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# How Hungry is AI? Benchmarking Energy, Water, and Carbon Footprint of LLM Inference

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## Abstract

This paper introduces a novel infrastructure-aware benchmarking framework for quantifying the environmental footprint of LLM inference across 30 state-of-the-art models as deployed in commercial data centers. Our framework combines public API performance data with region-specific environmental multipliers and statistical inference of hardware configurations. We additionally utilize cross-efficiency Data Envelopment Analysis (DEA) to rank models by performance relative to environmental cost. Our results show that o3 and DeepSeek-R1 emerge as the most energy-intensive models, consuming over 33 Wh per long prompt, more than 70 times the consumption of GPT-4.1 nano, and that Claude-3.7 Sonnet ranks highest in eco-efficiency. While a single short GPT-4o query consumes 0.43 Wh, scaling this to 700 million queries/day results in substantial annual environmental impacts. These include electricity use comparable to 35,000 U.S. homes, freshwater evaporation matching the annual drinking needs of 1.2 million people, and carbon emissions requiring a Chicago-sized forest to offset. These findings illustrate a growing paradox: although individual queries are efficient, their global scale drives disproportionate resource consumption. Our study provides a standardized, empirically grounded methodology for benchmarking the sustainability of LLM deployments, laying a foundation for future environmental accountability in AI development and sustainability standards.

## 1 Introduction

Large language models (LLMs) have moved beyond research labs and are now embedded in search engines, virtual assistants, education platforms, and enterprise tools [1, 2, 3, 4]. Models like GPT-4o [5] and Claude-3.7 Sonnet [6] represent state-of-the-art systems, while open-source alternatives such as LLaMA-3 [7] and DeepSeek-V3 [8] reflect growing accessibility and experimentation. On top of that, the emergence of reasoning models such as DeepSeek-R1 [9], o1 [10], and o3-mini [11] marks a shift toward multi-step logic and chain-of-thought reasoning.

However, the advancement of LLMs does involve shortcomings in environmental aspects. Training GPT-3 is estimated to consume 1,287 megawatt-hours (MWh) of electricity and emit over 550 metric tons of CO<sub>2</sub>e [12], while requiring more than 700 kiloliters (kL) of water for cooling alone [13], enough to fill two-thirds of an Olympic-sized swimming pool. Yet while training has been the focus of sustainability discussions, inference is emerging as the primary contributor to environmental costs. In contrast to training, which is conducted once or at intervals, inference occurs consistently and on a large scale. Recent estimates suggest inference can account for up to 90% of a model’s total lifecycle energy use [14, 15].

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Despite the growing environmental footprint of large-scale model deployment, a standard method to quantify the cost of inference at the prompt level remains absent. Existing frameworks [15, 19, 20] either lack the ability to benchmark proprietary models, the real-time granularity needed for deployment-specific prompt-level benchmarking, or are constrained to local setups, failing to capture the infrastructure complexity of production-scale inference. A core obstacle to developing more accurate assessments is the lack of information from commercial AI providers, as they do not disclose model-specific inference data, and existing environmental reports tend to aggregate emissions across entire cloud infrastructures without disaggregating by model or workload [17, 18]. This opacity hinders independent verification and undermines both scientific benchmarking and policy efforts aimed at regulating AI’s true environmental cost.

To address these issues, we introduce a novel benchmarking framework to quantify the operational environmental footprint of LLM inference at the per-prompt level. Unlike existing studies [13, 15, 19], our method adopts a more comprehensive strategy by integrating performance metrics such as latency and throughput from public APIs with published GPU and system power specifications. Furthermore, we scale these combined data points using region-specific multipliers, including Power Usage Effectiveness (PUE) [21, 22], Water Usage Effectiveness (WUE) [21, 22], and Carbon Intensity Factors (CIF) [23, 24] to account for infrastructural overhead. This method enables us to evaluate the energy, water, and carbon effects of both open-source and proprietary models, a gap that, to our knowledge, has not been comprehensively explored in prior research. Additionally, we employ statistical analysis, including ANOVA and Tukey HSD, to estimate underlying hardware configurations. This framework’s effectiveness is shown by its use in more than 30 commercially deployed models and assessments across various infrastructure scenarios. Moreover, to contextualize resource use relative to model capability, we apply cross-efficiency Data Envelopment Analysis (DEA) to assess how effectively each model converts environmental inputs into performance. As a key application of this framework, we perform a case study to estimate the annual footprint of GPT-4o text generation based on scaled usage data. Our framework enables infrastructure-aware decision-making, empowers accountability, and provides a foundational step toward sustainability standards in AI deployment.

The remainder of the paper is organized as follows. Section 2 reviews existing studies on the environmental impact of LLMs. Section 3 introduces key concepts, including hardware configurations and environmental multipliers. Section 4 details our framework for estimating inference-phase cost. Section 5 presents findings across 30 models. Section 6 provides a focused analysis of GPT-4o’s annual environmental footprint. Section 7 outlines key insights and implications. Section 8 summarizes the main takeaways and limitations and directions for future work.

## 2 Related Work

The environmental impact of AI systems has garnered increasing attention in recent years, with a growing body of work attempting to quantify the energy, carbon, and water costs associated with training and deploying LLMs.

Li et al. [13] analyzed GPT-3’s freshwater consumption, estimating over 5 million liters used during training and projecting that AI-related withdrawals could reach 6.6 trillion liters annually by 2027. Although their spatiotemporal methodology is a significant early contribution, it overlooks carbon emissions, depends on an outdated model, and requires previous knowledge of energy usage, which restricts its scalability. In parallel, Strubell et al. [25] estimated carbon emissions from training BERT and GPT-2 by accounting for GPU, CPU, and DRAM power draw alongside PUE adjustments. However, their analysis excludes inference and infrastructural overhead. Similar limitations appear in Meta’s LLaMA reports [7, 26, 27], which provide carbon footprints based on GPUs’ TDPs but disregard water use, system-wide energy consumption, and the inference phase entirely.

Regarding inference, Husom et al. [19] (MELODI) measure real-time energy consumption of GPUs and CPUs at the prompt level, but they neglect carbon emissions, water usage, and infrastructure overhead, only concentrating on small-scale open-source models. Samsi et al. [20] measure GPU power draw across prompt lengths but exclude proprietary systems and broader environmental factors, lacking a standardized scaling method for production-level inference. Yang et al. [28] evaluate over 1,200 vision models. However, their analysis does not include LLMs, API-based deployments, or essential infrastructure considerations like PUE and WUE.

Complementary studies, including Luccioni et al. [29], assess general-purpose and task-specific models in the A100 systems. While they provide valuable cross-model insights, they do not consider proprietary models, water usage, or carbon emissions. CodeCarbon [15] calculates carbon footprints based on device-level data and regional carbon intensity, but it lacks the granularity needed for prompt-level analysis and does not work with API-based inferences. On a larger scale, Harding and Moreno-Cruz [30] connect AI adoption to national productivity, allowing for extrapolation of energy and carbon effects. Though this provides a useful overarching view, it overlooks variability in per-prompt inference, the behavior of specific models, and the infrastructure used for deployment.

