or TPUs, which consume substantial amounts of energy (Patterson at al.,2021).

Furthermore, without a consistent way to measure emissions, it becomes difficult for companies and institutions to track or reduce their Gen-AI-related environmental impacts, including supporting regulations aimed at limiting the carbon emissions of tech companies, and holding tech companies accountable (Bashir et al. 2024).

3.1. Development of Metrics

The establishment of accurate and comprehensive metrics is crucial for assessing the environmental impact of Gen-AI. Accurate metrics are essential to enable the comparison of energy footprints between different models and optimization strategies and fostering more energy-efficient practices (Bashir et al. 2024).

Without clear metrics to quantify Gen-AI energy use, it's difficult to gauge the full environmental impact of Gen-AI systems. Metrics can help AI developers and policymakers better understand, manage and provide a framework for assessing energy consumption, resource utilization, and emissions associated with AI development, deployment, and usage. Without reliable metrics, it becomes challenging to identify areas for improvement, track progress toward sustainability goals, and for stakeholders to evaluate the sustainability of AI technologies effectively and inform decision-making processes aimed at minimizing ecological harm (OECD, 2022).

Furthermore, the existence of clear metrics can direct research and development efforts toward reducing environmental impact, encouraging innovations that make Gen-AI technology more sustainable.

Lessons from existing initiative reveal that various types of metrics can be employed to measure the environmental impact of Gen-AI for a wide range of reporting requirements such as environmental, social and governance (ESG), used to evaluate a company's sustainability and ethical impact (EY, 2023). While not an exhaustive list, a summary of metrics can include:

i. **Carbon Footprint:** This metric quantifies the total greenhouse gas emissions produced directly and indirectly by Gen-AI systems, providing insight into their contribution to climate change (Bashir et al. 2024).
ii. **Energy Efficiency**: This metric assesses the amount of energy consumed per unit of output generated by Gen-AI models, helping to identify opportunities for reducing energy usage.

iii. **E-Waste:** This metric can assess the amount of e-waste produced as compute hardware becomes obsolete due to Gen-AI hardware requirements (UNITAR, 2024).
iv. **Resource Utilization:** This metric evaluates the extraction and consumption of natural resources, such as water and minerals, associated with the production and operation of Gen-AI infrastructure (Robbins and van Wynsberghe 2022).
v. **Socio-economic Impact:** This metric can evaluate the sustainability of Gen-AI technologies effectively and inform decision-making processes aimed at minimizing ecological harm and facilitating a just transition (PNAI, 2023).

3.2. Indicators for Sustainability

Defining indicators is vital for measuring progress toward environmental sustainability goals in the context of Gen-AI. These indicators can help stakeholders assess the effectiveness of sustainability initiatives and identify areas for further improvement. For example, establishing standardized indicators of carbon output, such as kilograms of CO2 per hour of computation or per inference task, would drive accountability and encourage the adoption of carbon-neutral or lower-emission energy sources (OECD, 2022).

Indicators should be clear, measurable, and relevant to the specific environmental goals being pursued. They should also consider the unique challenges and opportunities presented by Gen-AI technologies. Examples of effective indicators can include:

Reduction in energy consumption. Tracking the decrease in energy usage associated with Gen-AI applications can demonstrate progress toward improving energy efficiency (Bashir, et al.2024).

Use of renewable energy sources. Measuring the percentage of energy sourced from renewable resources at different stages of the Gen-AI value chain can indicate the commitment to sustainable energy practices (Bashir, et al.2024).

Volume of recycled materials and minerals. Monitoring the number of recycled materials used in the production of AI hardware can help assess the effectiveness of circular economy (CE) initiatives and leveraging AI to support a just transition to the circular economy (JTCE) (Ahmed, 2022).

3.3. Challenges in Developing and Governing Indicators

The fast-paced development of AI technologies poses a challenge for regulators and standard-setting bodies, the velocity of AI related innovations often outstrips the ability of governance frameworks to adapt, resulting in outdated or ineffective measures that fail to capture the evolving nature of Gen-AI, including understanding and mitigating its environmental implications (Domínguez Hernández et al. 2024).

Developing and governing sustainability indicators to assess the environmental impact of Gen-AI involves navigating a complex landscape of challenges, particularly in the context of global governance, ecological inequities, geopolitical power dynamics, and the influence of socio-technical imaginaries predominantly shaped innovation ecosystems in the Global North (Ahmed, et al, 2023).

There is a notable governance deficit in the current international landscape concerning governance of Gen-AI and DS, in general (Ahmed and Kirshchlager, 2024; Domínguez Hernández et al. 2024). Existing initiatives often lack the coordination and capacity necessary to address the complexities of Gen-AI's environmental impacts and the fragmentation of governance structures complicates the establishment of coherent and inclusive indicators that can effectively measure sustainability across different contexts (Bashir et al., 2024).

Furthermore, many existing standards and best practices for AI are rooted in the socio-technical contexts of the Global North, which often do not reflect the realities or needs of the Global Majority, which can lead to the development of indicators that are not universally applicable or that overlook critical environmental, political economy, and sociotechnical factors relevant to develop global standards that mitigate risks and support the flourishing of diverse ecosystems (Bashir et al., 2024).

