Standardization for

AI Environmental

Sustainability

Towards a coordinated global approach

Updated version

February 20th, 2026

An update published for the AI Impact Summit

COALITION FOR SUSTAINABLE AI

This work stems from a global initiative launched on October 10, 2024, at UNESCO headquarters, bringing together experts from ISO, ITU and IEEE, in partnership with the OECD and UNESCO. Led by the French Ministry in charge of Environment, this initiative led to the publication of a first document to ensure better coordination between standardization bodies and optimize resources dedicated to assessing and reducing the environmental impact of AI. The first document was published in the context of the Paris AI Action Summit (February 10-11, 2025). This new version is an update of the document, elaborated through a new work session with standardization organizations on December 4th, 2025, and subsequent feedback given by experts. It is published in the context of the AI Impact Summit in India (February 19-20, 2026) to ensure continuous coordination between experts.

Lead organization

GOUVERNEMENT

Liberté
Égalité
Fraternité

COALITION FOR SUSTAINABLE AI

Partners

ISO

ITU

IEEE SA
STANDARDS ASSOCIATION

LIST OF CONTRIBUTORS

Per alphabetical order of last names

- Derick Ohmar Adil, ISO, Globe Telecom, Philippines**
- Isabel Barberá, Rhite, The Netherlands*
- Alexis Baria, UL Standards & Engagement, United States**
- Sylvain Baudoin, The Shift Project, France*
- Bertrand Braunschweig, BiLaB, France*
- Norbert Bensalem, Directeur Standardisation IBM France*
- Jean-Manuel Canet, Orange, France & ITU-T SG5, Switzerland*
- Nathalie Charbonniaud, Orange, France*
- Hélène Costa de Beauregard, Ecolab - French Ministry of Environment, France**
- Vincent Danno, independant expert, France*
- Renaud Di Francesco, Europe Technology Standards Office, Italy - In memoriam*
- Harm Ellens, Independant expert, Australia*
- Juliette Fropier, Ecolab - French Ministry of Environment, France
- Caroline Gans Combe, Omnes Education - INSEEC, France**
- Boris Gamazaychikov, Salesforce, USA/France*
- Arti Garg, AVEVA, US**
- Paolo Giudici, University of Pavia, Italy*
- Shubham Gupta, Noblesoft Solutions Inc., United States of America**
- Ahmed Haddad, Arcep, France*
- Miki Hashimoto, Mitsubishi Electric, Japan*
- Mathilde Jay, Ecolab - French Ministry of Environment, France**
- Young Im Cho, Gachon Univertiy, Korea*
- Susanna Kallio, Nokia, Finland
- Polina Koroleva, UNEP, Kenya
- Jacques Kluska, Schneider Electric, France*
- Valerie Livina, National Physical Laboratory, United Kingdom*
- Sasha Luccioni, Hugging Face, Canada*
- Nicolas Miailhe, Global Partnership on AI (GPAI), France*
- Grit Munk, Danish Association of Engineers, Denmark*
- Son Nguyen, Green Transformation and Sustainability Network, Vietnam**
- Arvin Obnasca, Be Ethical, Philippines*
- Enrico Panai, Association of AI Ethicists, France*
- Aaron Pietzonka, Ecolab - French Ministry of Environment, France*
- Vincent Poncet, Google, France*
- Pierre Riou, ACIMEO President, France*
- Robert (Bob) Spence, I-Partnerships (IEEE P7100 WG), United Kingdom
- Emilia Tantar, Black Swan LUX & CEN/CLC JTC 21 AI WG 2, Luxembourg*
- Marina Trancheva, AMPECO, Bulgaria**
- Aurore Tual, Thales, France*
- Reyna Ubeda, Telecommunication Standardization Bureau, International Telecommunication Union, Switzerland
- Arlette van Wissen, Royal Philips, The Netherlands*
- Annie Webster, University of Sydney, Australia**
- Frank Wisselink, Deutsche Telekom, Germany*
- David Wotton, Independant expert, Australia*

*Contributor of the 2025 version only.
**Contributor of the 2026 updated version only.

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 its environmental impacts.**

Besides reasons of compliance, measuring the environmental impact of AI systems should be a reflection of environmental sustainability as a value throughout the AI lifecycle which is globally applicable.

These initiatives face several difficulties, including a **limited number of experts** with dual competency in Artificial Intelligence and environmental sustainability, compounded by **knowledge gaps** 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.