Most efforts focus on training and local model evaluation, lacking standardized, scalable methods, and ignoring infrastructural overhead, as well as omitting resource categories such as water consumption and carbon emissions. Our work addresses these gaps by integrating API-based performance metrics with GPU and system power specifications and environmental multipliers to estimate the environmental impact of LLM inference at the prompt level in data centers. We infer deployment infrastructure through statistical analysis and apply DEA to contextualize environmental impact versus performance. Additionally, we conduct a case study estimating GPT-4o’s annual environmental footprint based on scaled usage data, providing the first infrastructure-aware, prompt-level benchmark of inference sustainability at scale.

### 3 Preliminaries

To capture infrastructure-level overhead in data center operations, we apply three standard environmental multipliers: Power Usage Effectiveness (PUE) [21, 22], Water Usage Effectiveness (WUE) [21, 22], and Carbon Intensity Factor (CIF) [23, 24].

**PUE** accounts for non-computational energy overheads such as cooling, lighting, and power distribution. Defined as the ratio of total data center energy consumption to IT-specific energy use.

**WUE** captures the water used per kilowatt-hour of IT energy, encompassing on-site cooling (Scope 1), off-site electricity generation (Scope 2), and embodied water from hardware manufacturing and transport (Scope 3). WUE can be computed based on either water withdrawal (the total volume drawn from natural or municipal sources) or water consumption (the portion of withdrawn water permanently lost, primarily through evaporation).

**CIF** measures carbon emissions per kilowatt-hour of energy consumed, largely driven by the regional electricity mix. Emissions are categorized as direct on-site combustion (Scope 1), off-site electricity generation (Scope 3), and embodied emissions from manufacturing and transport (Scope 3).

### 4 Methodology

This section presents our novel methodology for estimating the environmental footprint of LLM inference. Our framework integrates model-specific performance metrics with infrastructure-level environmental multipliers to calculate operational energy consumption, water usage, and carbon emissions per query. We also evaluate eco-efficiency using DEA, mapping sustainability trade-offs against a composite performance benchmark.

#### 4.1 Model Selection and Hardware Estimation

We analyze 30 large language models across OpenAI, Anthropic, Meta, and DeepSeek. Table 1 summarizes each model’s deployment context, including provider, cloud host, hardware type and specifications, and regional environmental multipliers (PUE, WUE, CIF). All models are usually run on NVIDIA DGX systems using A100, H100, H200, or H800 GPUs [31, 32, 33, 34, 35]. U.S.-based providers such as OpenAI and Anthropic have acquired large volumes of H200 and H100 chips [38, 47, 48], making them the most probable choice for recent deployments. DeepSeek, which operates under U.S. export restrictions, uses the H800, NVIDIA’s export-compliant GPU for the Chinese market [44, 50]. Both the H200 and H800 retain the same Hopper architecture and peak power draw as the H100, with system-level energy characteristics that are nearly identical [51]. While the H200 achieves greater energy efficiency due to faster memory and higher bandwidth, and the H800 may exhibit reduced performance due to export-related firmware limitations, both maintain the same peak power draw, thermal design profile, and system-level utilization characteristics as the

Table 1: Deployment and infrastructure specifications of models.

Model	Launch Date	Company	Host	Hardware	Critical Power (kW)	PUE	WUE (on-site, L/kWh)	WUE (off-site, L/kWh)	CIF (kgCO <sub>2</sub> e/kWh)
GPT-4.1	Apr, 2025								
GPT-4.1 mini	Apr, 2025								
GPT-4.1 nano	Apr, 2025								
o4-mini (high)	Apr, 2025								
GPT-4.5	Feb, 2025								
o3	Apr, 2025	OpenAI	Microsoft Azure	DGX H200/H100 [38, 35]	10.20 [39]	1.12 [40]	0.30 [41]	3.142 [42]	0.3528 [37]
o3-mini (high)	Jan, 2025								
o3-mini	Jan, 2025								
o1	Dec, 2024								
o1-mini	Sep, 2024								
GPT-4o (Mar '25)	May, 2024								
GPT-4o mini	July, 2024								
GPT-4 Turbo	Nov, 2023	OpenAI	Microsoft Azure	DGX A100*	6.50[43]	1.12	0.30	3.142	0.3528
GPT-4	Mar, 2023								
DeepSeek-R1	Jan, 2025	Deepseek	Deepseek	DGX H800 [8]	10.20 [44]	1.27 [45]	1.20 [45]	6.016 [42]	0.6 [46]
DeepSeek-V3	Dec, 2024								
Claude-3.7 Sonnet	Feb, 2025								
Claude-3.7 Sonnet ET <sup>†</sup>	Feb, 2025								
Claude-3.5 Sonnet	Jun, 2024								
Claude-3.5 Haiku	Nov, 2024								
LLaMA-3.3 70B	Dec, 2024								
LLaMA-3.2-vision 90B	Sep, 2024								
LLaMA-3.2-vision 11B	Sep, 2024								
LLaMA-3.2 3B	Sep, 2024								
LLaMA-3.2 1B	Sep, 2024								
LLaMA-3.1-405B	Jul, 2024	Meta	AWS	DGX H200/H100	10.20	1.14	0.18	3.142	0.385
LLaMA-3.1-70B	Jul, 2024								
LLaMA-3.1-8B	Jul, 2024								
LLaMA-3-70B	Apr, 2024								
LLaMA-3-8B	Apr, 2024								

<sup>\*</sup>DGX A100 was estimated for GPT-4o mini, GPT-4 Turbo, and GPT-4. Justification and estimation details are provided in Section 4.3.1.

<sup>†</sup>Extended Thinking (ET).

H100 [44, 51]. These architectural differences affect throughput and latency, resulting in higher or lower energy consumed per token, but do not impact total system power demand under load. We therefore treat H100, H200, and H800 as equivalent in our power modeling, since our estimates are based on power draw and utilization rather than task-level performance.

Environmental multipliers such as PUE, WUE, and CIF are assigned based on the cloud provider and regional deployment environments. OpenAI models, hosted on Microsoft Azure, use Azure-reported PUE, site-level WUE, and CIF values, supplemented by U.S. national averages for source WUE. For AWS-hosted Anthropic and Meta models, we apply AWS-reported PUE and site-level WUE, using U.S. national averages for source WUE and CIF due to limited public disclosures. For DeepSeek, we use Chinese data centers' national averages for all multipliers.

