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Environmental Engineering (EE); Guidelines for Assessing the Environmental Impact of Artificial Intelligence systems

Reference

DES/EE-EEPS77

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Foreword

This final draft ETSI Standard (ES) has been produced by ETSI Technical Committee Environmental Engineering (EE), and is now submitted for the ETSI Vote phase of the ETSI Membership Approval Procedure (MAP).

Modal verbs terminology

In the present document "**shall**", "**shall not**", "**should**", "**should not**", "**may**", "**need not**", "**will**", "**will not**", "**can**" and "**cannot**" are to be interpreted as described in clause 3.2 of the ETSI Drafting Rules (Verbal forms for the expression of provisions).

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Executive summary

The present document provides methodology for assessing environmental impact of AI systems. The methodology is based on Life Cycle Assessment (LCA) methodology standardized in Recommendation ITU-T L.1410 / ETSI ES 203 199 [1] and method for enabling effects for other sectors standardized in Recommendation ITU-T L.1480 [2]. The guidance in the present document focuses on AI system specific aspects which need to be taken into account in the assessment. Aggregation of AI impact on international, national or regional level is not part of the present document.

Introduction

The present document was developed jointly by ETSI TC EE and ITU-T Study Group 5. It was published respectively by ITU as Recommendation ITU-T L.1801 [i.14] and ETSI as ETSI ES 204 135 (the present document), which are equivalent in technical content.

As the demand for Artificial Intelligence (AI) technology increases, so does the environmental pressure it imposes. The environmental impact associated with AI, driven by significant energy costs, has become a critical issue that needs to be addressed for the future development of AI.

The present document provides a holistic framework for evaluating the environmental impact of AI systems, covering direct and indirect impacts, assessment, and mitigation strategies. The methods in Recommendation ITU-T L.1410 / ETSI ES 203 199 [1] and Recommendation ITU-T L.1480 [2] provide the baseline for this framework. This standard is built on those methods and provides additional guidance to the practitioner on how to apply the methods for AI systems.

For minimizing and mitigating the environmental impact of AI systems, it is important to take a life cycle approach understanding the whole life cycle of AI systems. For this, Life Cycle Assessment (LCA) is the most widely used and best available methodology for assessing the environmental impact, including GHG emissions. Therefore, Recommendation ITU-T L.1410 / ETSI ES 203 199 [1] has been taken as the baseline for this framework.

The present document can further help relevant parties ensure that current actions are effective in addressing the evolving climate change over the long term. The present document provides a focused framework for evaluating whether it is environmentally beneficial, from an environmental impact perspective, to use AI technology compared to not using AI or comparing the environmental impact of two AI systems. This assessment takes into account the full life cycle of AI systems, including the use of the AI system. It can help AI users choose a system or solution that will have less impact on the environment. The methodology followed in the present document does not presume a result of the assessment of the use of AI, which may either contribute to or undermine global sustainability.

AI and the Environment report from ITU [i.12] describes the earlier work in this area and contains references to ITU documentation and the outcome from FG AI4EE group. This report also includes possible mitigation actions for reducing the environmental impact of AI.

Annex A of the present document describes other initiatives on this topic.

1 Scope

The present document provides guidelines for assessing the environmental impact of Artificial Intelligence (AI) systems objectively and transparently. The scope includes:

- Overview of the impacts of AI systems on the environment.
- Framework for evaluating the environmental impact of AI.

The guidelines in the present document are based on the Life Cycle Assessment (LCA) methodology standardized in Recommendation ITU-T L.1410 / ETSI ES 203 199 [1] and method for enabling effects for other sectors standardized in Recommendation ITU-T L.1480 [2].

The present document does not cover the assessment of the environmental impact of AI systems aggregated at worldwide or national level, which may be covered in the future in another standard.

2 References

2.1 Normative references

References are either specific (identified by date of publication and/or edition number or version number) or non-specific. For specific references, only the cited version applies. For non-specific references, the latest version of the referenced document (including any amendments) applies.

Referenced documents which are not found to be publicly available in the expected location might be found in the ETSI docbox.

NOTE: While any hyperlinks included in this clause were valid at the time of publication, ETSI cannot guarantee their long-term validity.

The following referenced documents are necessary for the application of the present document.

