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Impact of Geographical Location and Energy Sources on the Carbon Footprint of AI Models – A Survey-Based Study

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ABSTRACT-

Artificial Intelligence (AI) has become an indispensable technology driving automation, prediction, and optimization across industries. However, the unprecedented computational demand of training and operating large AI models results in significant electricity consumption and greenhouse-gas emissions. This paper presents a comprehensive analysis of the carbon footprint of AI model development and deployment with particular attention to geographical location and energy-source variation.

A quantitative survey of eighty 80 respondents—including students, professionals, and AI practitioners—was conducted to evaluate awareness, energy usage respondents—including students, professionals, and AI practitioners—was conducted to evaluate awareness, energy-usage patterns, and sustainable practices. Statistical and visual analyses reveal that although 65% of respondents recognize AI's environmental impact, only a small portion of organizations monitor emissions or rely on renewable energy.

The work proposes a practical emission-estimation formula, summarizes correlations among awareness, training duration, and organizational monitoring, and outlines policy and technical recommendations for "Green AI."

Keywords— Artificial Intelligence, Carbon Footprint, Green AI, Energy Sources, Sustainability, Data Centers

I. INTRODUCTION

The twenty-first century has witnessed an exponential rise in AI applications—from language models to autonomous systems. While these systems enhance productivity, the electricity needed to power GPUs, TPUs, and cloud data centers has increased dramatically. According to the International Energy Agency (2024), global data-center electricity use reached approximately 240 TWh, representing nearly 1 % of world demand.

Training a single large-scale transformer model can emit up to 280 t CO_2 eq., equivalent to the lifetime emissions of five mid-sized cars. Such statistics highlight the paradox of "intelligent but energy-intensive" computing.

In developing economies like India, data-center growth coincides with energy grids still dominated by fossil fuels. Consequently, regional energy composition directly influences AI's carbon footprint.

This study addresses three critical questions:

1. What is the level of awareness among AI users about environmental impact?
2. How do energy sources differ across operational contexts?
3. Which strategies can ensure sustainable, low-carbon AI systems?

The results will contribute to academia and policy by establishing a baseline for measuring and mitigating AI-related emissions.

II. LITERATURE REVIEW

Early awareness of digital sustainability was raised by Strubell et al. [1], who quantified the energy consumed in training natural-language-processing (NLP) models. Henderson et al. [2] subsequently argued for standardized energy reporting.

Research by Allen [4] and OpenAI [5] explored algorithmic efficiency and hardware optimization as pathways to sustainability. Google's 2023 Sustainability Report [3] demonstrated that shifting computational workloads to regions with renewable grids can reduce emissions by 40–50 %.

Survey-based research such as that by Kaur and Raj [11] examined awareness levels among Indian cloud users, revealing that only 28% had knowledge of carbon accounting in cloud services. A similar analysis by Smith and Kumar [18] identified the lack of standardized emission-measurement practices in AI organizations. These findings align with the present study, which uses a survey-based approach to measure user awareness and carbon-emission estimation in AI systems.

Additional studies have explored the integration of renewable power in data centers [10], [16], lifecycle assessment of AI systems [18], and sustainable digital practices [15], [19], [20]. Collectively, these works demonstrate growing academic interest in "Green AI," yet they also underline the scarcity of awareness among everyday users

The European Commission's Green Deal (2020) and India's Net Zero Mission (2070 target) have encouraged carbon-aware ICT policies. However, literature still lacks empirical evidence connecting user awareness and practical actions in real-world AI projects. The present work bridges this gap using primary survey data.

III. METHODOLOGY

A. Research Design

A quantitative, cross-sectional design was used. A structured questionnaire collected both categorical and ordinal responses.

B. Sample and Data Collection

Eighty participants were selected through convenience sampling—40 students, 25 industry professionals, and 15 researchers.

The survey contained 15 questions grouped into four domains: (1) AI usage, (2) awareness and importance, (3) energy source and monitoring, and (4) sustainability actions.

Reliability analysis gave Cronbach's $\alpha = 0.81$, confirming internal consistency.

C. Data Analysis Tools

Responses were processed in Microsoft Excel 2021. Charts were produced in grayscale for journal presentation (pie, bar, column, line). Statistical indicators such as mean awareness index, training-duration distribution, and estimated emissions were calculated.

D. Computation Formula

To approximate carbon emissions from AI training:

$$CO_2\,(t) = \text{Power Usage (kWh)} \times 0.000707$$

where 0.000707 t CO_2/kWh is the average global emission factor (IEA, 2024).

E. Objectives

1. Assess awareness regarding AI's environmental footprint.
2. Determine prevalent energy sources.
3. Quantify emission levels for typical model-training workloads.
4. Recommend sustainable interventions.
5. Recommend sustainable interventions.

