AI ACTION SUMMIT

# Standardization for AI Environmental Sustainability

Towards a coordinated global approach

February 11th, 2025

This work stems from a global initiative launched on October 10 at UNESCO headquarters, bringing together experts from ISO, ITU and IEEE, in partnership with the OECD and UNESCO.

Led by the Ecolab of the General Commission for Sustainable Development located in the French Ministry in charge of Environment, this initiative made it possible to organize four working meetings to ensure better coordination between standardization bodies and optimize resources dedicated to assessing and reducing the environmental impact of AI. This document is published in the context of the Paris AI Action Summit (February 10-11).

**Lead organization**

MINISTÈRES AMÉNAGEMENT DU TERRITOIRE TRANSITION ÉCOLOGIQUE
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**Contributors**

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# CONTEXT

Faced with the rapid growth in AI use and the growing awareness of its environmental impact, numerous initiatives are underway around the world to better assess this impact, and to develop guidelines and standards on how to **calculate, report, reduce and prevent it.**

These initiatives are faced with several difficulties, starting with the **limited number of experts** on both Artificial Intelligence and environmental sustainability, and the **limited knowledge** due to the lack of robust qualitative and quantitative data.

To avoid the development of conflicting or contradicting methodologies that would undermine global efforts to increase the environmental sustainability of AI systems, and to make the most of the expertise available internationally on this topic, a common approach is essential to bring visibility to those initiatives that already exist and to define collaboration opportunities to enhance a common approach to Sustainable AI.

# OBJECTIVE

The objective of this approach is to ensure the efficient use of resources, enhance clarity, **promote consistency in AI environmental sustainability standardization**, and **facilitate the widespread adoption of best practices**.

The intention of its contributors is to work towards **non-conflicting standards** and to **foster collaboration** between international standardization bodies to minimize, as much as possible, their duplication, contradiction and overlap.

Partners of civil society, International Organizations, administrations and companies are gathering at the AI Action Summit in France on 10-11 February 2025 around the key topic of aligning AI with public interest. This document is building on this momentum and showing the engagement of experts and organizations to thoroughly and efficiently **advance on guidance and standards around the AI sustainability**.

A community of stakeholders should foster ongoing coordination and communication between multilateral organizations, businesses, and regulatory bodies on environmentally sustainable adoption of AI technologies. Establishing this community will **strengthen the collective commitment to sustainable AI**, ensuring that efforts are aligned and contribute to a **cohesive, actionable roadmap.**

# TARGET AUDIENCE

This document is intended for policymakers, scientists, AI developers, and industry leaders working on or interested in AI environmental sustainability, providing them with visibility into the progress made by standardization organizations and the work that still lies ahead.

It also serves as a valuable resource for stakeholders broadly involved in AI. This initiative offers an opportunity to showcase the areas of work of the standardization bodies for greater transparency and improved collaboration.

## STATE OF THE ART AND NORMATIVE REFERENCES

A number of documents relating to AI sustainability, including specifically within the Information and Communications Technology sector, have already been published and can serve as a solid basis for future standards and guidance. (See Appendix 2)

Additionally, several projects are currently underway. (See Appendix 3)

# TERMINOLOGY AND CONCEPTS

**Standards can vary in the exact terms but these are light, commonly-agreed definitions to facilitate the understanding of the document.**

→ **Artificial Intelligence System:** Machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. (EU AI Act Article 3 (1))

→ **Environmental sustainability:** State in which the ecosystem and its functions are maintained for the present and future generations. (ISO 17889-1:2021, modified — generation made plural)

→ **Environment:** Surroundings in which an organization operates, including air, water, land, natural resources, flora, fauna, humans and their interrelationships. (ISO 14001:2015)

→ **Environmental aspect:** Element of an organization's activities or products or services that can interact with the environment. (ISO 14001:2015)

→ **Environmental impact:** Any change to the environment, whether adverse or beneficial, wholly or partially resulting from an organization's environmental aspects. (ISO 14001:2015)

→ **General Purpose AI:** An AI model, including where such an AI model is trained with a large amount of data using self-supervision at scale, that displays significant generality and is capable of competently performing a wide range of distinct tasks regardless of the way the model is placed on the market and that can be integrated into a variety of downstream systems or applications. (EU AI Act Article 3 63))

→ **AI Compute:** The computational resources, including hardware and software infrastructure, required during training, inference, validation, or deployment of AI models. This encompasses the underlying electrical grid with its fuel mix of generation that defines carbon intensity, energy systems, data center infrastructure, and supply chains that provide the power and cooling necessary to sustain these operations.