[1] Recommendation ITU-T L.1410 (2024) / ETSI ES 203 199: "Methodology for environmental life cycle assessments of information and communication technology goods, networks and services".

[2] Recommendation ITU-T L.1480: "Enabling the Net Zero transition - Assessing how the use of information and communication technology solutions impacts greenhouse gas emissions of other sectors".

NOTE: At the time of drafting the present document, the equivalent ETSI ES 204 087 is under development and is expected to be submitted for Member Vote shortly.

2.2 Informative references

References are either specific (identified by date of publication and/or edition number or version number) or non-specific. For specific references, only the cited version applies. For non-specific references, the latest version of the referenced document (including any amendments) applies.

NOTE: While any hyperlinks included in this clause were valid at the time of publication, ETSI cannot guarantee their long-term validity.

The following referenced documents may be useful in implementing an ETSI deliverable or add to the reader's understanding, but are not required for conformance to the present document.

[i.1] Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence and amending Regulations (EC) No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828 (Artificial Intelligence Act).

[i.2] ISO 14040:2006: "Environmental management — Life cycle assessment — Principles and framework".

[i.3] ISO/IEC 22989:2022: "Information technology — Artificial intelligence — Artificial intelligence concepts and terminology".

[i.4] ISO/IEC 5338: 2023: "Information technology — Artificial intelligence — AI system life cycle processes".

[i.5] ETSI EN 303 800-2 / Recommendation ITU-T L.1025: "Environmental Engineering (EE); Assessment of material efficiency of ICT network infrastructure goods (circular economy); Part 2: Server and data storage product secure data deletion functionality".

[i.6] Farzan, M.; Kallio, S.: "A transparent and standards-based way to assess the environmental impact of AI systems", 2024.

[i.7] Recommendation ITU-T L.1420 (2012): "Methodology for energy consumption and greenhouse gas emissions impact assessment of information and communication technologies in organizations".

[i.8] GHG Protocol: "A Corporate Accounting and Reporting Standard".

[i.9] ILCD Handbook: "General guide for Life Cycle Assessment - Detailed guidance", 2010.

[i.10] ISO/IEC 22989:2022/DAmd 1: "Information technology — Artificial intelligence — Artificial intelligence concepts and terminology", draft Amendment 1.

[i.11] ISO/IEC 5230:2020: "Information technology — OpenChain Specification".

[i.12] ITU: "AI and the Environment - 2024 Report".

[i.13] IEA: "Energy and AI", April 2025.

[i.14] Recommendation ITU-T L.1801 (2026): "Guidelines for assessing the environmental impact of artificial intelligence systems".

3 Definition of terms, symbols and abbreviations

3.1 Terms

For the purposes of the present document, the following terms apply:

Artificial Intelligence (AI): <discipline> research and development of mechanisms and applications of AI systems

NOTE 1: Research and development can take place across any number of fields such as computer science, data science, humanities, mathematics and natural sciences.

NOTE 2: Source: ISO/IEC 22989:2022 [i.3].

AI agent: automated entity that senses and responds to its environment and takes actions to achieve its goals

NOTE: Source: ISO/IEC 22989:2022 [i.3].

AI system: engineered system that generates outputs such as content, forecasts, recommendations or decisions for a given set of human-defined objectives

NOTE 1: The engineered system can use various techniques and approaches related to artificial intelligence to develop a model to represent data, knowledge, processes, etc. which can be used to conduct tasks.

NOTE 2: AI systems are designed to operate with varying levels of automation.

NOTE 3: Source: ISO/IEC 22989:2022 [i.3].

automation: process or system that, under specified conditions, functions without human intervention

NOTE: Modified from Source: ISO/IEC 22989:2022 [i.3].

continual learning: incremental training of an AI system that takes place on an ongoing basis during the operation phase of the AI system life cycle

NOTE: Source: ISO/IEC 22989:2022 [i.3].

data sanitization: process of deliberately and irreversibly deleting or destroying any data stored in memory on a device to render it unrecoverable

NOTE: Source: ETSI EN 303 800-2 [i.5].

deep learning, deep neural network learning: <artificial intelligence> approach to creating rich hierarchical representations through the training of neural networks with many hidden layers

NOTE 1: Deep learning is a subset of ML.