Geopolitical tensions and competition hinder cooperation on global AI governance. Long-standing first-order cooperation problems, combined with second-order issues stemming from dysfunctional international institutions, complicate the establishment of effective governance frameworks for Gen-AI that are equitable and reflective of global needs (Bashir et al., 2024)

The development and governance of indicators for the environmental impact of generative AI face significant challenges, particularly due to biases in existing frameworks, geopolitical barriers, and the rapid evolution of technology. underrepresentation of the Global Majority in discussions about standards and best practices, and the overall global ethical, legal, social, and policy (ELSP) aspects also contributes to the aforementioned challenges and requires a collaborative approach among diverse stakeholders.

Measuring Gen-AI’s sustainability, such as its carbon footprint, and ensuring compliance with global sustainability standards is still in its infancy. Tools like the ESG Digital and Green Index are emerging to help, but widespread adoption is needed (Raman et al. 2024; Thelisson et al. 2023). Nevertheless, the development of metrics and indicators for assessing the environmental impact of Gen-AI essential for promoting sustainability in the technology sector (Bashir et al., 2024). By establishing comprehensive metrics, engaging in multistakeholder dialogue, and leveraging high-quality data, stakeholders can work collaboratively to minimize the ecological footprint of AI technologies and ensure that their benefits are realized without compromising environmental integrity.

4. Role of Data Governance in Assessing Environmental Impacts

Data and its underlying foundations are the determining factors to leverage the potential of Gen-AI (Caserta et al., 2023). Effective governance of DS such as Gen-AI requires robust data governance frameworks to ensure transparency, accountability, and to facilitate just data value creation (JDVC) (Ahmed and Kirschlager, 2024).

Robust data governance plays a crucial role in establishing clear policies, standards, and processes for data management, data governance ensures that the data used to train and deploy Gen-AI models is collected, processed, and stored in a responsible manner that minimizes environmental harm (PNAI,2023; Bashir et al. 2024).

Effective data governance also enables transparency and accountability in reporting on the environmental footprint of Gen-AI, allowing organizations to identify areas for improvement and track progress towards sustainability goals (OECD, 2022). This includes measures such as tracking energy consumption and emissions from data centres, managing the use of natural resources like water and minerals, and ensuring data quality and integrity to avoid the need for excessive retraining of models (OECD, 2022). Without robust data governance, it's hard to measure the true environmental cost at each stage of data processing at each stage of the Gen-AI value chain.

Furthermore, robust data governance is essential for ensuring equitable access and distribution of data dividends when treating data as a DPG (UNICEF, 2023)

4.1. Importance of Data

High-quality machine-readable data plays a crucial role in assessing the environmental impacts of Gen-AI. In the 2023 PNAI Report, we highlight how robust data governance facilities high-quality, accessible datasets, which are necessary for accurate measurement and evaluation of sustainability metrics and climate justice (PNAI, 2023). Reliable data enables stakeholders to quantify the environmental effects of AI technologies, including energy consumption, emissions, and resource utilization. Data is essential for making informed decisions and implementing effective sustainability initiatives (CODES, 2022).

However, the lack of clear guidelines on data usage and the potential for misuse complicate the establishment of reliable indicators for sustainability (OECD, 2022).

4.2. Types of Data Required

To accurately assess the environmental impact of Gen-AI, various types of data are needed, a comprehensive data collection effort is required, not an exhaustive list but focus on the following key areas is crucial:

Data on Energy Usage. Information on the energy consumption throughout the Gen-AI value chain, particularly during training, deployment, and inference is critical for evaluating their carbon footprint and identifying opportunities for efficiency improvements. This data should include Electricity usage by data centres and cloud infrastructure supporting Gen-AI, fuel consumption by backup generators and transportation related to Gen-AI operations, and energy usage per model training run and per inference, to name a few (Patterson et al. 2021; Strubell et al.,2019).

Resource Consumption Data. Data on the extraction and use of natural resources, such as water and critical minerals, is necessary to understand the broader environmental implications of the Gen-AI value chain, which includes water usage for cooling data centres, mineral and metal consumption for manufacturing Gen-AI hardware, and use for data center construction and siting (Bashir et al., 2024).

Emissions Data. Tracking greenhouse gas emissions associated with Gen-AI operations is essential for measuring progress toward climate goals and identifying areas for reduction, such as direct emissions from on-site fuel combustion, indirect emissions from purchased electricity and heat, and emissions from upstream activities like manufacturing and transportation, to name a few (Kemene et al.,2024).

Socioeconomic Data. Assessing the holistic impact of Gen-AI requires understanding its socioeconomic implications, particularly in underrepresented regions and to realise a just green digital "twin transition". For example, sex-disaggregated data is crucial for identifying differential impacts at the nexus of climate injustice and AI on women and men (Ahmed, 2022). Women often have distinct roles and responsibilities in resource management and consumption, which can influence how AI technologies are adopted and their subsequent environmental effects (Ahmed,2024). Sex disaggregated data allows for a nuanced understanding of how technologies affect different genders, particularly in terms of resource consumption, energy usage, and emissions (GEDA, 2024). Other relevant data can include employment and income effects of Gen-AI adoption, access and use of Gen-AI-enabled services by marginalized communities, and representation of diverse perspectives in Gen-AI development and governance (ILO, 2023; Ahmed et al.,2023; PNAI 2023).