Partners of civil society, International Organizations, administrations and companies are gathering at the AI Impact Summit in India on 19-20 February 2026 around the key topic the demonstrable impact of AI for the People, Planet and Progress. 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 AI sustainability.

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.

TARGET AUDIENCE

This document is intended for policymakers, government officials, scientists, AI developers and engineers, 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. Several were published in 2025. (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

→ **Life cycle of AI Compute Resources:**
- Raw material acquisition
- Production
- Transportation
- Use
- 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 1/2/3 emissions:** refer to the lastest version of the Greenhouse Gas Protocol definition of scope 1/2/3 emissions.

EXTENT OF THE UPCOMING WORK

A number of normative gaps relating to AI sustainability have been identified. As a first step of future standardization efforts, common structure across existing methodologies have been identified, helping to establish which approaches are best suited to specific contexts. Based on those identified gaps, collaboration between experts can take place across organizations. Those areas of work are identified below. They have been updated since the first publication of the global approach.

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 for example be part of the Scope 1/2/3 reporting in the Corporate Social Responsibility (CSR) strategy.

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.

Experts in environmental sciences, data (e.g., data scientists, statistical experts, and data governance practitioners), and AI lifecycle, at the minimum, 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. Assessing direct environmental impacts

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 operating system. **The scopes of the different evaluation methods must rely on the same set of metrics.**

Furthermore, the perimeter of this assessment should 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. Identifying best practices for mitigation of the environmental impact of AI

The third objective of standardization is to identify strategies to reduce the environmental impact of AI systems on at least one of the indicators.

The strategies can be identified for different '**action dimensions**' (like challenging the relevance of using AI, infrastructure sizing, model optimization, implementation efficiency, etc.), and **impact drivers** (e.g., using less resources, using low-carbon resources, etc.). 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 involved 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, efficient model architectures and training methods, etc.) will also help encourage the shared adoption of best practices.

4. Defining relevant 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, trade-offs** (e.g., between energy consumption and improving accuracy or testing for robustness) **and alternatives** (including non-AI) 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.

5. Assessing indirect environmental impacts

The fifth objective is to further develop methodologies for assessing the second and higher-ordered effects of AI systems. It includes both indirect positive effects (e.g. electricty consumption avoided thanks to an AI system, reuse of the heat produced by data centers, decarbonization of industrial process...), as well as negative effects such as the rebound effect (i.e. efficient gains driving increase usage).

These assessments should employ identical metrics to those used in evaluating the direct environmental impact of AI systems.

6. Standardizing new environmental indicators

The sixth objective is to develop methodologies for additional environmental indicators, drawing upon the maturity of the academic literature and industry experiences.

Areas such as biodiversity impact and noise pollution represent potential domains for exploration, contingent upon their assessed level of methodological maturity.

7. Establishing standards for AI sustainability literacy

The seventh objective is to focus on establishing comprehensive standards for sustainable AI literacy across stakeholder communities. These standards would define core competencies needed to understand, evaluate, and communicate about AI systems' environmental dimensions throughout their lifecycle.

Such literacy frameworks should address the knowledge requirements for diverse audiences, from AI developers and deployers to policymakers, end users and the general public, ensuring all participants in the AI ecosystem can make informed decisions regarding environmental implications. The standards should evolve alongside technical methodologies, maintaining alignment with current environmental assessment practices.

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.

This should include as well the assessment of the environmental impact of the **"use" or "inference"** phase (operation and monitoring/continuous validation/re-evaluation).

Both phases should be reported.

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.

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, measurement and common metrics, including key performance indicators.

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 **continuous development of methodologies to fairly and transparently allocate environmental costs among coexisting processes within mixed-use environments**. Real-time monitoring of resource use within shared facilities provides an important basis for allocation and estimation. While precise attribution may be difficult, the environmental impacts associated with shared infrastructure shall be accounted for rather than excluded, and the assumptions and uncertainties involved shall be documented.