NOTE 2: Source: ISO/IEC 22989:2022 [i.3].

embodied emissions: lifecycle(s) Greenhouse Gas (GHG) emissions from the following life cycle stages: raw material acquisition, production and end-of-life treatment

NOTE 1: Each life cycle includes transportation as generic process.

NOTE 2 The Greenhouse Gas (GHG) emissions include all life cycle stages other than the use stage.

NOTE 3: Source: ETSI ES 203 199 [1].

environmental impact: impact including positive and negative aspects on the environment

NOTE: Source: ETSI ES 203 199 [1].

expert system: AI system that accumulates, combines and encapsulates knowledge provided by a human expert or experts in a specific domain to infer solutions to problems

NOTE: Source: ISO/IEC 22989:2022 [i.3].

foundation model: AI model that can be used for or readily adapted to a wide range of tasks in one or more domains

NOTE 1: A typical way to build a foundation model is to apply supervised machine learning or self- supervised machine learning on a large amount of data.

NOTE 2: A foundation model can be used as part of various applications, tasks and use cases, which do not necessarily involve generative AI.

NOTE 3: Source: ISO/IEC 22989:2022/DAmd 1 [i.10].

functional unit: quantified performance of a product system for use as a reference unit

NOTE: Source: ISO 14040:2006 [i.2].

general AI, AGI, artificial general intelligence: type of AI system that addresses a broad range of tasks with a satisfactory level of performance

NOTE 1: Compared to narrow AI.

NOTE 2: AGI is often used in a stronger sense, meaning systems that not only can perform a wide variety of tasks, but all tasks that a human can perform.

NOTE 3: Source: ISO/IEC 22989:2022 [i.3].

generative artificial intelligence system, generative AI system, GenAI system: AI system based on techniques and models that aim to generate new content

NOTE 1: Examples of generated content can include text, audio, code, video and image.

NOTE 2: Generated content encompasses new information or new ways to express preexisting information. That preexisting information can be drawn from the input, a dataset involved in building the model or an external repository.

NOTE 3: Source: ISO/IEC 22989:2022/DAmd 1 [i.10].

inference: reasoning by which conclusions are derived from known premises

NOTE 1: In AI, a premise is either a fact, a rule, a model, a feature or raw data.

NOTE 2: The term "inference" refers both to the process and its result.

NOTE 3: Source: ISO/IEC 22989:2022 [i.3].

Machine Learning (ML): process of optimizing model parameters through computational techniques, such that the model's behaviour reflects the data or experience

NOTE: Source: ISO/IEC 22989:2022 [i.3].

machine learning algorithm: algorithm to determine parameters of a machine learning model from data according to given criteria

EXAMPLE: Consider solving a univariate linear function $y = \theta_0 + \theta_1 x$ where y is an output or result, x is an input, θ_0 is an intercept (the value of y where x=0) and θ_1 is a weight. In machine learning, the process of determining the intercept and weights for a linear function is known as linear regression.

NOTE: Source: ISO/IEC 22989:2022 [i.3].

model: physical, mathematical or otherwise logical representation of a system, entity, phenomenon, process or data

NOTE: Source: ISO/IEC 22989:2022 [i.3].

narrow AI: type of AI system that is focused on defined tasks to address a specific problem

NOTE 1: Compared to general AI.

NOTE 2: Source: ISO/IEC 22989:2022 [i.3].

Neural Network (NN): <artificial intelligence> network of one or more layers of neurons connected by weighted links with adjustable weights, which takes input data and produces an output

NOTE 1: Neural networks are a prominent example of the connectionist approach.

NOTE 2: Although the design of neural networks was initially inspired by the functioning of biological neurons, most works on neural networks do not follow that inspiration anymore.

NOTE 3: Source: ISO/IEC 22989:2022 [i.3].

open-source: software subject to one or more licenses that meet the Open Source Definition published by the Open Source Initiative (see opensource.org/osd) or the Free Software Definition published by the Free Software Foundation (see gnu.org/philosophy/free-sw.html) or similar license

NOTE: Source: ISO/IEC 5230:2020 [i.11].

parameters, **model parameter:** internal variable of a model that affects how it computes its outputs

NOTE 1: Examples of parameters include the weights in a neural network and the transition probabilities in a Markov model.