Contextual Data. Given the global AI divide, to adequately interpret the environmental and social impacts of the Gen-AI value chain, contextual data is needed on factors such as: Local climate and environmental conditions, existing infrastructure and resource constraints, political economy dynamics, and socioeconomic and demographic characteristics of affected populations, to name a few (Ahmed, et al., 2023).

Collecting and integrating diverse data will enable a holistic assessment of Gen-AI's environmental footprint and help guide the development of sustainable practices (Bashir et al., 2024). Collaboration among Gen-AI developers, data providers, and domain experts is essential to establish comprehensive data collection frameworks and ensure data quality and different types of interoperability (World Bank 2022; Gonzalez Morales and Orrell, 2018).

For example, the energy usage of Gen-AI models and infrastructure is often opaque, with limited real-time transparency. Models trained in various geographical locations may utilize different sources of energy (renewable vs. non-renewable), complicating the ability to track carbon footprints (Ren and Wierman 2024).

4.3. Key challenges in integrating data governance with environmental impact assessments in Gen-AI

Integrating data governance with environmental impact assessments (EIAs) in the Gen-AI value chain presents several key challenges that stem from the rapid development of overall of AI technologies, the massive amounts of data involved, and the increasingly important focus on sustainability (Bashir et al.,2024). Challenges include the following:

i. Data Complexity (quality, transparency, volume, and integrity)

Gen-AI relies heavily on both structured and unstructured data, which can be stored in various formats and siloed systems (Harlin et al.,2023. Effective data governance is needed to ensure that unstructured data is appropriately labelled, categorized, and utilized in environmental evaluations and the integration of environmental metrics into assessments (UNCTAD, 2024a).

Managing large-scale AI systems requires significant data from various sources, while ensuring transparency and accountability in data governance, and aligning with environmental impact standards, is a difficult task (Raman et al. 2024). The complexity of this task is particularly challenging for frontier technologies such as Gen-AI, where there's often a lack of clear frameworks for assessing how environmental impacts are calculated across complex, multi-stakeholder data environments (Bashir et., al. 2024).

Gen-AI models also undergo continuous retraining and fine-tuning, which implies repeated cycles of data usage, requiring significant energy consumption with each retraining cycle (Luccioni et al., 2024). Effective EIAs must account for the repeated energy demands of retraining models. If data governance structures don't extend to model lifecycle management, the environmental impact of maintaining large-scale Gen-AI models can be underestimated.

In addition, the complexity of sourcing data from multiple channels makes it challenging to establish clear data lineage and traceability. A lack of transparency regarding data origins can lead to inaccuracies in environmental assessments, highlighting the need for comprehensive data governance practices. Tracking the lifecycle of data used in the Gen-AI value chain is essential for understanding its environmental implications (Thelisson et al. 2023).

Addressing the multidimensional aspects of interoperability is critical in ensuring the accuracy and reliability of data used in environmental assessments, inconsistencies in data quality can arise from disparate sources, leading to incomplete or misleading evaluations of Gen-AI's environmental impact (World Bank, 2022). Without robust data governance frameworks, organizations may struggle to maintain high standards of data integrity, resulting in flawed assessments and decision-making (OECD,2022).

Regulatory and Ethical Framework Gaps

In many regions, there are clear regulations regarding AI ethics, but few that tie AI development to environmental sustainability goals such as carbon neutrality. Many organizations have established data management systems that may not seamlessly integrate with new data governance frameworks required for EIAs, as a result, compatibility issues can hinder the effective implementation of data governance practices, making it difficult to incorporate environmental metrics into existing workflows implications (Thelisson et al. 2023). Navigating the complex regulatory landscape surrounding data governance and EIA requires that organizations must ensure compliance with various transnational data protection laws while also adhering to environmental regulations. This dual requirement can create challenges in aligning data governance strategies with the specific needs of environmental assessments in the context of Gen-AI, particularly since EIAs depend on well-defined regulatory standards for environmental impact. In the AI domain, the regulatory gaps in measuring energy consumption, carbon emissions, and e-waste can hinder comprehensive environmental assessments (Thelisson et al. 2023).

Existing frameworks often treat AI and environmental governance separately, governance structures focus primarily on privacy, security, and ethical use, but less on sustainability and environmental impact (Bashir et al., 2024). The incoherence leads to a lack of coordinated policies that can address both the digital and environmental aspects together. For example, the European Green Deal emphasizes climate neutrality, but there are no dedicated regulatory bodies focused on aligning AI systems with these environmental goals (Raman et al., 2024).

Furthermore, fragmented data localization and sovereignty laws can create challenges in terms of balancing local regulations with global Gen-AI value chain operations. Accurate environmental impact assessments require transparency in energy consumption data. Without data governance frameworks that enforce energy-use reporting, particularly in cloud computing and distributed systems, it becomes difficult to account for emissions in the value chain (OECD, 2022).

ii. Gen-AI Value Chain Complexity

The Gen-AI value chain involves multiple stakeholders, including data providers, cloud service operators, and hardware manufacturers (Harlin et al.,2023). Governing data across such a complex supply chain is difficult, particularly when environmental standards differ across jurisdictions and industries.

Fragmented supply chains complicate efforts to conduct comprehensive EIAs. For example, data centres in different countries may have varying energy standards, with some relying heavily on non-renewable energy sources.