→ **Environmental Life Cycle Assessment (LCA):** Compilation and evaluation of the inputs, outputs and the potential environmental impacts of a product system throughout its life cycle. (ISO 14040:2006)

→ **Life cycle of AI Systems (ISO/IEC 5338:2023):**

- Inception
- Design and development
- Verification and validation
- Deployment
- Operation and monitoring
- Continuous validation
- Re-evaluation
- Retirement

→ **AI Compute Resources Lifecycle:**

- Raw material extraction
- Production
- Transportation
- Operation
- End-of-life

→ **Second-order effect:** The indirect impact created by the use and application of Information and Communication Technologies (ICTs), which includes changes of environmental load due to the use of ICTs that could be positive or negative. (ITU-T L.1480)

→ **Higher-order effect:** The indirect effect (including but not limited to rebound effects) other than first and second order effects occurring through changes in consumption patterns, lifestyles and value systems. (ITU-T L.1480)

→ **Rebound effect:** Increases in consumption due to environmental efficiency interventions that can occur through a price reduction or other mechanism including behavioral responses (i.e., an efficient product being cheaper or in other ways more convenient and hence being consumed to a greater extent). (ITU-T L.1480)

→ **Scope 1 emissions:** Direct greenhouse (GHG) emissions that occur from sources that are controlled or owned by an organization.

→ **Scope 2 emissions:** Indirect GHG emissions associated with resource purchases and uses, like electricity, steam, heat, or cooling.

→ **Scope 3 emissions:** GHG emissions as a result of direct real-time activities from assets not owned or controlled by the reporting organization, but that the organization indirectly affects in its value chain.

## EXTENT OF THE UPCOMING WORK

There are currently a number of normative gaps relating to AI sustainability. A first step of future standardization efforts will be to identify a **common structure** across existing methodologies and to **establish which approaches are best suited to specific contexts**. Based on those identified gaps, collaboration between experts can take place across organizations.

**1. Defining transparent and common indicators, and a reporting framework**

The first objective of standardization for AI sustainability will be to develop **common environmental indicators** that are measurable or can be estimated for each lifecycle stage of AI system resources. These indicators must be relevant to specific well-defined perimeters (organizational perimeter, service perimeter, etc.) that are shared across organizations (offering and consuming AI services).

Reporting on the indicators should be done in a **uniform, formalized and transparent way** to enable meaningful comparisons between different assessments (for different organizations or between updates).

In corporate organizations, according to their role in the value chain, this could be part of the Scope 1/2/3 reporting in the Corporate Social Responsibility (CSR) strategy, in line with water and material consumption reporting under the European Corporate Sustainability Reporting Directive (CSRD).

The proposed indicators should also align with **existing environmental reporting frameworks** like the Global Reporting Initiative (GRI), GHG Protocol or ISO 14000 standards that companies commonly use.

Statistical experts and data scientists, next to sustainability experts, are needed in the development of **robust environmental indicators** to ensure data quality, implementation feasibility, indicator validation, risk management and consistency across different countries and regions.

**2. Environmental assessment**

To manage the environmental impact of AI and to make informed decisions, the second objective of standardization will be to **establish methodologies for the assessment of the indicators**, including Life Cycle Assessment for AI systems and AI services. Existing assessment methodologies for the digital sector (see Appendix 1) could possibly be adapted for AI systems.

These methodologies should be generic enough to be applicable to the wide variety of AI systems (from general purpose to domain-specific AI, etc.). They may include several scopes: AI system, AI service based on several AI systems, use of AI at the level of an organization, use of AI at the territorial level (communities, countries, etc.), and different implementation and service models, such as cloud-based, on-premise, on edge, etc. and whether it is an embedded system or general-purpose system. **The scopes of the different evaluation methods must rely on the same set of metrics.**

Furthermore, the perimeter of this assessment must be as comprehensive as possible, covering the **entire lifecycle of AI systems**. This includes design, inference and tuning phases, as well as embodied impacts, e.g., production and end-of-life impacts of the hardware used to run the various phases mentioned earlier.

**3. Best practices for mitigation of the environmental impact of AI**

The third objective of standardization is to identify strategies for implementing **AI systems that can act to reduce the environmental impact** of systems on at least one of the indicators.

