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PRIORITY 3
BEST-PRACTICES AND KNOWLEDGE SHARING FOR THE DEVELOPMENT AND DEPLOYMENT OF EFFICIENT, RESILIENT, AND HIGH-PERFORMANCE AI

Overview of voluntary industry-led, academic, or multistakeholder initiatives aimed at enhancing the measurement, monitoring and reporting on the energy and resource requirements of AI models

This first "Overview of voluntary industry-led, academic, or multistakeholder initiatives aimed at enhancing the measurement, monitoring and reporting on the energy and resource requirements of AI models", is an overview requested under the G7 Energy and AI Work Plan adopted in November 2025 under Canada's presidency. This overview aims to improve the understanding and transparency in the energy and resource requirement of AI models, which is beneficial to better support investment and infrastructure planning, energy affordability, economic competitiveness, responsible resource use, and technological innovation. As new voluntary initiatives emerged over time, this overview will be updated, with additional initiatives added to the OECD AI Tools Catalogues.

The following table provides an overview of initiatives ranging from voluntary standards or methodologies to voluntary published Life-Cycle-Assessment (LCA) by AI models providers and open-source tools to assess the energy and resource requirements of AI models.

Theme	Level of the initiative	Lead of the Initiative	Title	Nature of the Initiative	Description	Scope: Type of AI (LLM v other AI models)	Scope: Training and/or Inference	Scope: Types of resources monitored/reported/measured	Indicators used	URL
Measurement	International	ISO	ISO/IEC TR 20226	Technical Report, (supporting future standards)	This technical report provides an overview of the environmental sustainability aspects (e.g. workload, resource and asset utilization, carbon impact, pollution, waste, transportation, location) of AI systems during their life cycle, and related potential metrics. Technical Reports (TR) focus on a particular subject and contain for example data, measurement techniques, test approaches, case studies, methodologies and other types of information that is useful for standards developers and other audiences.	All types of AI models	Inference	data (input/output quality, drift), models (performance, behavior), system resources (latency, uptime), and human interactions, using indicators like accuracy, error rates, drift metrics, bias/fairness measures, and operational KPIs (e.g., response time, failure rates).		https://www.iso.org/standard/86177.html
Measurement	International	ITU and ETSI	ITU-T L.1801 and ETSI ES 204 135	Methodology, Standard	This document provides methodology for assessing environmental impact of AI systems.	All types of AI models	Training and inference	All flows and processes, full life cycle raw materials and energy consumption	LCA environmental impact categories	https://www.itu.int/t/aap/recdetails/11384

Measurement	International	IEEE	IEEE P7100	Methodology, Standard	This standard defines a measurement framework for reporting on environmental indicators for AI systems across the full training and inference lifecycle. It provides harmonized measurements across five environmental impact domains (energy, water, carbon emissions, material resource depletion and e-waste, and compute efficiency) and includes methodologies to separate AI workload resource consumption from general-purpose compute in shared infrastructure.	All types of AI models	Training and inference; full AI system lifecycle	Energy consumption; Water consumption; Carbon emissions; Material resource depletion and e-waste; Compute intensity and efficiency; Secondary societal and ecosystem impacts	Energy consumption (kWh); Water consumption (L, L/kWh); GHG emissions (gCO2eq, Scopes 1–3); Material resource depletion and e-waste (kg, circularity %); Compute efficiency (FLOPs/job, FLOPs/kWh)	https://sagroups.ieee.org/eiai/
Measurement	European	CEN	CEN/CLC/TR 18145	Technical Report, (supporting future standards)	This documents provides detailed guidelines and best practices for creating AI systems that are not only efficient but also environmentally responsible. It includes: 1) Inventory of impacts and techniques to support environmentally sustainable use of AI, and an equitable access to computation resources. 2) Potential benefits of using AI from a sustainability perspective. 3) Quantification of methods of measuring the environmental sustainability impacts of AI.	All types of AI models	N/A	N/A	N/A	https://www.en-standard.eu/pd-cen-clc-tr-18145-2025-environmentally-sustainable-artificial-intelligence/
Measurement	National	AFNOR	AFNOR Spec 2314	Methodology, Standard (General framework - pre-standard)	This document sets out calculation methodologies and best practices for measuring and reducing the environmental impact of AI, and for communicating with accurate and verifiable claims.	All types of AI models	Training and inference	All flows and processes, full life cycle raw materials and energy consumption	LCA environmental impact categories	https://www.boutique.afnor.org/fr-fr/norme/afnor-spec-2314/referentiel-general-pour-lia-frugale-mesurer-et-reduire-limpact-environneme/fa208976/421140
Reporting	Company	Google	Measuring the environmental impact of delivering AI at Google Scale	Technical Report, (supporting future standards)	This initiative establishes a comprehensive, full-stack framework to measure the energy consumption, carbon emissions, and water usage of AI inference workloads within a production environment at global scale	LLM	Inference	See paper for inclusions on scope Energy (Wh), emissions (gCO2e), direct water usage (ml) are reported	Energy (Wh) Emissions (gCO2e) Direct water usage (ml)	https://services.google.com/fh/files/misc/measuring_the_environmental_impact_of_delivering_ai_at_google_scale.pdf
Reporting	Company	Mistral AI	Mistral AI's Large 2 Model - Lifecycle Analysis	LCA analysis	First-of-its-kind comprehensive study to quantify the environmental impacts of Mistral LLMs.	Mistral Large 2	Training and Inference - Training - Inference (for a 400-token response - excluding users' terminals)	GHG Emissions Resource Depletion Water Use	Greenhouse Gas Emissions (g CO2e) Materials Consumption (mg Sb eq) Water Consumption (L)	https://mistral.ai/news/our-contribution-to-a-global-environmental-standard-for-ai

