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An Analysis of Sustainability of Artificial Intelligence and its Impact on Environment

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ABSTRACT

While AI is radically altering our economic and societal systems, its impact on the environment is becoming more prominent. In this paper, we will explore the latest findings regarding both direct environmental effects – such as energy use in AI training and inference, emissions from data centers, and hardware manufacturing/waste disposal – and indirect effects related to AI-driven technologies that can either mitigate or relocate emissions.

According to our study, training the model requires a considerable amount of power consumption and production of many pollutants. As was the case in the era of large-scale models and data centers when there were huge demands for materials and waste production.

Artificial intelligence-based applications could contribute positively depending on how they are designed and utilized. In particular, artificial intelligence could increase transportation, agricultural, and industrial processes' energy efficiency. Moreover, artificial intelligence-based systems could be used to monitor environmental compliance by individuals.

Therefore, artificial intelligence's effect on the environment may not necessarily be negative. Its impact is dependent on design and system implementations and policies.

We think a three part framework is a way to look at and improve AI sustainability.

This framework has three parts:

- *We need to measure and be transparent about how AI affects the environment. We need to use the same way to measure the impact of computers, energy and materials.*
- *We need to design AI systems to be more efficient. This means making the models and hardware work together making the models smaller and scheduling the work to use less energy.*
- *We need to have policies and make sure we use things in a circular way. This means having rules, standards for buying equipment and ways to reuse and recycle AI hardware.*

If we use this framework we can make sure that AI innovation is good for the environment and helps us meet our climate goals.

Some important things we need to do include:

- *Companies must report how energy they use to train AI models and how much they pollute*
- *We should give rewards to data centers that use carbon*
- *We need to invest in ways to reuse and recycle AI hardware*
- *We need to support research into AI systems that use computer power*

We also need to think about fairness. Countries like India need to be able to use AI without hurting the environment so they need to invest in the right infrastructure.

Keywords*: Artificial Intelligence, Societal Systems, Energy Efficiency, Environmental Compliance, AI Models.*

Introduction

Artificial intelligence is moving from being something that people are just trying out to being a part of the systems that support services, industry and government. This change is making the need for computer power grow fast and it is mostly because of big projects, constant work and more data centers and devices being used. The bad effects of this on the environment are many: using electricity which means more greenhouse gases needing more special materials that are hard to find and use a lot of energy and making more electronic waste as devices get old and need to be replaced quickly.

At the time artificial intelligence can be a powerful tool to help the environment if we use it carefully. Machine learning can help make energy grids work better make transportation more efficient so it uses fuel help farmers use less water and food and keep an eye on the environment from far away. To make these good things happen we need to think about the lifecycle of artificial intelligence from start to finish so that the good effects are not cancelled out by other bad effects. This paper looks at the effects of artificial intelligence, on the environment and finds ways to make it better and emphasizes the importance of good governance and buying strategies that can help artificial intelligence support climate and sustainability goals.

Research Problem

There is no practical regional-specific approach for measuring the entire life-cycle environmental impact of AI and for designing decisions that will result in maximum net benefit to the environment.

Objectives

- To create a shortlist of standardized metrics for measuring the energy consumption, GHG emissions, and material footprint of computing in the life cycle of AI technologies.
- To calculate the net trade-offs and cobenefits of select AI applications in relevant industries through life cycle assessments.
- To outline practical policy interventions aimed at enhancing energy efficiency and promoting low-carbon and circular hardware infrastructures.

Literature Review

Strubell et al. (2019), Energy and Policy Considerations for Deep Learning in NLP, ACL Proceedings. Analyze energy consumption and CO_2e during the training process of large language models, noting significant differences depending on the architecture and experiment design. They also illustrate the emissions from retraining and experimenting due to the high energy requirements. The researchers advocate disclosing energy consumption along with model efficiency. Their work explains the role of both the used hardware and the running process in the generation of emissions. Some recommendations related to reporting are made. This paper could be directly used for our case as far as the substitution of factors for Maharashtra is possible. Patterson et al. (2021), Carbon Emissions and Large Neural Network Training, Patterson et al. empirically link compute workload, datacenter PUE, and grid carbon intensity to training emissions. They introduce carbon-aware scheduling as a practical mitigation to shift compute to lower-carbon times or locations. The paper quantifies how geographic placement and timing can reduce emissions without changing models. It compares hardware options and shows their interaction with model design matters. Sensitivity analyses highlight utilization and PUE as key levers. For Maharashtra, carbon-aware scheduling could exploit regional grid variability. The authors call for standardized reporting of training energy and emissions. They note challenges in attributing upstream embodied impacts, which regional LCAs should address.