## 4.2 Per-Query Energy Consumption Estimation

To estimate the per-query energy consumption, we introduce a formula that serves as the core of our infrastructure-aware framework. This model integrates performance data [52], which evaluates LLMs under standardized conditions. For each model, we extract latency and tokens-per-second (TPS) across three prompt configurations that represent real-world use: short-form (100 input, 300 output tokens), medium (1,000 input, 1,000 output), and long-form (10,000 input, 1,500 output). Metrics are reported as distributions over the 5th, 25th, 50th (median), 75th, and 95th percentiles, reflecting variability across multiple test runs for each model and prompt configuration. We compute runtime estimates by pairing available latency and TPS quantiles to construct a joint distribution that captures decoding throughput and fixed overhead variability. This modeling ensures that downstream energy calculations reflect the stochastic nature of inference workloads. Our model computes the per-query energy as:

$$E_{\text{query}} (\text{kWh}) = \left( \underbrace{\frac{\text{Output Length} + \text{Latency}}{3600}}_{\text{Total inference time (hours)}} \right) \cdot \left( \underbrace{P_{\text{GPU}} \times U_{\text{GPU}}}_{\text{GPU power (W)}} + \underbrace{P_{\text{non-GPU}} \times U_{\text{non-GPU}}}_{\text{Non-GPU power (W)}} \right) \cdot \text{PUE} \quad (1)$$

, where  $P_{\text{GPU}}$  and  $P_{\text{non-GPU}}$  represent the maximum rated GPU and non-GPU system power, respectively, measured at the node level.  $U_{\text{GPU}}$  denotes the aggregate GPU power draw, incorporating both the number of GPUs assigned and their per-GPU load, while  $U_{\text{non-GPU}}$  similarly reflects the aggregate power utilization of non-GPU components. Latency refers to the time to first token generation, which corresponds to the time required to process the input prompt. TPS represents the generation rate of

output tokens; therefore, dividing the output length by TPS yields the time required to generate the response. The formula is evaluated across all quantile pairs and output lengths to produce a range of energy estimates per model configuration and output size, incorporating the PUE factor to account for data center-level overheads.

### 4.3 Hardware-Class Attribution

We stratify LLMs into five hardware classes based on model size: **Nano** (<7B), **Micro** (7–20B), **Small** (20–40B), **Medium** (40–70B), and **Large** (>70B), assigning 1, 2, 4, or 8 GPUs accordingly. Models that do not disclose parameter counts, such as OpenAI and Anthropic flagship models (e.g., GPT-4o, Claude-3.7 Sonnet), are classified as **Large**, OpenAI Mini variants (e.g., GPT-4o mini) as **Medium**, and models labeled “Nano” such as GPT-4.1 nano as **Small** based on reported model performance (e.g., TPS, latency, and reasoning capabilities) [52].

AI companies and cloud providers typically rely on dynamic batching to optimize GPU utilization while maintaining low latency [53]. Although actual batch sizes fluctuate depending on incoming demand, they are generally constrained to a narrow range below 16 to preserve responsiveness. Benchmarks [52] show that even for large prompts, most models maintain a first-token latency below 1 second. Moreover, prior studies [54, 55] show that these latency values are consistent with batch sizes in the range of 4 to 16. This suggests that real-world deployments prioritize small, latency-sensitive batches over maximal throughput. Accordingly, we adopt a batch size of 8 for all primary calculations, as it represents a practical midpoint between common deployment scenarios. A detailed sensitivity analysis exploring the impact of alternative batch sizes is provided in Appendix A. The number of GPUs and their allocated power draw utilization rates for H100 systems are estimated from Splitwise [55], the Latency Processing Unit study [56], and LLM-Inference-Bench [54]. For A100 systems, we adopt measurements from Patel et al. and Kakolyris et al.’s work [57, 58]. Per-request GPU and non-GPU utilization rates are calculated as:

$$U_{\text{GPU total}} = \frac{G \times D_{\text{GPU}}}{N \times B}, \quad U_{\text{non-GPU total}} = \frac{G \times D_{\text{non-GPU}}}{N \times B} \quad (2)$$

where  $G$  is the number of GPUs assigned per model,  $N = 8$  is the number of GPUs per node, and  $B = 8$  is the batch size.  $D_{\text{GPU}}$  denotes the assigned GPUs’ power draw, expressed as a fraction of their maximum power draw, while  $D_{\text{non-GPU}} = 0.5$  represents the conservatively assigned fixed utilization fraction for non-GPU components (e.g., CPU, memory, storage, cooling), relative to their peak power draw [39]. We exclude idle power consumption from unutilized GPUs in partially loaded nodes, as deployment-specific telemetry is unavailable to determine whether such capacity is reassigned, load-balanced, or remains idle. Table 2 summarizes GPU and non-GPU power utilization rates across model classes. Values are rounded to typical intervals observed during inference, accounting for input processing spikes, output length, decoding complexity, and a batch size of 8 parallel requests.

Table 2: Estimated node-level GPU and non-GPU utilization by model class for H100 and A100.

Class	GPU Count	$D_{\text{GPU}}$ Range (H100)	$D_{\text{GPU}}$ Range (A100)	$U_{\text{GPU total}}$ (H100)	$U_{\text{GPU total}}$ (A100)	$U_{\text{non-GPU total}}$
Nano	1	35–65%	80–90%	0.55–1.00%	1.25–1.5%	0.87%
Micro	1	50–80%	90–100%	0.75–1.25%	1.5–1.6%	0.87%
Small	2	55–80%	N/A	1.70–2.50%	N/A	1.6%
Medium	4	50–70%	100–110%	3.00–4.50%	6.25–7%	3.125%
Large	8	45–60%	100–120%	5.50–7.50%	12.5–15.0%	6.25%

#### 4.3.1 GPT-4, GPT-4 Turbo, and GPT-4o mini Hardware Estimation

In our experiment, we observed a performance discrepancy: GPT-4o mini showed significantly lower throughput and higher latency on OpenAI’s API compared to Microsoft Azure under identical prompt settings, as shown in Figure 1. Both variants also underperformed relative to OpenAI’s GPT-4o, with 60% and 27% lower TPS, respectively. Given GPT-4o mini’s smaller size and H200’s architectural advantages, its performance would be expected to match or exceed GPT-4o if served on H200 infrastructure. The observed gap is inconsistent with H200 deployment and suggests that GPT-4o mini is running on A100 or H100 systems. Notably, Azure’s version outperforms OpenAI’s