Measurement, Monitoring	Company	CodeCarbon	Ecologits	Assessment Tool	EcoLogits is a suite of open source tools for estimating the environmental footprint of generative AI models at inference	LLM	Inference - **including** the evaluation of the impacts associated with hosting and running the model inferences - **excluding** impacts from training, networking and end-used devices are excluded	Electricity Consumption Carbon Emissions Abiotic Resource Primary Energy Water	Electricity Consumption (mWh) Greenhouse Gas Emissions (mgCO2eq) Material Consumption (µg Sb eq) Primary Energy Use (kJ) Water Consumption (mL)	https://ecologits.ai/ https://ecologits.ai/latest/methodology/
Measurement, Monitoring and Reporting	Multi-stakeholder	Salesforce, Hugging Face, Cohere and Carnegie Mellon University	AIEnergyScore	Methodology, Assessment Tool, LeaderBoard, Labelling	The goal of AI Energy Score is to establish a standardized approach for evaluating the energy efficiency of AI model inference. By focusing on controlled and comparable metrics, such as specific tasks and hardware, the AI Energy Scores aims to provide useful insights for researchers, developers, organizations, and policymakers. AI Energy SCore is using Code Carbon Python Package	all types of AI models	Inference	Energy consumption	Electricity Consumption (mWh)	https://huggingface.co/AIEnergyScore
Measurement	Multi-stakeholder	Green Software Foundation	Software Carbon Intensity for AI Specification	Methodology	This specification extends the Software Carbon Intensity (SCI) methodology to the unique characteristics of Artificial Intelligence (AI) systems. It provides a standardized method for measuring and reporting the rate of carbon emissions per functional unit across the entire AI lifecycle It Monitors the energy consumption and embodied carbon of all physical and virtual hardware resources required to power the model(s), including, but not limited to CPUs, GPUs, and specialized AI accelerators (like TPUs), alongside the memory (RAM) and storage infrastructure	This specification covers a broad spectrum of AI systems, including classical machine learning, generative AI, and agentic AI, and is designed to support current and future developments in the field.	Training and Inference	Energy consumption Carbon emission	gCO2/R	https://github.com/Green-Software-Foundation/sci-ai/blob/dev/SPEC.md https://greensoftware.foundation/standards/sci-ai/ -
Measurement, Monitoring	Academia	SymbioticLab, University of Michigan (Prof. Mosharaf Chowdhury)	The ML.ENERGY Initiative	Methodology, Assessment Open-Source Tool, Leaderboard, Optimization Framework	A set of tools to measure, understand, optimize, and expose the energy consumption of modern ML workloads, through Zeus (energy measurement and optimization across GPU/CPU/accelerator platforms) and the ML.ENERGY Benchmark and Leaderboard (inference energy benchmarking for generative AI models under realistic service conditions).	All types of AI models	Training and inference	Energy consumption	Electricity Consumption (Joules; Wh)	https://ml.energy/
Measurement, Monitoring	Academia	University of Cambridge (led by Dr Loïc Lannelongue and Prof Michael Inouye)	Green Algorithms	Assessment Open-Source Tool	A set of calculators that researchers can use to estimate the carbon footprint of their projects: - Online Calculator: to easily estimate the carbon footprint of a computation. - Green Algorithms 4 HPC: A tool that calculates the carbon footprint of all computations run on an HPC platform.	All types of AI models	Training and inference	Energy consumption Carbon emission	Electricity consumption (kWh) Greenhouse Gas Emissions (kgCO2eq)	https://www.green-algorithms.org/
Measurement	Academia / Company	UGA (University Grenoble Alpes) & Bull	Alumet	MonitoringOpen-Source Tool	Alumet is a high-performance, high-frequency and high-precision monitoring tool. It gathers performance and energy measurements from numerous sources (kernel, CPU, GPU, sensors embedded in "edge" devices, etc.). It provides, in real time, an estimate of the energy consumption	All types of AI models	Training and inference	Energy consumption Carbon emission		https://alumet.dev/

					and carbon footprint, for the whole system and for individual applications at different levels. Alumet can be deployed locally or at scale in distributed systems (HPC or K8S clusters).					