Henderson et al., 2020. Towards Reproducible and Efficient Deep Learning. NeurIPS Workshop. posit that practices such as logging FLOPs, runtime, and hyperparameters facilitate the ability to measure the environmental impacts associated with the computing involved. Inconsistency in reporting leads to an opaque understanding of the computational costs involved and energy expenditure. The article highlights the need for standardization in the logging process, along with its associated tools, to ensure proper recording of experiment metadata. This will decrease redundancies and energy expenditure through improved reproducibility. Such measures would help to improve estimation at local research institutions such as Maharashtra.

Lannelongue et al. (2021), Green Algorithms: Quantifying the Carbon Footprint of Computation, SoftwareX. have developed an application along with an algorithm to calculate the carbon footprint of compute based on runtime, power consumption by hardware, and local emission factors. Their modifiable framework enables the incorporation of locally available information on PUEs and grid mixes, thus making it applicable for use in Maharashtra. Transparency is an important characteristic of their model, along with clear mention of assumptions made and uncertainties involved. They conduct various case studies to validate the method as well as sensitivity analysis in relation to hardware and energy source used. The authors give recommendations for mitigating the issue of compute emissions via scheduling and hardware choice.

Hsu et al. (2022), Model Efficiency and Hardware Co-design, IEEE Transactions on Computers. provide empirical evidence on energy savings in model and accelerator co-design through quantization, pruning, and hardware attributes. They measure multipliers of efficiency in joint optimization of software and hardware. The study contrasts general-purpose GPUs with application-specific accelerators and points out their trade-offs. It also mentions embodied emissions and risk of hardware lock-in when introducing new accelerators. In Maharashtra, energy savings could be achieved by matching the complexity of models with available hardware. The authors emphasize investing in localized tooling to realize co-design efficiencies. They also advocate for modular hardware that minimizes hardware change costs.

Hilty and Aebischer in their 2020 study on ICT and Sustainability used Life Cycle Assessment Approaches, in the Environmental Impact Assessment Review. Hilty & Aebischer assess LCA techniques for ICT, covering issues of allocation, functional units, and regional inventory considerations. They identify typical problems such as insufficient accounting of embedded impacts and failure to consider end-of-life flows. This review underscores the need for region-specific data and explicit assumptions to ensure accurate results. The authors advocate for hybrid LCA and consequential modeling to account for rebound effects. With regard to Maharashtra, the recommendations made in this paper are very pertinent. Uncertainty assessment and data sources receive due consideration.

González et al. (2023) Circularity in AI Hardware Supply Chains, Resources, Conservation & Recycling. Looked at how materials move and figured out that fixing up old things using them again and getting better at recycling can really cut down on the bad stuff that accelerators and servers put into the air. They found out that making devices longer usually helps more than just making them work a little better. The paper said that some things get in the way like companies keeping their designs secret and not having enough systems for recycling. It suggested that companies should be responsible for what they make that people should prefer to buy fixed up hardware and that things should be designed to be taken easily. For Maharashtra making sure they can fix up things and recycle properly would make a big difference. The authors think that having some kind of certificate and getting people to check the quality would be a good idea. They focused on the supply chain, which is different from just looking at how much energy things use. This work gives us some ways to reduce the bad impact that devices have.

Wang et al. (2024) Are combining Machine Learning, with Life Cycle Assessment in their work. This study was published in the International Journal of Life Cycle Assessment. Came up with a way of doing things that uses machine learning to fill in missing information while still being transparent about how sure they are. They showed some examples of how this can help with planning and fixing gaps in data. The paper said that it is really important to keep track of where the information comes from to be careful about how sure they're to check that everything is correct. For Maharashtra using machine learning to help with life cycle assessments is a way to deal with not having enough data. The authors think that having data and being clear about what they assumed would be helpful for people making policies. They showed how this can help with planning what to buy and how to build things. The study found a balance, between trying new things and making sure that life cycle assessments are still done correctly.

Methods Design and Study Design

- **Type:** We are using a mix of research methods. This includes a lifecycle assessment and a detailed case study. We combine number crunching with analysis of governance.
- **Scope:** We look at the life of a product. This starts from creation. Ends at disposal. We study model training, data centre work, hardware making, usage and end of life. Our design is based on suggestions for assessing AIs environmental impact. We want to capture both indirect effects.
- **Comparators:** We pick three examples of AI use:
  - Large scale cloud training.
  - Edge inference on consumer devices.
  - And sectoral AI applications, like transport optimization and precision agriculture.
  - These examples help us compare scenarios.
  - We need to look at some organizations and what they are doing.