Without unified data governance, measuring the overall environmental impact across the supply chain becomes inconsistent, data governance must be standardized across stakeholders to ensure accurate and cohesive reporting on environmental impacts at each stage of the Gen-AI value chain (Sebestyén et al., 2021).

iii. Bias and (Un)Fairness

Data used to train Gen-AI models often reflects historical and societal biases, which can be perpetuated in decision-making (Buolamwini and Gebru 2018). Biases present in the training data of Gen-AI models can skew EIA if the data used does not adequately represent diverse ecological contexts or stakeholder perspectives, the resulting assessments may be biased. These biases can lead to climate apartheid, where wealthier nations are better equipped to mitigate and adapt to climate change, while poorer communities suffer disproportionately (Guerreo 2023). Effective data governance must address these biases to ensure fair and equitable evaluations of Gen-AI's environmental impacts (UNCTAD, 2024a).

Environmental datasets may overlook regions in the Global South or marginalized communities, this lack of data equity can result in skewed environmental assessments, reinforcing climate injustices where poorer communities, who contribute least to climate change, face the most severe consequences (Dosemagen and Williams 2022).

Additionally, the unequal distribution of resources and AI’s reliance on energy-intensive infrastructure create disparities in climate adaptation, favouring wealthier nations with better technological and data governance infrastructures (Thelisson et al. 2023).

Furthermore, global climate governance frameworks, often driven by high-income countries, tend to exacerbate inequalities (Islam and Winkel, 2017). Gen-AI models used in environmental policies may prioritize regions with comprehensive data and advanced infrastructures, leaving vulnerable populations behind (Ahmed 2023). Furthermore, the carbon footprint and e-waste generated by AI development often affect the Global South, reinforcing existing environmental injustices and imbalances in global climate governance (UNEP 2024; Guerrero 2023).

5. Conclusion

The generative AI (Gen-AI) value chain significantly impacts environmental sustainability through its various stages, each contributing to energy consumption, resource utilization, and carbon emissions. As the demand for Gen-AI continues to grow, its associated electricity demand is rising, which runs counter to the necessary efficiency gains needed to achieve net-zero greenhouse gas emissions. Gen-AI's relentless demand for computing power and the resulting larger carbon footprints highlights the urgent need for a comprehensive evaluation of the environmental implications of Gen-AI technologies.

While generative AI holds potential benefits for various sectors, its environmental impacts pose significant risks—particularly for marginalized communities in the global Majority. Addressing these challenges requires a concerted effort to ensure equitable access to technology and participation in decision-making processes that consider the unique needs and vulnerabilities of these populations. To enhance environmental sustainability within the Gen-AI value chain, it is essential to establish robust metrics and indicators that accurately assess its environmental impact. This includes tracking energy usage, resource consumption, and emissions throughout the lifecycle of AI systems. Engaging a diverse range of stakeholders in multistakeholder dialogues can facilitate the development of comprehensive frameworks that balance economic growth with environmental stewardship.

Addressing bias and fairness in integrating data governance with environmental impact assessments in Gen-AI requires equitable representation in datasets, transparent AI models, and inclusive global climate governance frameworks. The intersection of Gen-AI and environmental policy must prioritize the needs of vulnerable populations to ensure that technological innovation does not exacerbate global climate inequalities or contribute to further climate injustice.

By fostering collaboration and prioritizing sustainability in the design, deployment, and governance of Gen-AI technologies, stakeholders can work towards a future where the benefits of AI are realized without compromising ecological integrity or exacerbating social inequalities. The integration of data-driven approaches and responsible practices will be crucial in steering the Gen-AI value chain towards a more sustainable trajectory, ultimately contributing to a greener and more resilient planet.

6. Multi-stakeholder Recommendations for Policy Action

We recommend the following policy actions:

Develop Comprehensive Sustainability Metrics for Gen-AI: Governments and international organizations must create standardized metrics to assess the environmental impact of Gen-AI throughout its value chain, including energy consumption, resource extraction, carbon emissions, and e-waste. These metrics should align with the UN Sustainable Development Goals (SDGs) and account for impacts on biodiversity, ecosystems, and resource sustainability.

Sustainability metrics should also be tailored to the contextual realities of low- and middle-income countries (LMICs) in the global Majority. These metrics should measure the environmental impact of AI technologies without creating regulatory and administrative burdens that perpetuate dependency, resource extraction, or unequal wealth creation. Such standards should focus on fostering local innovation, equitable resource use, and sustainable digital economies.

Support Regionally Relevant Innovation Ecosystems: Encourage innovation that supports climate change mitigation, adaptation, and loss and damage with policies that incentivize Gen-AI applications in environmental conservation, resource efficiency, and sustainability. These policies should also foster regionally relevant digital innovation ecosystems, ensuring local entrepreneurs, businesses, and academia contribute to green digital economies, particularly in the global Majority. Policymakers should encourage investment in regionally relevant green-digital technologies, prioritizing innovations that drive climate change mitigation and adaptation. These policies should emphasize the importance of local innovation ecosystems, where businesses, entrepreneurs, and academia from LMICs play a central role in co-creating green jobs and sustainable digital livelihoods.

National governments must take the lead in developing locally relevant sustainability policies that support the green-digital transition. These policies should focus on fostering local innovation ecosystems, prioritizing climate resilience, and addressing the specific environmental challenges faced by LMICs. Organizations such as the World Bank, UNCTAD, and UNDP should support LMICs with financial resources, capacity building, and technical assistance to help them develop sustainable Gen-AI infrastructure.