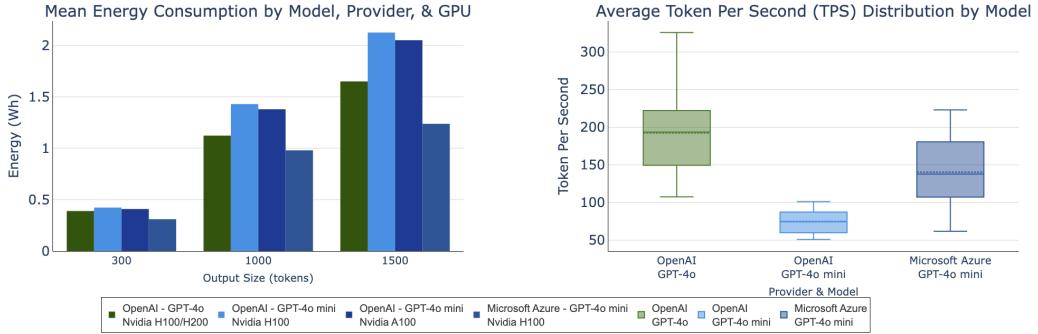


Figure 1: (Left) Mean energy consumption of GPT-4o and GPT-4o mini across providers and GPU types, measured by output size. (Right) Distribution of TPS (averaged across output sizes)

by 47% on average, further supporting the likelihood that Azure uses H100 and OpenAI retains A100. Therefore, to validate our hardware estimations, we tested this hypothesis using two-way ANOVA and Tukey HSD (Table 3). At 300-token prompts, energy consumption was statistically similar across platforms, as expected given the small computational load. However, at larger output sizes, significant differences emerged: OpenAI’s presumed A100 deployment differed from Azure’s H100 deployment with  $p < 0.05$ , and Azure’s H100 also outperformed OpenAI’s assumed H100 with  $p < 0.05$ , reinforcing the likelihood that OpenAI’s GPT-4o mini is not served on H100. We therefore consider GPT-4o mini to be running on A100. Additionally, with reports that GPT-4 was trained and deployed on A100 systems [59], and given the architectural continuity between GPT-4 and GPT-4 Turbo and their low throughput, high latency, and impending deprecation [60], we also consider they are running on A100 architecture since it is unlikely that they have migrated to newer hardware.

Table 3: Tukey HSD Adjusted  $p$ -values for energy consumption differences by provider, GPU system, and prompt size

Provider (System)	Provider (System)	300 tokens	1000 tokens	1500 tokens
Azure (H100)	OpenAI (A100)	0.979	0.0009	<0.0001
Azure (H100)	OpenAI (H100)	0.951	0.0001	<0.0001

#### 4.4 Per-Query Water Consumption and Carbon Emissions Estimation

This study focuses exclusively on operational emissions and resource consumption during the inference phase of the model. Accordingly, embodied emissions and water use from hardware manufacturing and supply chains (Scope 3) are excluded due to their limited relevance to real-time deployment and the risk of inflating per-query estimates when applied without deployment-specific attribution or when model lifecycles remain ongoing. For water usage, we focus solely on water consumption (water permanently removed from the source). For carbon emissions, we exclude Scope 1 emissions as they are generally negligible compared to Scope 2 emissions due to the infrequent use of on-site fuel combustion for backup generators and facility heating in data centers [36]. For example, Scope 1 emissions accounted for only 1.6% of Microsoft’s Scope 2 emissions in 2023 [37], a figure that includes executive air travel, ground transportation, refrigerant leakage, and on-site fuel use, further diminishing the share attributable to data center operations. Accordingly, our analysis focuses exclusively on Scope 2 emissions, which capture the carbon intensity of electricity consumed during inference. A more detailed discussion of these considerations is provided in Appendix B.

Water consumption and carbon emissions per query are calculated as:

$$\text{Water (L)} = \underbrace{\frac{E_{\text{query}}}{\text{PUE}} \cdot \text{WUE}_{\text{site}}}_{\text{On-site cooling}} + \underbrace{E_{\text{query}} \cdot \text{WUE}_{\text{source}}}_{\text{Off-site electricity}} \quad (3)$$

$$\text{Carbon (kgCO}_2\text{e)} = E_{\text{query}} \cdot \text{CIF} \quad (4)$$

#### 4.5 Eco-Efficiency via Data Envelopment Analysis (DEA)

We apply cross-efficiency DEA to evaluate the effectiveness of each model in converting environmental resources into functional intelligence. Inputs include per-query energy consumption, PUE, WUE<sub>source</sub>, WUE<sub>site</sub>, and CIF. The output is the Artificial Intelligence Index, a composite score weighted across multiple benchmark domains [52]. Specifically, reasoning and knowledge tasks (MMLU-Pro [61], HLE [62], GPQA [63]) collectively contribute 50% of the index (1/6 each); mathematical proficiency (MATH-500 [64], AIME [65]) contributes 25% (1/8 each); and coding ability (SciCode [66], LiveCodeBench [67]) accounts for the remaining 25% (1/8 each).

In contrast to standard Charnes-Cooper—Cooper—Rhodes (CCR) or Banker-Charnes-Cooper (BCC) models, which enable each model to choose its optimal weightings, sometimes inflating performance, cross-efficiency assesses each model based on its own and all peer weightings. This approach reduces self-evaluation bias and recognizes models that maintain strong performance from various efficiency viewpoints. The resulting scores offer a more robust and comparative measure of eco-efficiency. Full results and additional discussion are provided in Appendix C.

## 5 Experimental Evaluation

We benchmark the environmental footprint of 30 LLMs across three modalities: energy consumption, water usage, and carbon emissions, based on equations 1, 3, and 4, respectively. For the long-form query evaluation, GPT-4 and LLaMA-3 (8B and 70B) are excluded due to context window limitations.

### 5.1 Energy Consumption

Figure 2 and Table 4 highlight how energy consumption scales with prompt length and model architecture, revealing substantial disparities across systems. GPT-4.1 nano remains the most efficient overall, requiring only 0.454 Wh for long prompts (approximately 7,000 words of input and 1,000 words of output). In contrast, o3 consumes 39.223 Wh, while DeepSeek-R1 and GPT-4.5 consume 33.634 Wh and 30.495 Wh, respectively, which is over seventy times the energy use of GPT-4.1 nano. To contextualize, a single long query to o3 or DeepSeek-R1 may consume as much electricity as running a 65-inch LED television ( $\approx 130$  W) for roughly 20–30 minutes. Although o3 and DeepSeek-R1 rely heavily on chain-of-thought prompting, GPT-4.5 stands out for its relatively high energy use, despite not being a multi-step reasoning model. This suggests inefficiencies rooted in model architecture.

Claude-3.7 Sonnet ET presents a notable exception. While it supports chain-of-thought reasoning, it consumes only 17.045 Wh for long-form input, which is less than half the energy of o3. Similarly, GPT-4o, OpenAI’s current default model, demonstrates strong energy efficiency, requiring just 1.788 Wh for long prompts and 0.42 Wh for short ones. Interestingly, GPT-4o mini, although substantially smaller in parameter count, consumes slightly more energy per query than GPT-4o due to its deployment on less efficient A100 hardware instead of H100s or H200s, illustrating that deployment infrastructure can overshadow model size in determining real-world energy use.

### 5.2 Water and Carbon Emissions

Figure 3 showcases the water consumption and carbon emissions of models across different prompt sizes. The most resource-efficient systems, including GPT-4.1 nano, LLaMA-3.2 1B, and LLaMA-3.2 3B, maintain carbon emissions below 0.3 grams per query while using less than 2 milliliters of water across all input lengths.