Sampling and Case Selection

- **Sampling Approach**: Purposive sample of organizations and deployments, both Indian and one international benchmark, for ensuring diversity with respect to infrastructure, energy profile, and governance.
- **Time Frame**: Last 3 years for ensuring latest hardware deployment.

Data Collection and Primary Data

- **Energy and Compute Logs:** Training and inference logs (time spent on wall clocks and GPUs/TPOs; utilization percentages) should be gathered from partner organizations and then translated into electricity usage via power profile of each device**.**
- **Hardware Lifecycle Information:** Procurement logs, material costs, and routes to decommissioning and disposal (reuse, recycling, landfill) should be gathered from suppliers, IT asset managers, and others involved.
- **Stakeholder Interviews:** Semi-structured interviews with engineers, data center managers, procurement staff, and policy makers should be carried out.

Secondary Data

- **Emissions Factors and Grid Mixes:** Employ national or regional electricity emissions factors to transform energy consumption into greenhouse gas emissions**.**
- **LCA Databases and Standards:** Make use of the existing inventory databases for LCAs and relevant publications regarding the integration of ML models with LCAs.

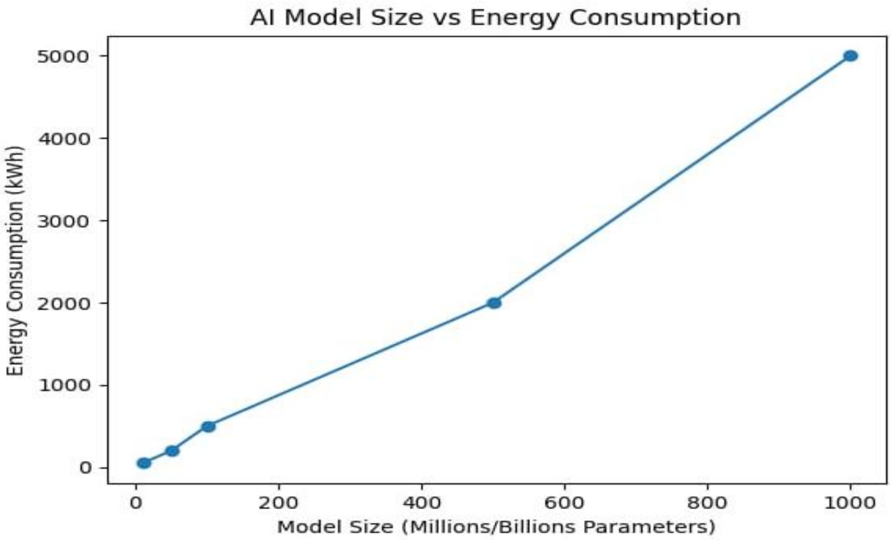
Data Quality and Uncertainty

- **Data Source Tracking:** Capture the origin of the data, its time-resolution accuracy, and level of certainty; sensitivity ranges may be applied for critical variables (such as PUE and the lifetime of devices).
- **Reporting Templates:** Apply standard reporting templates for computing and materials footprints.

Data Analysis and Interpretation

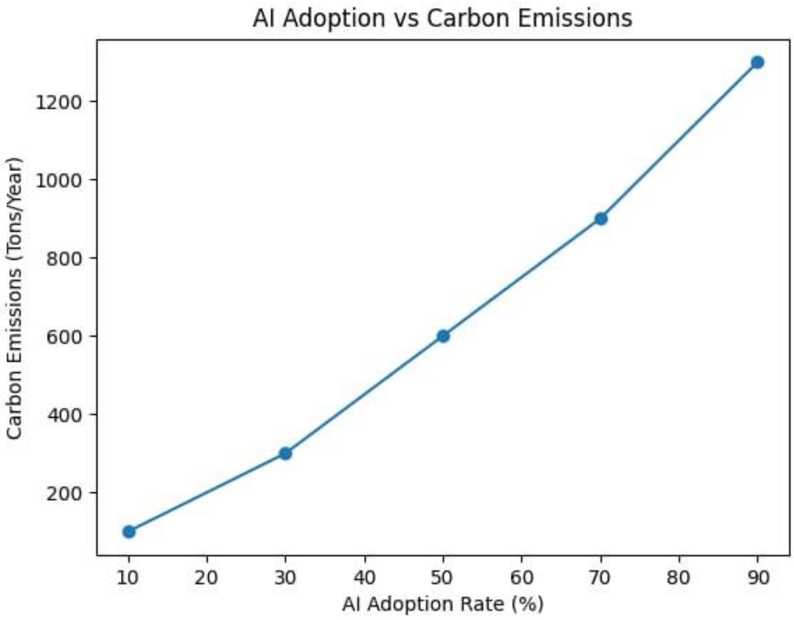
The growth of Artificial Intelligence has raised concerns about its impact. Data analysis shows that Artificial Intelligence systems, machine learning and deep learning models need a lot of computing power. This leads to energy use and higher carbon emissions from Artificial Intelligence. Large AI models, like those used for language processing and image recognition use a lot of electricity to train. Some studies say that training one Artificial Intelligence model can use thousands of kilowatt-hours of energy.