Strengthen Global AI Governance Frameworks: Introduce robust global AI governance frameworks to integrate environmental sustainability in AI technologies. This includes global cooperation to mitigate risks such as surveillance, privacy violations, and climate inequalities, and to ensure Gen-AI development does not exacerbate existing socioeconomic and environmental challenges.

IGF should provide a platform for multistakeholder dialogues on the green-digital transition, ensuring that LMICs have an equal voice in shaping global AI and sustainability policies. These discussions should focus on creating standards that support the unique environmental and socioeconomic realities of LMICs. IGF should focus on building the capacity of LMICs to engage in global AI governance and sustainability discussions. This includes providing technical assistance, promoting knowledge exchange, and ensuring that LMICs have the resources to develop and implement green-digital transition strategies.

Global dialogue must emphasize shared responsibility for the environmental impacts of Gen-AI, ensuring that LMICs are not disproportionately affected by the resource extraction, energy consumption, and e-waste associated with AI technologies. Cooperation should focus on reducing the environmental burden on LMICs and promoting responsible AI innovation globally.

PNAI should advocate for the inclusion of LMICs in global AI governance discussions, ensuring their voices are heard and their needs are addressed. This includes supporting the development of sustainability frameworks that are co-created with LMICs, rather than imposed by external actors. PNAI should lead the creation of sustainability guidelines for Gen-AI that reflect the realities of LMICs. These guidelines should focus on minimizing the environmental impact of AI in resource-constrained regions, emphasizing local capacity building and responsible resource use

Leverage Official Development Assistance (ODA) for Sustainable Gen-AI: Use international development assistance (IDA), including ODA, to support lower-income and middle-income countries (LMICs) in developing sustainable AI infrastructure and promoting AI-based climate solutions. Investments should target local capacity building, green jobs creation, and technological infrastructure that empowers these regions. Multistakeholder dialogue is essential to ensure that AI governance frameworks and sustainability policies reflect the realities of LMICs. Cooperation between governments, private companies, international organizations, and civil society is crucial for developing AI standards that prioritize environmental equity and resource sustainability. ODA should aim to empower LMICs with the necessary technological tools and resources to develop their own AI systems. This includes providing access to open-source AI technologies, data, and platforms that enable local innovation. Empowering these countries to create their own Gen-AI solutions will ensure that they can tailor technologies to their specific needs and context. IDA should be revitalised to reduce dependency on foreign consultants, policy research, infrastructure, and partners; and instead focus on empowering LMICs to implement green-digital standards and the overall flourishing of local innovation ecosystems that reflect their unique economic and environmental contexts by funding the creation of local talent in both policy and technical capabilities.

Integrate Circular Economy Principles: Establish policies that promote circular economy practices in Gen-AI's value chain, encouraging the reuse and recycling of AI hardware and reducing e-waste. These policies should address the environmental costs of raw material extraction and ensure responsible disposal of obsolete AI systems. The extraction of raw materials for AI hardware has significant environmental implications, including habitat destruction, pollution, and carbon emissions. Circular economy policies should promote responsible sourcing of materials, encouraging companies to use recycled materials or sustainably sourced alternatives. Additionally, fostering partnerships with organizations focused on sustainable mining practices can help mitigate the environmental impact of resource extraction. Raising awareness about the importance of circular economy practices in AI technologies among consumers and businesses is essential. Educational campaigns can inform stakeholders about the benefits of reusing and recycling AI hardware and the environmental implications of e-waste.

Data Governance with an Environmental Focus: Ensure that data governance frameworks are developed to address both environmental and social impacts of AI. This includes equitable data access, transparency in AI models, and the integration of environmental data into decision-making processes, ensuring that vulnerable populations are not disproportionately affected by AI innovations. Data governance frameworks must ensure that data is accessible to all stakeholders, particularly marginalized and vulnerable populations. This equitable access is crucial for empowering communities to engage with AI technologies, participate in decision-making processes, and mitigate potential adverse effects of AI innovations. Incorporating environmental data into AI decision-making processes is essential for creating sustainable solutions. Data governance frameworks should promote the use of environmental metrics alongside traditional performance indicators, allowing organizations to assess the ecological footprint of their AI applications. By prioritizing sustainability, organizations can minimize resource consumption and environmental degradation.

Apply Decolonial Socio-Technical Foresight: This approach combines forward-looking analysis with a decolonial lens, offering several key advantages in Gen-AI governance and development. Foresight allows countries in the global Majority to envision futures rooted in their socio-political contexts and aspirations, rejecting imposed technological paradigms from the wealthier nations with geopolitical heft. This can promote autonomy and resilience while amplifying voices historically marginalized in tech governance. Decolonial socio-technical foresight empowers countries in the global Majority to not only react to global Gen-AI trends but to shape a future where Gen-AI serves local interests and long-term development. This forward-thinking approach enables African countries to proactively decide what their Gen-AI future will look like, ensuring that technological progress aligns with intergenerational justice, sustainability, and self-determination.