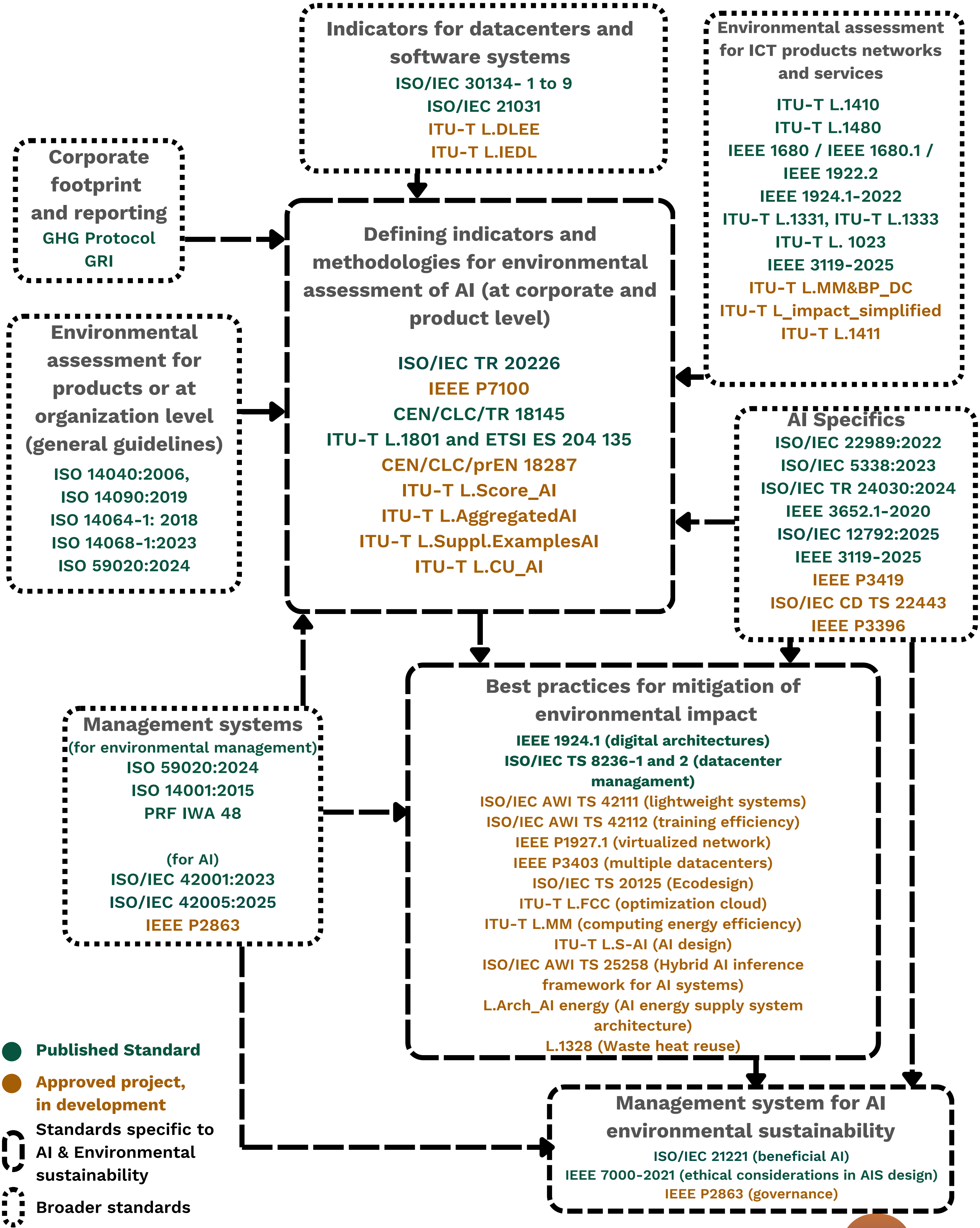
- **Access to environmental data:** The lack of collected and/or shared robust data on key parameters for calculating the environmental impact of AI systems poses challenges for testing a methodology across multiple systems and indicators. Given that energy consumption data are more readily available, a direct environmental assessment first limited to GHG emissions could be considered. In the longer term, adding indicators such as water consumption, material consumption, etc., must be a priority.

For developing more accurate assessment, it is encouraged to share information about embodied emissions of common hardware, foundational models, etc.

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:
<u>Published</u> standards relevant to AI sustainability

Defining indicators and methodologies for environmental assessment of AI (at corporate and product level)

- ISO **TR** 20226:2025—Environmentally sustainable aspects of AI Systems (**TR - Technical Report**)
- CEN/CLC/TR 18145:2025—Environmentally sustainable Artificial Intelligence
- ITU-T L.1801 and ETSI ES 204 135- Guidelines for Assessing the Environmental Impact of Artificial Intelligence systems

Indicators for datacenters and software systems

- ISO/IEC 30134-1 to 9—Information technology —Datacenters—Key performance indicators
- ISO/IEC 21031:2024—Information technology — Software Carbon Intensity (SCI) specification

Environmental assessment for products or at organization level (general guidelines)