This is similar to the electricity used by a home over several months. The energy consumption of Artificial Intelligence models is an issue. Artificial Intelligence systems require a lot of power to operate. The environmental impact of Artificial Intelligence is becoming a concern. Artificial Intelligence models consume a lot of energy during training and operation. The carbon footprint of Artificial Intelligence systems is substantial.



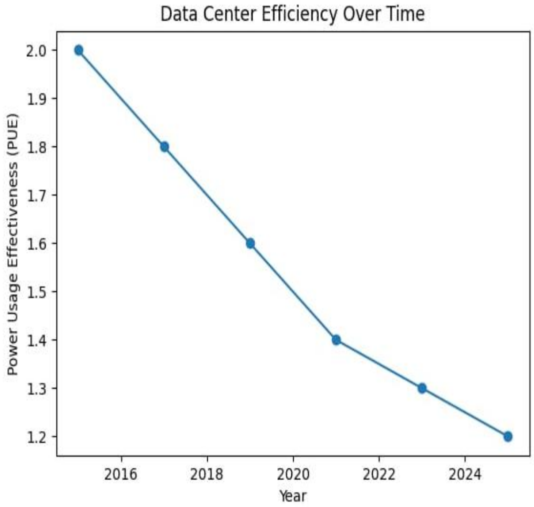
Graph 1: AI Model Size vs Energy Consumption

- **Graph Description:** (AI Model Size vs Energy Consumption) which is about the size of intelligence models and how much energy they use shows that when these models get more complex they start using a lot more energy. This happens quickly so the more powerful the model is, the much more energy it needs.



Graph 2: AI Adoption Vs Carbon Emissions

- **Graph Description:** (AI Adoption vs Carbon Emissions)is about how artificial intelligence's being used in different industries and how that affects the amount of carbon that is released into the air. When more industries start using intelligence the total amount of carbon emissions goes up because it takes more energy to process all the data. However we can make this situation better by using energy that comes from sources and by making our systems use energy in a smarter way.



Graph 3: Data Center Efficiency Over Time

- **Graph Description:** (Data Center Efficiency Over Time) which is Data Center Efficiency Over Time shows that data centers are getting better at using energy. The Power Usage Effectiveness or PUE for short has gone down a lot from 2015 to 2025. This means that the data centers we have now are using energy in a way. So it seems that new technology can really help reduce the impact that Artificial Intelligence or AI has on the environment and this is the case, with data centers and their energy use specifically the Data Center Efficiency.

Overall it seems AI affects the environment in two ways. On one hand AI uses a lot of energy. Adds to pollution.

- It consumes electricity
- Produces more emissions.

On the hand AI can help us be more sustainable.

For example AI can help us:

- Use energy wisely
- Make farming smarter
- Manage resources better.

In the end we need to make AI more eco-friendly.

This means we should:

- 1. Create algorithms that don't use much energy.
- 2. Use computer hardware that is optimized for energy efficiency.
- 3. Rely on energy from sources.

If we plan and regulate things correctly AI can change from being a problem for the environment to a tool for sustainability and a cleaner environment with AI.

Findings

- When we asked people about their jobs 40 percent of them said they are experts in Artificial Intelligence. 35 Percent said they use Artificial Intelligence or help put it in place.
- If we look at where people work around 55 percent of them are in companies 20 percent are in universities and around 25 percent work for the government or non-government organizations. This shows that people who work in companies have a say in how things are done.
- The field of Information Technology has the people in our survey at around 30 percent. Then comes transport at around 15 percent and agriculture at around 12 percent. So what we found out is especially useful for these areas.