The strategies can be identified for different '**action dimensions**' (like infrastructure, model optimization, implementation efficiency), and **impact drivers** (e.g., using less resources, using renewable resources).
These strategies, accompanied by their advantages and disadvantages, implementation contexts, key success factors (or conditions of relevance) and associated tracking (or follow-up) indicators, can be identified as best practices shared by all AI participating stakeholders.

Strategies can be accompanied with guidelines on how to **facilitate stakeholder engagement and collaboration**.
**Technical standards** for emerging technologies that can improve environmental impact (immersive cooling, automated data collection, server virtualization) will also help encourage the **shared adoption of best practices**.

**4. Management systems**

The fourth objective is to be able to **make decisions on the initialization, continuity or retirement of an AI system**, taking into account all the AI systems in an organization, their benefits and cost for the environment.

With this holistic view in mind, some guidance should be given on **how to prioritize different mitigations** and considerations for trade-offs (e.g., between energy consumption and improving accuracy or testing for robustness) that need to be taken into account.

For organizations, guidance should be elaborated on the **relevant management systems** to **systematically support the environmental sustainability of** AI and **balancing competing priorities** at the level of an organization.

# SCOPE OF STANDARDIZATION

**1.** Indicators for the environmental assessment of AI systems include, but are not limited to, **global warming potential** (kg CO2eq), **energy consumption** (kWh or MJ), **water consumption and withdrawal** (m3 or L), and **raw material consumption** (kg). **It is essential to take into account the energy grid interconnection and national fuel mixes to quantify the carbon footprint from the electricity generation for the AI needs.**

**2.** The target of the environmental assessment should be that **the entire lifecycle of the AI system must be subjected to an environmental life cycle assessment**. This should include evaluating the environmental impact of the "**training**" phase (inception/design & development/ verification & validation/deployment), while considering the **genealogy of models** that may have served in the steps of pre-training, post-training, fine-tuning, instruction tuning and distillation.

These should be assessed separately from the "use" or "inference" phase (operation and monitoring/continuous validation/re-evaluation). These phases might be attributed differently across entities or organizations involved in the development and use of AI. Different scopes may be useful for different stakeholders:

- A **reporting of the AI systems** that could be aggregated for corporate reporting, like emissions per year;
- A **reporting per unit of work** (per token in the context of LLMs, or per a specific size of image for an image classifier), for users to consider the criteria to choose a system and to be able to include their use of the system in their own corporate inventory.

**3.** The **data lifecycle of an AI system** can bring significant added environmental costs for collection, pre-processing, transfer, update, and storage. **These costs** attributed to training, testing, input or output data **should be included in the assessment**, for the relevant life cycle stages, as far as the assessor is able to determine.

**4. Indirect effects** include second-order and higher-order effects (as defined in the Terminology and concepts section), for example rebound effects. The indirect effects of an AI system **should be assessed at least qualitatively**.

If quantitative assessment is not feasible, a justification must be provided. The assessment of indirect effects should be separated from the assessment of direct, first order effects.

**5. All equipment used throughout the lifecycle of the AI system should be documented**.
This includes, but is not limited to, the equipment dedicated to: computing infrastructure, data collection devices, storage systems, user devices (e.g., robots, smart devices), and network equipment.

Since these physical devices might serve multiple AI systems or other services, a way to **allocate environmental impact of the equipment** – particularly its production and end-of-life – **to a specific system needs to be defined**.

For example, the environmental impact could be proportionally attributed based on the duration of the equipment's use by the system over its total life cycle.

**6.** Best practices should be developed across **several areas: equipment, data management, model performance, hardware utilization, and measurement**. Key initial best practices, such as dynamic sizing of computing resources or green coding, are already shared across the digital sector and need to be implemented at scale.

Best practices around organizational governance are also needed to ensure that the correct monitoring and mitigation of the environmental impacts of AI is put forward, considering complementary incentives like performance and monetary cost.

Choices on what the priority is for **system optimization** should be documented, given that there are many trade-offs between different types of performance metrics that can 'interfere' with sustainability, like optimizing for fairness, robustness, or privacy. **Evaluating the relevance of AI as a solution compared to less environmentally costly alternatives is a best practice in itself**.