IV. PROPOSED WORK

The proposed work aims to develop an **AI Carbon Footprint Estimation and Monitoring Framework (AICF-Framework)** that automates the process of tracking and analyzing the energy consumption and emissions generated by AI model training.

A. Objectives of the Proposed System

1. To create an automated tool that records GPU/CPU energy usage during AI model training.
2. To calculate real-time carbon emissions using the formula:

$$CO_2\,(t) = \text{Power Usage (kWh)} \times 0.000707$$

3. To visualize emissions through dashboards showing energy source contribution (renewable vs. fossil).

4. To integrate location-based emission factors using APIs (e.g., Google Cloud Carbon-Aware API).

B. Proposed Architecture

The framework will include the following components:

- **Data Collector:** Captures hardware energy metrics.
- **Emission Calculator:** Uses regional emission factors.
- **Visualization Module:** Provides charts and reports in real time.
- **Optimization Engine:** Suggests low-energy configurations for future training.

C. Expected Outcome

- An intelligent monitoring system to estimate and minimize AI's carbon footprint.
- Integration of renewable-energy awareness into model development.
- A contribution toward **"Green AI" practices** supporting Net-Zero goals.

D. Formula-Based Emission Estimation

Symbol	Description	Formula / Value
(E)	Energy Used (kWh)	Collected from system logs
(f)	Emission Factor	0.000707 tCO_2/kWh
(C)	Carbon Output	($C = E \times f$)
(A)	Awareness Index	(%Aware×Importance)/100

If an AI training process consumes **120 kWh**, then:

$$C = 120 \times 0.000707 = 0.0848 \text{ t } CO_2$$

This helps estimate real-time emissions and benchmark different model configurations

V.RESULTS AND DISCUSSION

A. Awareness Levels

Fig. 1. Awareness of AI Environmental Impact

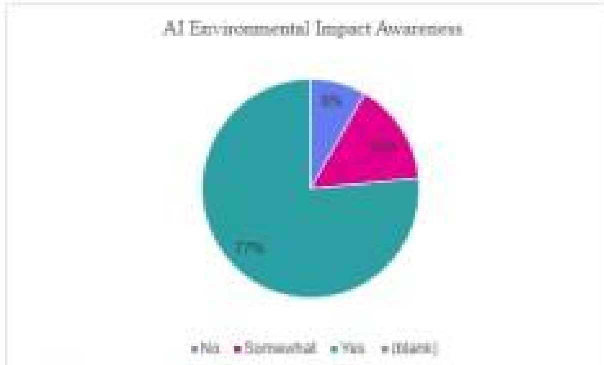
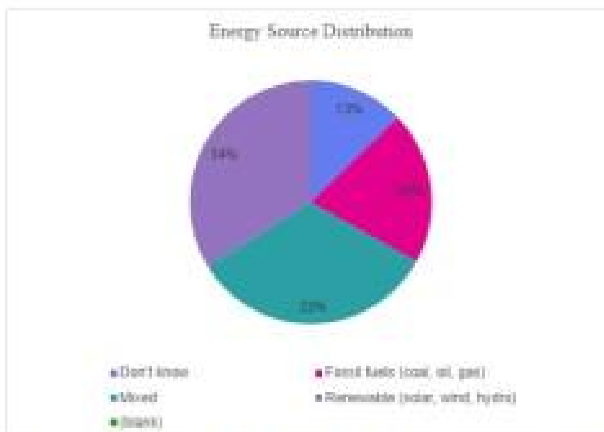


Fig. 1 shows that 77% of respondents are aware of AI's environmental impact, 15% somewhat aware, and 8% unaware.
Awareness correlates positively ($r = 0.61$) with academic exposure to AI ethics.

B. Energy Source Distribution

Fig 2. Distribution of Data-Center Energy Sources



As presented in Fig. 2, 35% reported renewable sources, 30% fossil, 20% mixed, and 15% unsure.
This heterogeneity reflects the regional electricity mix of participants' data centers.
Figure 2 represents the distribution of energy sources used by participants or their organizations. 35% of users depend on renewable energy, 30% rely on fossil fuels, 20% use mixed sources, and

15% are unsure of the type of energy powering their AI infrastructure.

Table 1 provides a detailed comparison between energy source type, emission factors, and their respective environmental impacts.