By contrast, models such as DeepSeek-R1, DeepSeek-V3, o3, and GPT-4.5 exhibit substantially larger environmental footprints across all input sizes. DeepSeek-R1 consistently emits over 14 grams

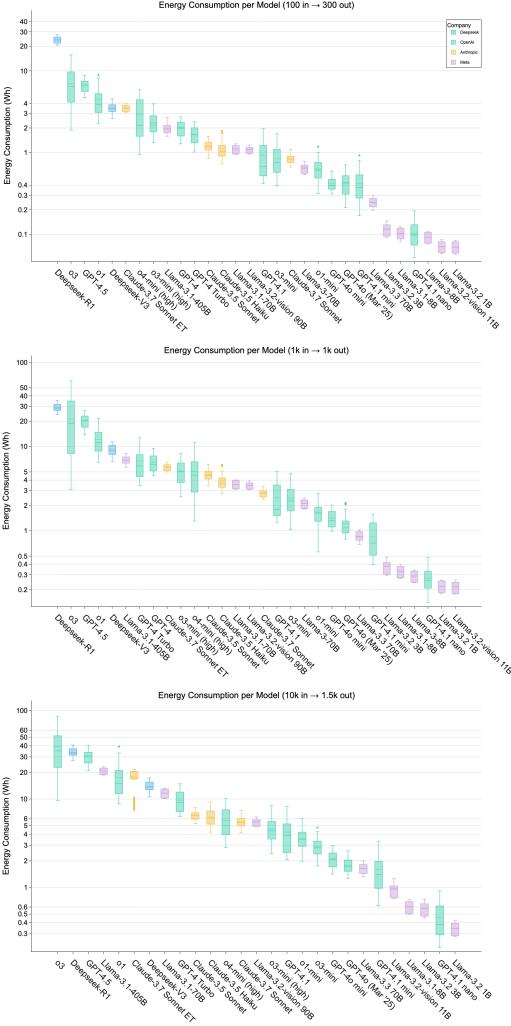


Figure 2: Energy consumption per model across different prompt sizes (Wh, log-scale).

of carbon dioxide and consumes more than 150 milliliters of water per query. For reference, this is equivalent to driving 50 meters in a gasoline-powered car and using two-thirds of a standard water cup. These figures suggest that environmental impacts are shaped not only by model architecture but also by deployment strategies and regional infrastructure conditions. In particular, the elevated emissions and water usage observed in DeepSeek models likely reflect inefficiencies in their data centers, including higher PUE and suboptimal cooling technologies.

While these per-query values may seem modest when isolated, their impact becomes considerable at scale. A single model, such as GPT-4o, serving hundreds of millions of daily requests, can emit as much carbon as thousands of transatlantic flights and consume water equivalent to the annual drinking needs of millions of people. We revisit this scaling analysis in greater detail in Section 6.

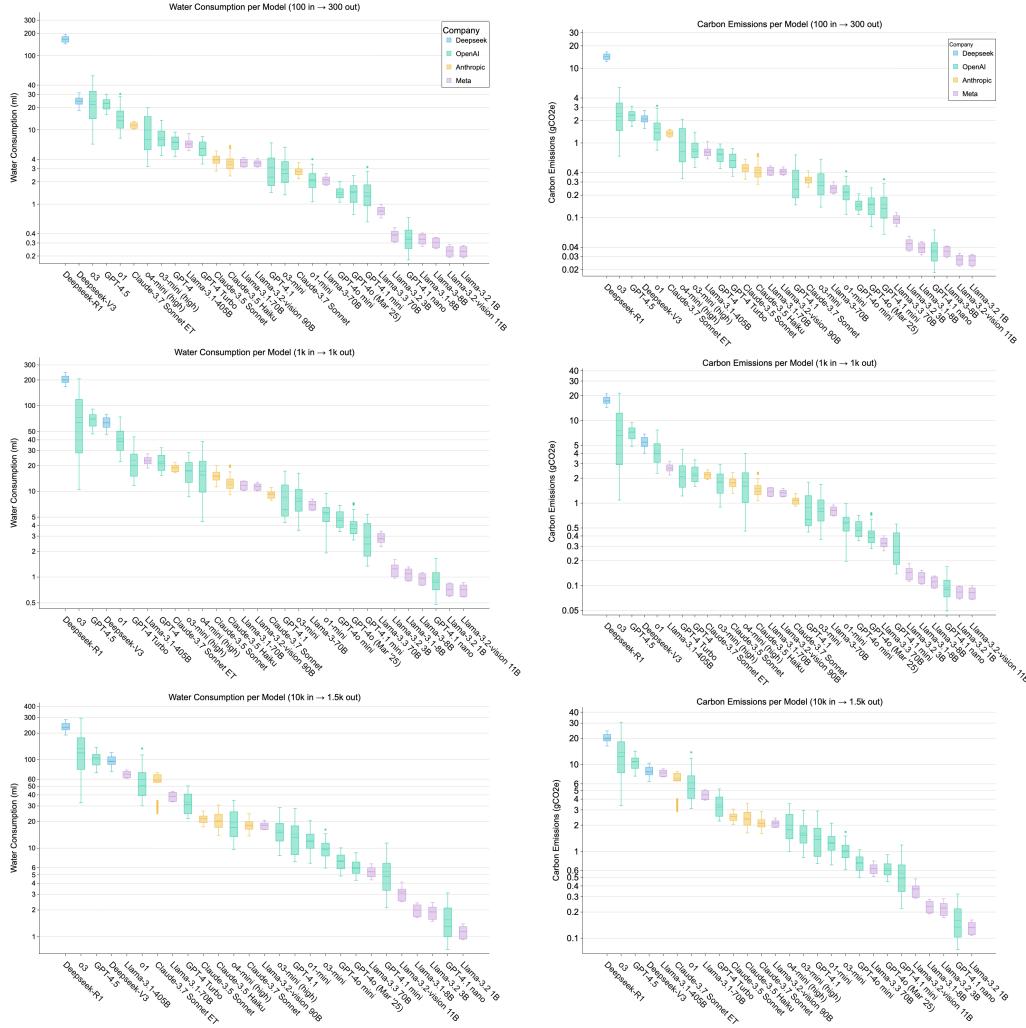
## 6 GPT-4o Case Study

### 6.1 Energy Cost of a Single GPT-4o User Session

Based on Reuters [68], the average ChatGPT user sends approximately 8 queries per day as of April 2025. Based on this, we quantify the per-user energy impact of GPT-4o interactions against familiar digital activities as presented in Figure 4. A single short GPT-4o query consumes 0.42 Wh ( $\pm 0.13$

Table 4: Energy consumption (mean  $\pm$  std dev) per model for medium-sized prompt (Wh).