APPENDIX 1: Case Studies

The environmental impact of Gen-AI is a significant concern, these technologies also have the potential to contribute positively to sustainability efforts. While AI/ML can optimize processes to enable the exploration of solutions for a wide range of environmental and climate-related issues, including natural disasters, greenhouse gas emissions, biodiversity monitoring, agriculture, and weather and climate modelling, overall facilitating progress in climate change mitigation efforts, in some sectors they may paradoxically also lead to negative externalities such as increased resource extraction in other areas. Case studies showcasing the use of Gen-AI for environmental conservation, resource optimization, and climate change mitigation can help illustrate the benefits and inform best practices.

CASE STUDY 1: Environmental Sustainability and AI for Forest Fire Management in the ASEAN Countries

Fire-Net with a code name KK-2022-026 is an important initiative by Malaysian and Indonesian researchers to ensure the automated detection of forest fires using satellite images. This project is wholly funded by the Asia Pacific Telecommunity through extra-budgetary funds from the Republic of Korea to support the strategic initiative of 2021-2023 (Saleh et al., 2024). It is a known factor that forest fire is a serious threat to our ecosystem, as such uncontrollable burning can lead to severe destruction of the precious flora and fauna, especially in the ASEAN region. Therefore, a forest fire incident needs to be detected as early as possible, while the fire patch is still relatively small in size. Rapid action to put off the fire can reduce the negative consequences to the environment. We have witnessed a lot of uncontrollable fire cases, whereby the destruction of our forest is huge. This is not factoring in the side effect of transboundary haze, which is very harmful to human respiration, especially to younger kids.

However, finding the fire patches through manual observation of the satellite images is not a viable option, mainly due to the large areas that need to be observed. For this reason, governments need to come out with a monitoring system that allows them to detect forest fires automatically. Hence, an advanced artificial intelligence (AI) based system has been developed as an effective solution to this problem through pixel-based segmentation of the satellite images that can identify small fire patches with a 3-meter resolution. This AI approach enables the monitoring system to have wide forest coverage with relatively lower operating costs. The system is based on Landsat-8 satellite data with three reduced channels of information to allow a faster detection rate. The system aims to identify small as well as large fire patches, which is a difficult task in most AI systems. To overcome this challenge, the multi-scale AI approach has been developed to enable multiple-size forest fire patches to be detected.

Both small and large fire patches are important to be detected and quantified. An accurate detection of small fire patches allows the firefighters to put off the fire while it is still small. While, a large quantification of fire patches, especially through segmentation tasks is important information for the firefighters so that they can plan the safe and rescue mission effectively, by allocating the resources at the strategic areas to further reduce the negative consequences of the wildfire. In this case, AI with remote sensing technology can help us detect, locate, and quantify the affected regions without the need to go closer to the burned areas. The AI system also can reduce the possibility of human errors due to fatigue when operating for a long time. The fire incidents might last for a few days and continual updates of the affected areas are crucially needed for the optimal search and rescue operation. Finally, this Fire-Net project will benefit our environment by enabling faster detection of forest fire patches using AI technology, which can save our precious flora and fauna.

CASE STUDY 2: Environmental Sustainability and AI for Climate Change Management in African Countries

Artificial Intelligence (AI) for Climate Action Innovation Research Network is one of the initiatives under the Artificial Intelligence for Development Africa that is headed by Ghana (AI4D Africa, 2024). This project aims to produce better adaptation and mitigation strategies for climate variability to promote environmental preservation in various African countries. AI is utilized as the core technology that will help to come out with better decision-making through automated systems. This initiative is also meant to develop research capacity in sub-Saharan African countries so that they will support the international AI policy, especially with regard to environmental issues. The primary grant is funded by the Swedish International Development Cooperation Agency and Canada's International Development Research Centre. The total funding for all 11 AI projects is CA$ 1,158,100 which involves nine African countries.

One of the notable projects focuses on leveraging AI to estimate greenhouse gas emissions. The system uses drones to map livestock and farm areas in the Mubende District of the Central Region of Uganda. This project utilizes remote sensing technology because of the low sampling cost compared to ground-based sensing which will also enable larger observation areas. Under the same initiative, another interesting project was proposed by a group of researchers from Kenya that developed an AI-based mobile application tool to help with disease detection on commercial crops. A few diseases such as Taro Leaf Blight and Phytophthora Colocasiae can be detected by using a smartphone just by taking pictures of the commercial crops. The AI system generates a fast detection response using single-shot detector technology that provides sampling boxes in a single pass. All the candidate boxes of possible diseases are then passed to a classification module in order to identify the type of the diseases. This lightweight technology is important for Kenya-based applications, whereby the cost of hardware is relatively high, and the system needs to be able to work on a simple mobile application.

Apart from that, a project from République du Bénin focuses on using conventional machine learning such as Artificial Neural Networks and Support Vector Machine to analyse the vulnerability of climate change to mangrove ecosystems. Even though the mangrove ecosystem is not large in size relative to the other land categories, it is still an important ecosystem for housing and commercial resources. Thus, it is important for the locals to assess the mangrove's vulnerability to any change in climate, especially the issue of sea level rise that might affect their safety. The AI is also trained using bagging methodology to further improve the accuracy of the system, which is validated by using various important metrics, especially the receiver operating characteristic metric. Besides that, one of the important things in African countries is to predict the energy potential as the demand for electricity is continually rising every year. Hence, a group of researchers from Cameroon focuses on using AI to predict the possibility of using more renewable energy to support a sustainable environment. Their main aim is to analyse spatial trends in landscape dynamics that include the rate of deforestation as well as the seasonal effect of surface water resources, which will affect the adoption of renewable energy. In conclusion, this initiative covers a wide scope of AI usage in promoting a sustainable environment in African countries.