**7. These standards and best practices should support codes of conduct of companies and institutions making them more robust, reliable, comparable and compatible.**

# CHALLENGES TO ADDRESS

**On-going and future standardization efforts still face a number of challenges:**

- **Rapid advancement of AI**: The developments in AI systems are advancing at an extremely rapid pace and methodologies and best practices must remain adaptable to emerging technologies coming up in the following years. Experts in standardization will need to **monitor the adaptation of standards to current state-of-art**.

- **Raising awareness**: The publication of a standard does not guarantee its practical implementation due to barriers such as industry reluctance, feasibility of data collection, cost implications, or a lack of enforcement mechanisms. Experts will need to **raise awareness** through workshops, policy briefs, or industry partnerships on the availability and implementation of the standards, **encourage the publication of data**, and **facilitate guidance** for the implementation.

- **Complexity of AI system development:** AI systems are not static products. Over their lifetime, they will be repeatedly used as well as retrained, which adds complexity to **defining the scope of the perimeter of an environmental evaluation**. Furthermore, the environmental cost of experimentation, including failed, intermediate or incomplete training runs, is hard to attribute to a specific AI system.

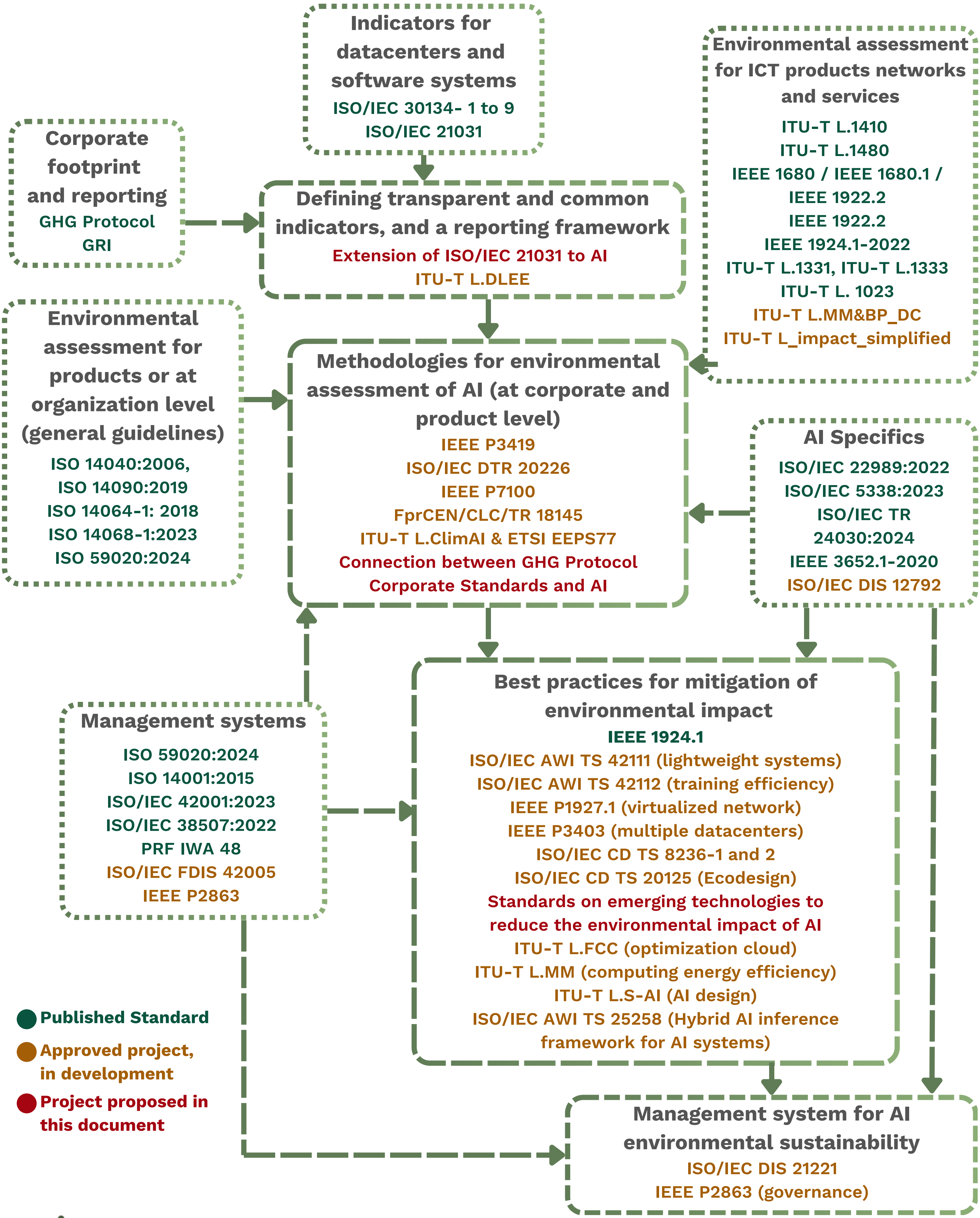
- **Exhaustive reporting**: Guidelines for **reporting the environmental sustainability** (including impact) of AI Systems should **identify the stakeholders responsible for this reporting** throughout the value chain, and encourage communication along the value chain. While some AI-dedicated computational facilities exist and can be directly monitored for electricity and water consumption, most AI training and inference activities occur in mixed-use facilities. These facilities handle diverse processes across shared hardware resources such as GPUs and CPUs, making it challenging to isolate the environmental impact of specific AI operations. This complexity requires the development of **methodologies to fairly allocate environmental costs among coexisting processes within mixed-use environments**. Despite these challenges, real-time monitoring of resource consumption in such facilities remains an important basis for estimating the environmental impact of AI solutions within a given organization. While difficult to allocate precisely, this environmental impact should still be accounted for, certainly not excluded, for instance through the analysis of system logs.