- ISO 14040:2006—Environmental management — Life cycle assessment — Principles and framework
- ISO 14090:2019 Adaptation to climate change — Principles, requirements and guidelines
- 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 zero - Part 1: Carbon neutrality.
- ISO 59020:2024 — Circular economy — Measuring and assessing circularity performance

Management systems

<u>For environmental management (main general guidelines)</u>

- ISO 14001:2015—Environmental management systems — Requirements with guidance for use
- PRF IWA 48—Framework for implementing environmental, social and governance (ESG) principles
- ISO 59020:2024 — Circular economy — Measuring and assessing circularity performance
- ISO 59010:2024 — Circular economy — Guidance on the transition of business models and value networks
- ISO 59040:2025 — Circular economy — Product circularity data sheet
- ISO 14015:2022 — Environmental management — Guidelines for environmental due diligence assessment
- ISO 14016:2020 — Environmental management — Guidelines on the assurance of environmental reports
- ISO 14017:2022 — Environmental management — Requirements with guidance for verification and validation of water statements
- ISO 20400:2017(en) Sustainable procurement — Guidance

<u>For Artificial Intelligence</u>

- ISO/IEC 42001:2023— Artificial intelligence — Management system
- ISO/IEC 42005:2025— Artificial intelligence (AI) — AI system impact assessment

Environmental assessment for ICT products networks and services

- ITU-T L.1410/ES 203 199—Methodology for environmental life cycle assessments of information and communication technology goods, networks and services
- ITU-T L.1480/ES 204 087—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 1680.1-2018—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

- IEEE 1924.1-2022—IEEE Recommended Practice for Developing Energy-Efficient Power-Proportional Digital Architectures
- ITU-T L.1331/ES 203328—Assessment of mobile network energy efficiency
- ITU-T L.1333—Carbon data intensity for network energy performance monitoring
- ITU-T L.1023—Assessment method for circular scoring (of information and communication technology (ICT) goods)

AI Specifics

- ISO/IEC 22989:2022—Artificial intelligence concepts and terminology
- ISO/IEC 5338:2023— Artificial intelligence — AI system life cycle processes
- ISO/IEC 42005:2025—AI system impact assessment
- ISO/IEC TR 24030:2024— Artificial intelligence (AI) — Use cases
- IEEE 3652.1-2020—IEEE Guide for Architectural Framework and Application of Federated Machine Learning
- ISO/IEC 12792—Transparency taxonomy of AI systems
- IEEE 3119-2025 - IEEE Standard for the Procurement of Artificial Intelligence and Automated Decision Systems

Best practices for mitigation of environmental impact

- ISO/IEC TS 8236-2:2025— Provisioning, forecasting and management — Part 1&2: Data centre IT equipment & facility infrastructure
- IEEE 1924.1-2022-IEEE Recommended Practice for Developing Energy-Efficient Power-Proportional Digital Architectures

Management systems for AI environmental sustainability

- ISO/IEC TR 21221:2025 — Artificial intelligence — Beneficial AI systems
- IEEE 7000-2021 - IEEE Standard Model Process for Addressing Ethical Concerns during System Design. [AI System Design]

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.

2026

January-June	July-December
• ISO/IEC TS 20125—Information Technology – Digital Services Ecodesign – Ecopractices for Life Cycle Stages • IEEE P7100—Standard for Measurement of Environmental Impacts of Artificial Intelligence Systems • 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 • ITU-T L.impact_simplified—Simplified assessments of the GHG emissions impact of the use of ICT solutions • ISO/IEC CD TS 22443 Artificial intelligence — Guidance on addressing societal concerns and ethical considerations	• CEN/CLC/prEN 18287 Sustainable Artificial Intelligence – Guidelines and metrics for the environmental impact of artificial intelligence systems and services • ISO/IEC AWI TS 42112—Guidance on machine learning model training efficiency optimisation • ITU-T L.Suppl.ExamplesAI – “Examples of Assessments of AI Systems”

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

2027

- ISO/IEC TS 42111—Guidance on lightweight AI systems
- 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
- ITU-T L.Score_AI – “Guidance for Scoring AI Systems from the Perspective of Environmental Impact”
- ITU-T L.AggregatedAI – “Guidelines for Assessing the Environmental Impact of Artificial Intelligence Aggregated at Worldwide, Country, and City Levels”
- IEEE P3396 - Recommended Practice for Defining and Evaluating Artificial Intelligence (AI) Risk, Safety, Trustworthiness, and Responsibility
- ITU-T L.CU_AI - Guidelines for Circular Utilization of artificial intelligence Computing Power Resources