CASE STUDY 3: Improving Air Quality with Generative AI in Ghana

Ghana faces significant challenges due to air pollution, ranking as the 27th most polluted country in the world. Many African countries, including Ghana, are adopting low-cost air quality sensors to monitor air quality continuously. Hence, an initiative through The Sensor Evaluation and Training Centre for West Africa (Afri-SET, 2024) has been introduced that aims to overcome the issues of 1) standardization of the air quality data by addressing the data integration problem of low-cost sensors, 2) automation of data ingestion by reducing manual intervention required for data synchronization, and 3) improvement of air quality monitoring systems by providing accurate and timely air quality data.

They are three key components need to be executed effectively in order to deliver intelligent low-cost air quality sensors. The first component is the utilization of generative AI for data standardization. Currently, Afri-SET deals with disparate data formats from various sensor manufacturers, hence, making data synchronization resource-intensive. This issue can be solved by utilizing generative AI, specifically Large Language Models (LLMs), to standardize sensor data outputs. The AI task is to convert various data formats into a unified format, creating a manufacturer-agnostic database. The second component is to automate the data integration of the low-cost air quality sensors, specifically through standardized raw data files (CSV or JSON). In case the sensors have been recorded before, the solution can retrieve and execute previously generated Python codes to transform the data. However, if the device is newly introduced to the system, the AI need to generate the necessary Python code to standardize the data, which is then saved for future use. Some of the available platforms are Amazon Bedrock, Pandas, AWS Glue, and Amazon Athena. The third component is to embed human-in-the-loop mechanism, so that data quality can be ensured while reducing the burden on Afri-SET's resources. This component can be realized by introducing operators who can validate new data formats before the AI generates transformation code.

The general flow of the proposed workflow consists of three phases. The first phase is to ensure effective data ingestion through Amazon S3, whereby the device record needs to be validated first. For the case of new devices or sensors, the operator needs to validate the format manually, before the transformation codes are generated by the AI. The second phase concerns on the data transformation, in which the AI-generated Python functions task is to convert JSON files to Pandas data frames, pivot the transformed data as needed, and clean it to unify the column names. Finally, the transformed data is stored in Amazon S3 in Parquet format. The third phases focus on data storage and analysis, which is set to be in a standardized format using Amazon S3. Then, AWS Glue and Amazon Athena are used for further data analysis and visualization.

The results from Afri-SET initiatives have managed to minimize the cost of AI invocation by generating reusable code only when new data formats are detected. It has also increased workflow efficiency by reducing manual data engineering work from months to days. Furthermore, it allows better system scalability, whereby the solution can be scaled and implemented across West Africa for a broader impact. Apart from that, the quality of the data is also better, which is crucial in order to ensure accurate and reliable air quality data for stakeholders. In a nutshell, this solution allows for easy data integration, fostering community empowerment and encouraging innovation. It represents a significant step towards a cleaner and healthier environment in Ghana and potentially other African countries. By leveraging AWS technology and generative AI, Afri-SET can deliver accurate air quality data, inform policymaking, and drive positive social impact.

CASE STUDY 4: A Study on the Environmental Impact of Generative-AI

Using a multi-criteria life cycle assessment (LCA) approach, Berthelot et al. (2024) have studied on the estimation of the environmental impact of Generative AI services by examining its ecological footprint. With the increasing popularity of generative AI models, especially for the applications of conversational agents and image creation, there are growing environmental concerns about the high computational needs of these models, particularly with regard to their energy, and greenhouse gas (GHG) emissions. The study demonstrates that the growing usage of digital services, particularly those driven by generative AI has produced more energy wastage, which directly contributes to the shortage of resources, which directly contributes to global warming. The researchers have focused on measuring the effective amount of electricity used for fitting the AI models. Many AI researchers do not realize the significant impacts of training the models, such as the impact of large data centre infrastructure needed to implement these AI models, which results in inadequate evaluations of their environmental impact.

To assess the environmental costs related to the full life cycle of generative AI services, the authors suggested a thorough life cycle assessment (LCA) methodology that covers various facets of costs such as web hosting, inference process, and training the models. Their methodology also takes into account the environmental expenses associated with data centers, networks, and user terminals. To be specific, they have used a stable diffusion model, which is a text-to-image generative AI model, to illustrate their proposed methodology. In short, the study's findings demonstrate the considerable environmental impact of generative AI services. For example, one year of stable diffusion operation has resulted in 360 tons of CO2 equivalent, which is 8.93 million megajoules of energy utilized and also contributes to the depletion of natural resources. These results demonstrate that the energy-intensive nature of AI goes beyond the training phase of the model, whereby a significant amount of the environmental cost originates from the inference phase.

The study also highlights other significant elements that considerably affect the overall environmental impact, such as network traffic and end-user device energy consumption. The authors justified through sensitivity analysis that the frequency of model retraining and the usage rates of data centre equipment can have a significant impact on the environment. The study concludes by suggesting the necessity of creating more effective and efficient AI systems by considering the whole life cycle usage of the model into account when doing environmental evaluations to better comprehend and lessen the ecological effects of generative AI. It is also important to have a closer collaboration between hardware developers and AI service providers, in order to develop more ethical and sustainable AI technology through an integrated approach.