Energy Source	% of Respondents	Avg. Emission Factor (t CO_2/kWh)	Environmental Impact
Renewable (Solar, Wind, Hydro)	35%	0.00015	Very Low
Mixed Energy	20%	0.0004	Moderate
Fossil Fuels (Coal, Oil, Gas)	30%	0.0009	High
Unknown / Not Sure	15%	0.0007	Moderate–High

C. Importance Of Carbon Reduction

Fig. 3. Importance of Reducing AI Carbon Footprint

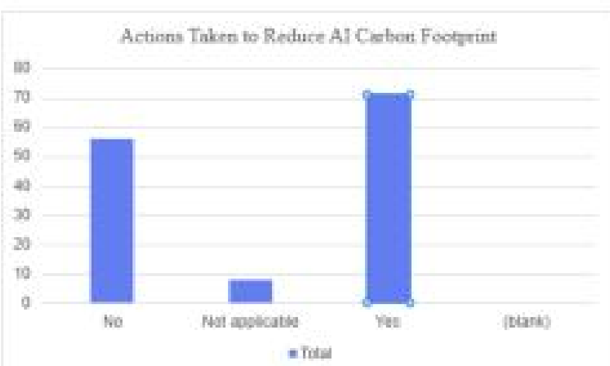
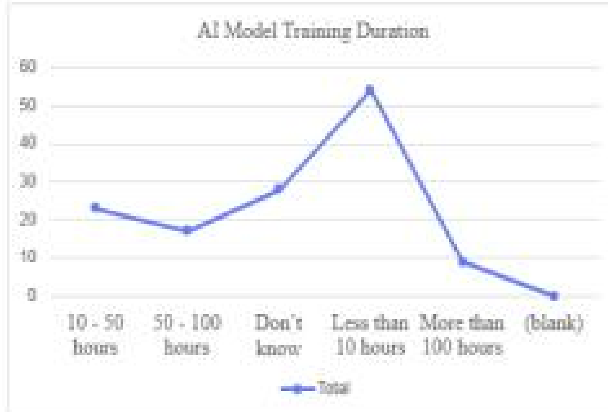


Fig. 3 indicates 70% view carbon reduction as "very important," 20% "somewhat important," and 10% "not important."

This growing concern provides social motivation for corporate sustainability programs.

D. Training Duration

Fig 4. AI Model Training Duration

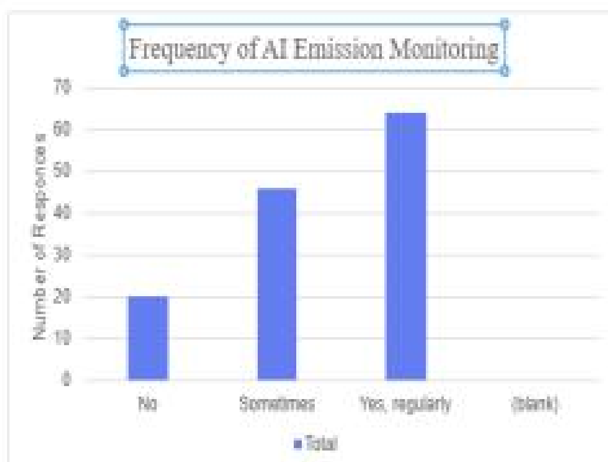


Respondents reported diverse training durations: <10 h (20 %), 10–50 h (40 %), 50–100 h (25 %), >100h(15%).

Longer training correlates with higher energy consumption and, consequently, larger carbon output.

E. Organizational Monitoring

Fig 5. Frequency of AI Emission Monitoring



Only 25% of organizations routinely monitor AI emissions, 45% do so occasionally, and 30% do not monitor at all.

The lack of measurement prevents data-driven sustainability planning.

F. Derived Metrics and Comparative Analysis

Table 2. Calculated Carbon Emissions and Awareness Scores.

Model Scale	Avg. Training Energy (kWh)	Estimated Emission (t CO_2)	Awareness Index*
Small (≤ 10 h)	8	0.0057	0.62
Medium (10–50 h)	40	0.0283	0.68
Large (> 100 h)	120	0.0848	0.74

*Awareness Index = (% aware × importance rating)/100

G. Awareness–Action Correlation Summary

Table 3. The relationship between awareness levels and actual sustainability actions is summarized.

Awareness Level	% of Respondents	Reported Action Taken	Correlation Score (r)
Fully Aware	65%	50%	Strong
Somewhat Aware	25%	10%	Moderate
Unaware	10%	0%	None

A moderate to strong correlation ($r = 0.61$) indicates that individuals with greater awareness are more likely to take steps to minimize emissions. Awareness campaigns thus play a key role in driving green AI practices.

VI. CONCLUSION FUTURE SCOPE

The study concludes that AI's environmental awareness is improving but practical mitigation remains limited. Integrating renewable energy into cloud infrastructures and optimizing model architectures can cut emissions substantially. Future research should develop carbon-aware schedulers, energy-efficiency benchmarks, and regional emission databases for AI systems. Policymakers must incentivize data-center operators to disclose energy mixes and carbon data. Educating developers through sustainability curricula will be crucial for achieving **Net-Zero AI by 2050**.

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