Model	Energy Consumption (100 input-300 output) (Wh)	Energy Consumption (1k input-1k output) (Wh)	Energy Consumption (10k input-1.5k output) (Wh)
GPT-4.1	$0.918 \pm 0.498$	$2.513 \pm 1.286$	$4.233 \pm 1.968$
GPT-4.1 mini	$0.421 \pm 0.197$	$0.847 \pm 0.379$	$1.593 \pm 0.801$
GPT-4.1 nano	$0.479 \pm 0.277$	$0.747 \pm 0.367$	$1.424 \pm 0.708$
o4-mini (high)	$2.916 \pm 1.605$	$5.039 \pm 2.764$	$5.666 \pm 2.118$
GPT-4.5	$6.722 \pm 1.207$	$20.500 \pm 3.821$	$30.495 \pm 5.424$
o3	$7.026 \pm 3.663$	$21.414 \pm 14.273$	$39.223 \pm 20.317$
o3-mini (high)	$2.319 \pm 0.670$	$5.128 \pm 1.599$	$4.596 \pm 1.453$
o3-mini	$0.850 \pm 0.336$	$2.447 \pm 0.943$	$2.920 \pm 0.684$
o1	$0.446 \pm 0.108$	$1.598 \pm 0.528$	$3.605 \pm 0.904$
o1-mini	$0.421 \pm 0.127$	$1.418 \pm 0.379$	$1.730 \pm 0.473$
GPT-4 (Mar '25)	$0.421 \pm 0.082$	$1.418 \pm 0.332$	$2.106 \pm 0.477$
GPT-4o mini	$1.656 \pm 0.389$	$6.758 \pm 2.928$	$9.726 \pm 2.686$
GPT-4-Turbo	$1.978 \pm 0.419$	$6.512 \pm 1.501$	—
GPT-4	$23.815 \pm 2.160$	$29.000 \pm 3.069$	$33.634 \pm 3.798$
DeepSeek-V1	$3.514 \pm 0.482$	$9.129 \pm 1.294$	$13.838 \pm 1.797$
DeepSeek-V3	$0.499 \pm 0.102$	$2.176 \pm 0.277$	$5.518 \pm 0.751$
Claude-3.2-Somnet	$3.490 \pm 0.304$	$5.683 \pm 0.508$	$17.045 \pm 4.400$
Claude-3.2 ET	$0.092 \pm 0.014$	$0.289 \pm 0.045$	—
LLaMA-3.8B	$0.636 \pm 0.080$	$2.105 \pm 0.255$	—
LLaMA-3.1-70B	$0.103 \pm 0.016$	$0.329 \pm 0.051$	$0.603 \pm 0.094$
LLaMA-3.1-70B	$1.101 \pm 0.132$	$3.558 \pm 0.423$	$11.628 \pm 1.385$
LLaMA-3.1-400B	$1.907 \pm 0.315$	$6.911 \pm 0.769$	$20.401 \pm 1.796$
LLaMA-3.1	$0.070 \pm 0.011$	$0.200 \pm 0.035$	$0.342 \pm 0.056$
LLaMA-3.2-B	$0.115 \pm 0.019$	$0.377 \pm 0.066$	$0.573 \pm 0.098$
LLaMA-3.2-vision 11B	$0.071 \pm 0.011$	$0.214 \pm 0.033$	$0.938 \pm 0.163$
LLaMA-3.2-vision 90B	$1.077 \pm 0.096$	$3.447 \pm 0.302$	$5.470 \pm 0.493$
LLaMA-3.3 70B	$0.247 \pm 0.032$	$0.857 \pm 0.113$	$1.646 \pm 0.220$



(a) Water consumption per model across different prompt sizes (ml, log-scale).

(b) Carbon emissions per model across different prompt sizes (gCO<sub>2</sub>e, log-scale)

Figure 3: Water consumption and carbon emissions per model.

Wh), exceeding the footprint of a Google search (0.30 Wh) by approximately 40%. Scaling to a typical daily usage pattern, the cumulative energy reaches 3.73 Wh ( $\pm 0.358$  Wh). For medium-length queries, this increases to 9.71 Wh ( $\pm 1.106$  Wh). These results highlight that even limited daily engagement with GPT-4o can impose an energy cost comparable to charging two smartphones to full capacity (approximately 10 Wh), illustrating the tangible environmental footprint of conversational AI. While the individual per-query costs appear modest, their aggregation across millions of users introduces a rapidly compounding, largely invisible load on the environment.

## 6.2 Estimated 2025 Annual Energy Consumption of GPT-4o Inference

To estimate the annual energy demand of GPT-4o in 2025, we consider a baseline of 1 billion queries per day across all ChatGPT deployments, a figure reported by OpenAI as of December 2024 [69]. Given GPT-4o’s status as the default model, we conservatively attribute 700 million daily queries to GPT-4o. To simulate real-world usage dynamics, we apply a monthly prompt growth rate of 20% from January to May 2025, reflecting the documented increase in ChatGPT’s weekly active user base from 300 million to 800 million between December 2024 and April 2025 [70]. This is followed by a decaying growth pattern from June to December, yielding a total of approximately 772 billion GPT-4o queries in 2025, which is around 15% of the annual number of Google searches in 2024 [71].

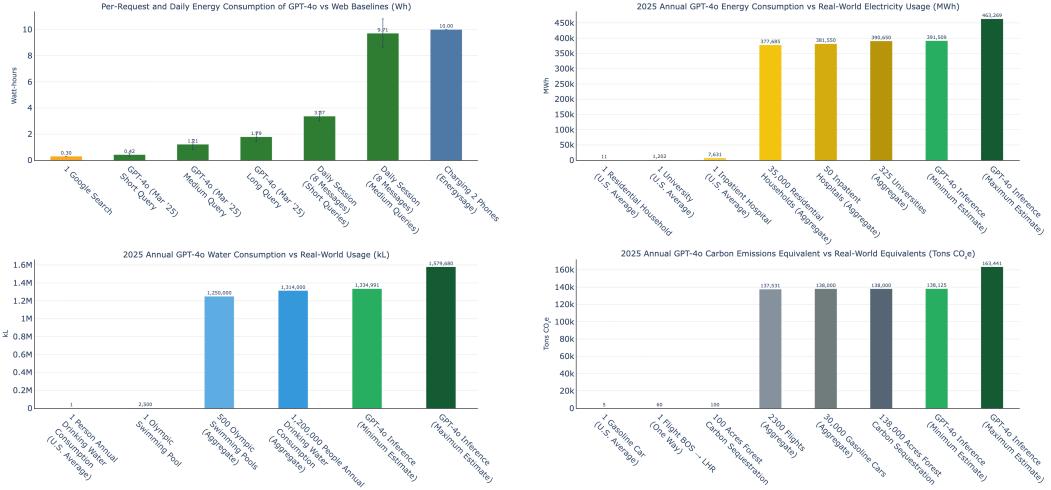


Figure 4: (Top Left) Per-query and daily energy consumption of GPT-4o. (Top Right) Estimated total annual energy usage of GPT-4o in 2025. (Bottom Left) The estimated 2025 annual water consumption of GPT-4o. (Bottom Right) The estimated 2025 annual carbon emissions of GPT-4o.