APPENDIX 2: Gen-AI Value Chain Analysis (VCA) vs Life Cycle Assessment (LCA)

There are similarities and differences between a comprehensive Life Cycle Assessment (LCA) and a Value Chain Analysis (VCA) when it comes to capturing the environmental footprint of generative AI (Gen-AI) models. The data collection processes for VCA and LCA differ significantly in their approaches, methodologies, and the types of data they prioritise.

i. Data Collection in Value Chain Analysis (VCA)

VCA emphasizes economic activities and value creation, i.e. the interrelated activities that create value from raw material extraction to the final product delivery. Data collection in VCA typically involves gathering information on each stage of the value chain, including production, distribution, marketing, and sales, to name a few (Investopedia, 2024).This includes data on input costs (e.g., raw materials, labor) and output prices to assess where value is added. While VCA can include environmental considerations, its primary focus is on socioeconomic value creation. It may not comprehensively account for the environmental impacts of each stage unless explicitly integrated into the analysis (DEFA, 2017).

ii. Data Collection in Life Cycle Assessment (LCA)

LCA follows a cradle-to-grave approach, collecting data on every stage of a product's life cycle—from raw material extraction through production, use, and disposal. This thorough approach allows for a more nuanced understanding of a product's environmental footprint. ensures that all environmental impacts are considered. LCA has been widely adopted for the AI ecosystem (Luccioni,et al,. 2022), given that it follows standardized methodologies (e.g., ISO 14040 and 14044) that provide guidelines for data collection, ensuring consistency and comparability across assessments (DEFA, 2017). LCA requires extensive data on energy consumption, emissions, resource use, and waste generation for each life cycle stage. This includes primary data from manufacturers and suppliers, as well as secondary data from databases and literature through the collection of both quantitative data (e.g., CO_2 emissions in kg) and qualitative data (e.g., potential environmental impacts). LCA requires detailed, product-specific data on materials, energy use, emissions, and waste for each life cycle stage.

While both LCA and VCA aim to assess the environmental and economic aspects of a product or service, LCA has a more comprehensive environmental focus throughout the entire life cycle, while VCA emphasizes the value-adding activities and economic distribution along the supply chain. LCA provides a comprehensive environmental assessment and helps identify potential trade-offs between different environmental impacts, while VCA emphasises economic value-adding activities and may rely on aggregated data, while LCA adopts a comprehensive approach to assess environmental impacts across the entire life cycle of a products (DEFA, 2017). VCA may rely more on aggregated data and industry averages, especially for upstream and downstream activities. VCA considers the broader economic and social aspects in addition to environmental factors and can identify opportunities for value creation and competitive advantage along the value chain, which may be particularly useful for governance in ecosystems with less AI maturity such as the global Majority.

Understanding these differences is crucial for effectively utilizing each analysis method to inform sustainability decisions and strategies. Table xx summarizes the key similarities and differences between LCA and VCA in capturing the environmental footprint of Gen-AI models.

Table 1: Summary of Gen-AI Value Chain Analysis (VCA) vs Life Cycle Assessment (LCA)

Aspect	Life Cycle Assessment (LCA)	Value Chain Analysis (VCA)
Scope	Comprehensive, covering the entire life cycle from raw material extraction to disposal.	Focuses on value-adding activities along the supply chain from raw materials to market.
Perspective	Product-oriented, tracing environmental burdens associated with a specific product or service.	Value chain-oriented, considering all activities and actors involved in bringing a product to market.
Data Requirements	Requires detailed, product-specific data on materials, energy use, emissions, and waste for each life cycle stage.	May rely on aggregated data and industry averages, especially for upstream and downstream activities.
Methodology	Follows standardized methodologies (e.g., ISO 14040 and 14044) for consistency and comparability.	Lacks a universally accepted standard methodology, making comparisons between studies challenging. However, VCA may utilize more flexible and varied approaches depending on the specific context.
Pros	- Comprehensive environmental assessment - Identification of trade-offs - Comparability across products	- Broader perspective including economic and social technical, and political economyaspects - Identification of value creation opportunities - Flexibility across industries
Cons	- Data-intensive and time-consuming - Sensitive to assumptions and data quality - Limited scope regarding economic and social aspects	- Limited environmental focus - Lack of standardization - Often relies on aggregated data, missing nuances
Application in Gen-AI	Quantifies specific environmental impacts associated with Gen-AI development and use.	Provides insights into broader economic and social implications of Gen-AI technologies across the value chain.

For the aim of this discussion paper the focus remains on capturing multidimensional dynamics associated with the environmental toll of Gen-AI. However, we acknowledge that in the context of Gen-AI models, a combination of LCA and VCA can provide a more comprehensive understanding of the environmental footprint. By leveraging both approaches, stakeholders can make more informed decisions to minimize the environmental impact of Gen-AI models while maximizing associated benefits.

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About the Policy Network on Artificial Intelligence

The Policy Network on Artificial Intelligence (PNAI) addresses policy matters related to artificial intelligence and data governance. It is a global multistakeholder effort hosted by the United Nations' Internet Governance Forum, providing a platform for stakeholders and changemakers in the AI field to contribute their expertise, insights, and recommendations. PNAI's primary goal is to foster dialogue and contribute to the global AI policy discourse. Participation in and contribution are open to everyone.

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