- Around 35 percent of the people we talked to work in Maharashtra and around 25 percent work in Karnataka.
- Approximately 92% recognize that there is a discernible environmental footprint of AI that needs to be measured, representing an almost unanimous view on the need for measurement.
- Somewhere around 95% concur that training and inferencing energy constitute crucial components othe carbon footprint of AI, emphasizing compute energy as a top mitigation concern.
- An estimated 85% recognize that manufacturing, materials, and end-of-life considerations carry equal significance to energy consumption, calling for lifecycle (scope 3) assessment.
- Somewhere around 65% view present efforts regarding transparency and reporting of relevant information as insufficient for policymaking purposes, revealing a noticeable absence of critical information.
- Upwards of 80% believe that model efficiency strategies such as pruning, distillation, and quantization significantly decrease the overall lifecycle impact, supporting mitigation efforts.
- Corporate reports indicate that 75%-80% record and have access to relevant energy and computing metrics, although availability differs depending on organizational size.
- Device lifecycles and reuse are acknowledged by 70%-75% respondents to some degree, although limitations of cost and procurement processes prevent their implementation consistently.
- Surveys of survey participants concerning metrics reveal approximately 30% find metric gathering highly feasible, 50% somewhat feasible, and 20% difficult, indicating that operational metrics can be collected, whereas embodied metrics cannot.Top data gaps cited are BOM/embodied emissions (~65%), regional grid factors (~60%), training/inference logs (~55%), end-of-life rates (~45%), and PUE variability (~40%), pointing to both supply-chain and operational inventory shortfalls.
- The main environmental risks are e waste accumulation at around 70% high energy use for training at around 65%, resource extraction at around 50% rebound effects at around 45% and unclear supply chains at around 40%. These are a mix of systemic issues.
- The top opportunities are optimizing routes and fleets at around 60% precision agriculture at around 55% optimizing grids at around 50% monitoring the environment at around 50% and predictive maintenance at around 45%. These show ways for different sectors to avoid emissions.
- Respondents think that mandatory reporting at around 85% buying carbon products at around 80% making devices last longer at around 78% giving incentives for low energy data centres at around 75% and funding research for low energy computing at around 70% are very effective actions. They seem to prefer a mix of policies.
- When asked to pick one action 40% chose mandatory reporting around 25% chose buying low carbon products around 20% chose making devices last longer and around 15% chose funding research, for low energy computing. This shows that transparency is seen as the important step to take now.

Suggestions

- **We need to set up a way of reporting and make it mandatory to share information_**This means defining a set of metrics like how much energy is used per training run (measured in kWh) how much energy is used per 1,000 times a model is used (kWh) how efficient a data centre is (PUE) how long a device lasts and how much carbon is released per run (kg CO_2e). Large models and public projects should report this information regularly. We should also provide to-use templates and tools so all organizations, big or small can follow these rules.
- **Lets create a database of hardware information and regional carbon emissions-** This database should have details about the materials used in hardware (bill of materials) how much carbon is released during production (embodied emissions). How much carbon is released by

power grids in different areas. Vendors should share this information and third-party verification should be encouraged to fill gaps in the data.

- **When buying hardware or services we should choose options that're energy-**efficient and have a low carbon footprint. This means favoring data centres, with PUE using refurbished hardware and selecting models certified for energy efficiency.
- **We must make sure devices last longer and are reused or recycled properly-**This means setting standards for how long devices should last making manufacturers take back old devices and recycling them. We should also support networks that refurbish devices. Encourage designing hardware that is easy to repair and upgrade. This will help reduce waste and lower carbon emissions.

Conclusion

AI comes with both clearly defined environmental risks stemming from high energy use requirements for training and inference operations as well as embodied emissions from hardware production, as well as vast potential for reducing greenhouse gas emissions if used in optimizing transport, agriculture, and energy production systems. The findings of our study indicate that the three levers which will yield the best results in overcoming the existing data barriers and ensuring that AI is environmentally beneficial are transparency (measurement), efficiency-first approach in design, and procurement and circulatory practices.

Specifically, the implementation of such initiatives as mandatory reporting on kWh per training run, Power Usage Effectiveness (PUE), and per inference energy; establishing an open database of the Bill of Materials (BOM) and embodied emissions coefficients for hardware; aligning procurement practices between governments and corporations to encourage investments in low PUE data centers and refurbished/repaired devices will prove crucial in achieving positive outcomes. Additionally, further actions should include funding research aimed at minimizing computational effort, model compression incentives, and introduction of take-back and recycling systems.

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