- **Access to environmental data**: The lack of robust data on key parameters for calculating the environmental impact of AI systems poses challenges for testing a methodology across multiple systems and indicators. Given that environmental reporting is already strongly needed, a **tiered approach to environmental assessment** could be considered, where evaluating the energy consumption during the use phase of the equipment supporting the AI system could be the basis. In the longer term, **adding indicators such as carbon impact, water consumption, material consumption, etc., and incorporating more stages of the environmental life cycle** (production, end-of-life, etc.) **must be a priority**.

**With this proposed approach, experts from multilateral organizations, companies, and administrations call to action and express their shared commitment to collaborate in ensuring that organizations can rapidly, efficiently, and accurately adopt standards for improved AI sustainability.**

**As experts, they wish to reconvene before future AI summits or other international events of interest to monitor implementation and to update this document.**

# *Appendix 1: Diagram for published and in-development standards*



# *Appendix 2:*
# *Published standards relevant to AI sustainability*

### Standards on the environmental assessment of digital services, best practices for mitigating the environmental impacts and relevant indicators

- ITU-T L.1310—Energy efficiency metrics and measurement methods for telecommunication equipment
- ITU-T L.1410—Methodology for environmental life cycle assessments of information and communication technology goods, networks and services
- ITU-T L.1480—Enabling the Net Zero transition: Assessing how the use of information and communication technology solutions impact greenhouse gas emissions of other sectors
- IEEE 1680-2009—IEEE Standard for Environmental Assessment of Electronic Products
- IEEE 1680.1-2009—IEEE Standard for Environmental Assessment of Personal Computer Products, Including Notebook Personal Computers, Desktop Personal Computers, and Personal Computer Displays
- IEEE 1680.1-2018—IEEE Standard for Environmental and Social Responsibility Assessment of Computers and Displays
- IEEE 1922.2-2019—IEEE Standard for a Method to Calculate Near Real-Time Emissions of Information and Communication Technology Infrastructure
- ITU-T L.1331/ES 203328—Assessment of mobile network energy efficiency
- ITU-T L.1333—Carbon data intensity for network energy performance monitoring
- IEEE 1924.1-2022—IEEE Recommended Practice for Developing Energy-Efficient Power-Proportional Digital Architectures
- ISO/IEC 21031:2024—Information technology — Software Carbon Intensity (SCI) specification
- ISO/IEC 30134-1 to 9—Datacenters—Key performance indicators
  - Part 1: Overview and General Requirements
  - Part 2: Power Usage Effectiveness (PUE)
  - Part 3: Renewable Energy Factor
  - Part 4: IT Equipment Energy Effectiveness for Servers (ITEEsv)
  - Part 5: IT Equipment Utilization for Servers (ITEUsv)
  - Part 6: Energy Reuse Factor (ERF)
  - Part 7: Cooling Efficiency Ratio (CUR)
  - Part 8: Carbon Usage Effectiveness (CUE)
  - Part 9: Water Usage Effectiveness (WUE)