Within these queries, we conservatively assume an 80%/20% split between short and medium-length prompts based on typical usage patterns. Scaling the per-query energy estimates accordingly, we find that GPT-4o inference would require approximately 391,509 MWh annually at minimum and 463,269 MWh at maximum, as seen in Figure 4. These values exceed the total electricity consumption of 35,000 U.S. residential households (377,685 MWh), 50 inpatient hospitals (381,550 MWh), and even 325 universities (390,650 MWh) annually.

### 6.3 Estimated 2025 Annual Water Footprint of GPT-4o Inference

As showcased in Figure 4, we translate estimated cooling and infrastructure-related water usage into real-world benchmarks. Based on scaled inference volumes, GPT-4o’s annual water consumption is projected to be between 1,334,991 kiloliters (kL) and 1,579,680 kL. These quantities are roughly equivalent to filling over 500 Olympic-sized swimming pools (1,250,000 kL). Importantly, this consumption refers to evaporated freshwater permanently removed from local ecosystems rather than recycled. GPT-4o alone is responsible for evaporating an amount of freshwater equivalent to the annual drinking needs of almost 1.2 million people.

### 6.4 Estimated 2025 Annual Carbon Footprint of GPT-4o Inference

We further examine GPT-4o’s environmental footprint through estimated carbon emissions from electricity usage, as seen in Figure 4. Our projections indicate annual emissions of approximately 138,125 tons of CO<sub>2</sub>e at minimum and 163,441 tons at maximum. These figures are comparable to the annual emissions of 30,000 gasoline-powered cars or the cumulative emissions from approximately 2,300 transatlantic flights between Boston and London. In sequestration terms, offsetting GPT-4o’s annual emissions would require over 138,000 acres of average U.S. forest, an area roughly equivalent to the size of Chicago. These results showcase that the aggregation of hundreds of millions of requests per day can already impose a substantial environmental burden. This burden is only expected to grow as AI usage continues to scale.

## 7 Discussion and Policy Implications

### 7.1 The Critical Role of Infrastructure in AI Sustainability

Our findings indicate that infrastructure is a crucial determinant of AI inference sustainability. While model design enhances theoretical efficiency, real-world outcomes can substantially diverge based

on deployment conditions and factors such as renewable energy usage and hardware efficiency. For instance, GPT-4o mini, despite its smaller architecture, consumes approximately 20% more energy than GPT-4o on long queries due to reliance on older A100 GPU nodes. Similarly, DeepSeek models exhibit disproportionately high water footprints, not solely due to model characteristics but due to data center inefficiencies. These observations suggest that true sustainability will depend on integrating more efficient hardware, sustainable cooling strategies, renewable energy sourcing, evaluation practices, and deployment infrastructures.

## 7.2 Rebound Effects and the Jevons Paradox

Although large language models consume significantly less energy, water, and carbon per task than human labor [72], these efficiency gains do not inherently reduce overall environmental impact. As per-task efficiency improves, total AI usage expands far more rapidly, amplifying net resource consumption, a phenomenon aligned with the Jevons Paradox [73], where increased efficiency drives systemic demand. The acceleration and affordability of AI remove traditional human and resource constraints, enabling unprecedented levels of usage. Consequently, the cumulative environmental burden threatens to overwhelm the sustainability baselines that AI efficiency improvements initially sought to mitigate. As such, sustainable AI deployment must focus on systemic frameworks that assess how well models balance capability with environmental cost. In response, we propose DEA as a principled method for benchmarking model-level eco-efficiency.

## 7.3 Policy Implications

As AI systems scale globally, ensuring environmental sustainability requires both model-level optimizations and systemic regulation of infrastructure. Government agencies should encourage thresholds on the permissible environmental footprint per inference regarding energy, water, and carbon emissions that AI models must not exceed. These thresholds can be met through architectural innovations, such as sparsity and quantization, or through infrastructure-level optimizations like more efficient hardware, cleaner energy sourcing, and improved cooling systems. Our methodology offers a standardized, scalable framework to quantify these efforts. Incorporating technologies like dielectric liquid cooling offers a promising path to reduce or eliminate water use in data centers drastically [75]. Transparency must also be elevated through system-level reporting of per-inference energy, water, and carbon metrics. Additionally, deployment strategies, such as batching, should be integrated into sustainability planning, as larger batch sizes can reduce per-query energy use by improving hardware utilization with only minimal impact on latency.

## 8 Conclusion, Limitations, and Future Work

This paper introduces the first large-scale, infra-aware framework for benchmarking the environmental footprint of LLM inference, integrating API performance, environmental multipliers, and statistical inference to assess energy, water, and carbon costs under real-world conditions. By applying cross-efficiency DEA, we contextualize environmental impact in terms of functional performance, revealing that eco-efficiency hinges not only on model design but also on infrastructure. Our GPT-4o case study highlights a core paradox: even modest per-query costs, when scaled across hundreds of millions of daily queries, translate into massive aggregate resource use. This amplifies Jevons Paradox: as AI becomes cheaper and faster, total usage expands, intensifying environmental strain despite gains in per-query efficiency. Without structural shifts in how LLMs are designed and deployed, these invisible costs will continue to rise, threatening to offset the societal benefits that made these systems valuable in the first place.

Despite our efforts to provide a comprehensive analysis, certain limitations are inherent and merit acknowledgment. To avoid overstating model-specific footprints, we conservatively include only the energy drawn by actively assigned GPUs, as we lack telemetry to determine whether unused GPUs' capacity is reassigned, load-balanced, or left inactive. Isolating non-GPU power consumption was also difficult. We applied a fixed utilization estimate from prior studies, acknowledging that their variation across inference workloads is typically significantly lower than that of GPUs. Where facility-specific data were unavailable, we used regional or national averages for PUE, WUE, and CIF. Moreover, for proprietary models without disclosed size, we classified their scale based on observed API performance. Future work should address these limitations as more detailed telemetry

and facility-level reporting become available. Additionally, future studies should also extend beyond text generation to evaluate image, video, and audio generation, which are likely to impose greater environmental costs due to higher computational intensity.

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Table 5: Estimated node-level GPU and non-GPU utilization by batch size for GPT-4o.

Batch Size	$D_{\text{GPU}}$	$U_{\text{GPU total}}$	$U_{\text{non-GPU total}}$
4	40-55%	10-13.5%	12.5%
8	45-60%	5.5-7.5%	6.25%
16	55-70%	3.5-4.5%	3.125%

## Appendices

### A Batch Size Sensitivity Analysis (GPT-4o)

In our main analysis, we adopt a batch size of 8 for all per-prompt energy estimations. This choice reflects a middle ground in real-world deployments, where AI providers typically batch requests in the range of 4 to 16 to balance latency constraints with energy efficiency. However, the specific batch size used during inference can significantly influence energy consumption due to changes in GPU and system utilization.