### Standards on environmental assessment

- ISO 14040:2006—Environmental management — Life cycle assessment — Principles and framework
- ISO 14001:2015—Environmental management systems — Requirements with guidance for use
- ISO 14090:2019 Adaptation to climate change — Principles, requirements and guidelines
- PRF IWA 48—Framework for implementing environmental, social and governance (ESG) principles
- ITU-T L.1023—Assessment method for circularity performance scoring
- ISO 14064-1:2018—Greenhouse gases Part 1: Specification with guidance at the organization level for quantification and reporting of greenhouse gas emissions and removals
- ISO 14068-1:2023—Climate change management — Transition to net zeroPart 1: Carbon neutrality.
- ISO 59020:2024 — Circular economy — Measuring and assessing circularity performance

### Relevant contributions other than standards

- UNESCO Recommendation on the Ethics of Artificial Intelligence
- OECD Measuring the environmental impacts of artificial intelligence compute and applications
- AFNOR-Spec 2314, General Framework for frugal AI
- Green Grid U.S. EPA Energy Star for data centers
- European Energy Efficiency Directive (for datacenters)
- European Commission JRC life cycle assessment

## *Appendix 3: Project standards*

**Note** : This calendar is tentative and non-comprehensive. Standards are contribution-driven, therefore the final publishing date has a lot of uncertainties.

# 2025

## January-June

- ISO/IEC TS 20125—Digital Services Ecodesign
- ISO DTR 20226—Environmentally sustainable aspects of AI Systems
- ISO/IEC 42005—AI system impact assessment
- ISO/IEC 12792—Transparency taxonomy of AI systems
- FprCEN/CLC/TR 18145—Environmentally Sustainable AI
- Launch of “AI Energy Score” rating system, leaderboard, and submission portal
- ISO/IEC DIS 21221—Beneficial AI systems

## July-December

- ITU-T L.ClimAI & ETSI EEPS77—Guidelines for Assessing the Impact of Artificial Intelligence on Greenhouse gas emissions
- IEEE P7100—Standard for Measurement of Environmental Impacts of Artificial Intelligence Systems
- ISO/IEC CD TS 8236-1—Information technology — Provisioning, forecasting and management—Part 1: Data Centre IT Equipment
- ISO/IEC TS 8236-2—Part 2: Data centre facility infrastructure
- ITU-T L.FCC—Energy consumption management and optimization platform Framework for cloud computing
- ITU-T L.MM_Computing_power/ETSI DES/EE-EEPS75—Standardization of computing power efficiency measurement methods for computing center and Guidelines on improving the computing energy-efficiency of data centre
- ITU-T L.S_AI—Recommendation for the design of environmentally Sustainable AI-based and XR-based Systems
- ITU-T L.CFSP—Guidelines for the assessment of the carbon footprint of Software products
- ITU-T L.MM&BP_DC—Measurement methodology and Best Practices for decarbonization of Data Center and Telecommunication Room in support of Net Zero
- Connection between GHG Protocol Corporate standard and AI
- ITU-T L.impact_simplified—Simplified assessments of the GHG emissions impact of the use of ICT solutions

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## 2026

### January-June

- Definitions relating to Sustainable AI in ISO/IEC 25059:2025—Software engineering — Systems and software Quality Requirements and Evaluation (SQuaRE) — Quality model for AI systems
- ITU-T L.DLEE—Deep Learning Computation Energy Efficiency Evaluation Framework and Metrics

### July-December

- ISO/IEC AWI TS 42112—Guidance on machine learning model training efficiency optimisation
- Sustainability Fact Labels (SFL) for AI systems, AI applications and AI components (ISO)

## 2027

### January-June

- Standards on emerging technologies to reduce the environmental impact of AI

### July-December

- Extension of Software Carbon Intensity (SCI) to AI (ISO)

## 2028

- ISO/IEC TS 42111—Guidance on lightweight AI systems
- Consolidated AI resource utilization reporting method for AI tasks and application processes

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## OTHERS

- IEEE P1927.1—Standard for Services Provided by the Energy-Efficient Orchestration and Management of Virtualized Distributed Data Centers Interconnected by a Virtualized Network
- IEEE P2863—Recommended Practice for Organizational Governance of Artificial Intelligence
- IEEE P3404—Standard for Requirements and Framework for Sharing Data and Models for Artificial Intelligence across Multiple Computing Centers
- IEEE P3419—Standard for Large Language Model Evaluation
- ITU-T L.FNEE—Assessment of Fixed Network Energy Efficiency
- ISO/IEC AWI TS 25258—Hybrid AI inference framework for AI systems