To assess this effect, we present a sensitivity analysis using GPT-4o as a representative model. The only parameter varied is batch size, allowing us to examine how plausible batching configurations can significantly shift energy outcomes. This variation underscores the rationale behind our use of batch size 8 as a representative midpoint in real-world deployments.

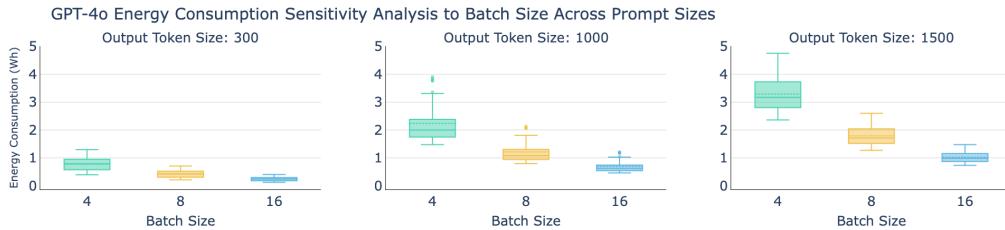


Figure 5: GPT-4o per-prompt energy consumption (Wh) across batch sizes and prompt lengths.

Table 5 summarizes the utilization rates applied to each batch size, following the same method used in our methodology section 4, which drives the corresponding per-prompt energy estimates shown in Figure 5.

The results show substantial efficiency gains with higher batching: moving from batch size 4 to 8 reduces energy per prompt by approximately 45%, while increasing from 8 to 16 yields a further 43% reduction. If we had used a batch size of 4 throughout our study, energy estimates would have been significantly higher, overstating the environmental footprint of LLM inference. Conversely, using a batch size of 16 would have resulted in notably lower energy values, possibly underestimating the footprint in more latency-constrained or low-traffic scenarios.

These differences highlight the critical role that batching decisions play in shaping the environmental footprint of large-scale LLM deployments. As AI models utilize dynamic batching to address traffic and latency issues, adjusting the batch size can significantly impact the environmental footprint of each prompt. Large-scale providers like OpenAI have a significant advantage in this regard, as their high traffic volume allows them to rely on higher batch sizes without sacrificing latency to the same extent as smaller or less active deployments.

### B Scope 3 Considerations

While this study focuses on operational emissions and resource consumption during inference (Scopes 1 and 2), it is important to briefly discuss the Scope 3 impacts associated with the manufacturing, transportation, and end-of-life disposal of the hardware used to power LLMs.

Scope 3 emissions are typically the most significant contributor to the lifecycle footprint of data center infrastructure, encompassing embodied carbon from GPU fabrication, water usage in semiconductor

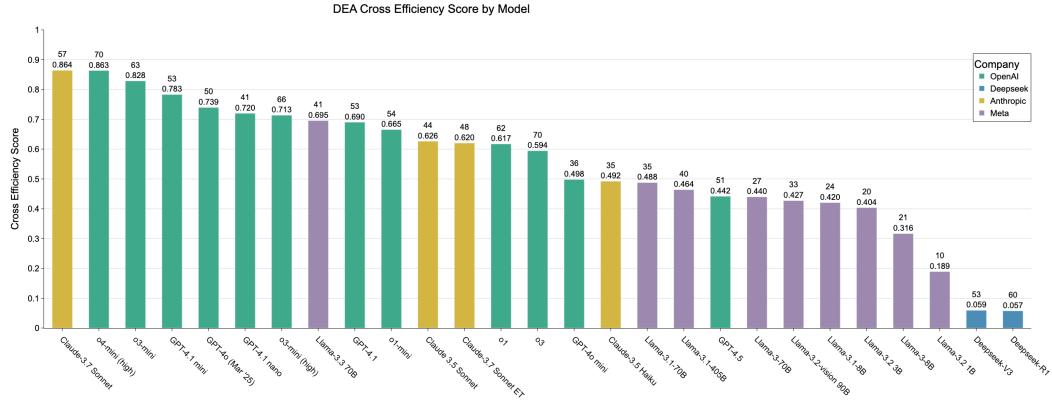


Figure 6: Cross efficiency DEA scores. Bar labels show the AI Index (top) and cross-efficiency score (bottom).

manufacturing, emissions from global logistics, and hardware retirement. For instance, Microsoft’s Scope 3 CO<sub>2</sub>e emissions in 2023 accounted for 66% of the total emissions [17]. Yet, these values are highly variable across vendors, manufacturing locations, and fabrication nodes, and they lack deployment-specific attribution when applied to real-time inference tasks.

Moreover, given that many large-scale models are continually updated and deployed across evolving infrastructures, ascribing a fixed fraction of embodied emissions or water per query is both methodologically fragile and likely to result in overestimation. Applying complete hardware manufacturing footprints to ongoing inference, without amortizing them over the expected hardware lifespan or query volume, risks artificially inflating per-query environmental costs.

In light of this, we excluded Scope 3 from our prompt-level framework, as its inclusion would introduce non-trivial uncertainty and potentially distort comparative eco-efficiency across models. Nevertheless, the long-term sustainability of AI infrastructure will depend on extending lifecycle accountability beyond the inference phase; future work is encouraged to adopt comprehensive lifecycle analyses (LCA) that integrate Scope 3 considerations once transparent and standardized data become available.

## C Cross-efficiency DEA Results

Before presenting the eco-efficiency results, it is worth noting that GPT-4, GPT-4 Turbo, LLaMA-3 (8B and 70B), and LLaMA-3.2 Vision 11B were excluded due to the lack of benchmark results on certain tests due to model limitations. Since cross-efficiency requires complete inputs and outputs, these models could not be fairly evaluated.

As shown in Figure 6, Anthropic’s newest model dominates the eco-efficiency frontier. Claude-3.7 Sonnet scored highest (0.886), combining strong reasoning with an efficient infrastructure footprint. OpenAI’s o4-mini (high) (0.867) and o3-mini (0.840) also performed well, offering solid multi-step reasoning at lower resource cost. These results suggest that downsizing reasoning models can yield substantial sustainability gains with minimal performance trade-offs.

At the opposite end, DeepSeek-R1 (0.058) and DeepSeek-V3 (0.060) had the lowest scores. Despite high intelligence ratings, their energy, water, and carbon demands are disproportionately high, indicating severe infrastructural inefficiencies. Among OpenAI models, GPT-4.1 mini (0.802) and GPT-4.0 (0.762) were strong performers, balancing intelligence and environmental impact. In contrast, GPT-4.5 ranked among the least efficient, showing that newer architectures do not always yield more sustainable outcomes. LLaMA models clustered near 0.5, limited by weaker reasoning scores. Although resource-efficient, their modest performance kept overall eco-efficiency low.

In summary, eco-efficiency relies on both output quality and environmental cost. Anthropic’s newest model and OpenAI’s smaller reasoning models excel in both areas, while DeepSeek and LLaMa models demonstrate the limitations of concentrating on capability or sustainability alone.