NOTE 2: Source: ISO/IEC 22989:2022 [i.3].

token: unit of content that an AI model treats as semantically meaningful

NOTE: Source: ISO/IEC 22989:2022/DAmd 1 [i.10].

training model, training: process to determine or to improve the parameters of a machine learning model, based on a machine learning algorithm, by using training data

NOTE: Source: ISO/IEC 22989:2022 [i.3].

3.2 Symbols

Void.

3.3 Abbreviations

For the purposes of the present document, the following abbreviations apply:

AGI	Artificial General Intelligence
AI	Artificial Intelligence
API	Application Programming Interface
CF	Carbon Footprint
CI/CD	Continuous Integration / Continuous Delivery
CPU	Central Processing Unit
EoLT	End of Life Treatment
EPD	Environmental Product Declaration
FG	Focus Group
FLOP	Floating Point Operations Per second
GenAI	Generative AI
GHG	Greenhouse Gas
GPU	Graphics Processing Unit
ICT	Information and Communication Technology
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LLM	Large Language Model
ML	Machine Learning
NN	Neural Network
PoC	Proof-of-Concept
PUE	Power Usage Effectiveness
RFC	Request for Comments
SVM	Support Vector Machine
TPU	Tensor Processing Unit
WUE	Water Usage Effectiveness

4 Void

5 Void

6 Overview of AI system characteristics

6.1 General

AI is a rapidly advancing field with the potential to enhance economic, environmental and social benefits significantly across various sectors. There are two perspectives associated with AI: AI for Sustainability and Sustainability of AI. AI for Sustainability is about the use of AI systems to enable sustainability goals and the environmentally sustainable development of different areas and industries, whereas Sustainability of AI is about considering the impact of AI itself, where the entire lifecycle of AI system should be analysed starting from design, production of hardware, training, tuning and re-tuning, deployment, use and end of life of the AI system. The main focus of the present document is on the latter, to provide a methodology for assessing the environmental impact of AI systems. However, the present document also includes a methodology to compare different AI systems and to start to assess the benefits/impact AI brings to sustainability and other sectors.

On one hand, designing, deploying, training and using the AI system has its own environmental impact, therefore assessing and minimizing the environmental impact of AI systems is important. On the other hand, AI can be used for the benefit of the ecosystem by protection and improvement of the quality of the environment, biodiversity, improving circularity, climate change mitigation and adaptation [i.1].

A general overview of AI systems and their applications have been developed by the IEA and is available in the report on Energy and AI [i.13]. Some AI infrastructure and types of applications are provided in Figure 1.

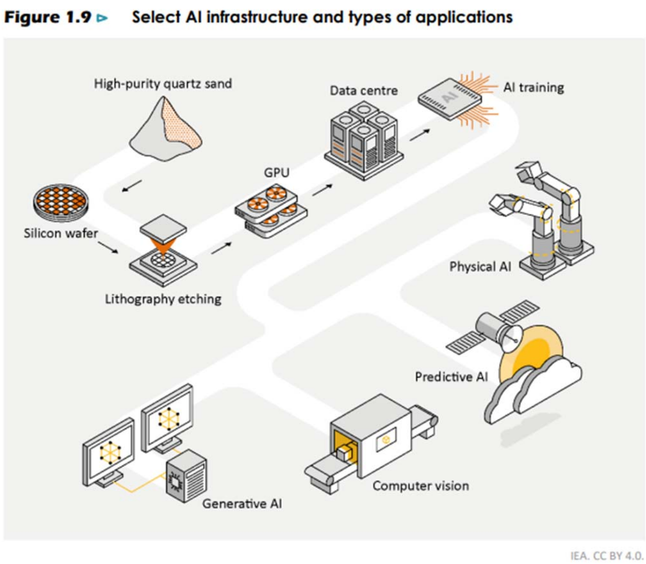

Figure 1: Select AI Infrastructure and types of applications [i.13]

6.2 AI system life cycle

Some aspects of the life cycle stages of an AI system are unique compared to a non-AI product or traditional software. Figure 2 illustrates the AI life cycle stages and major processes of an AI system based on ISO/IEC 5338 [i.4]. Depending on the intended purpose of the AI system, there might be some variation to this. However, the life cycle description should include all stages from inception to retirement or a subset of these stages in a limited focus.

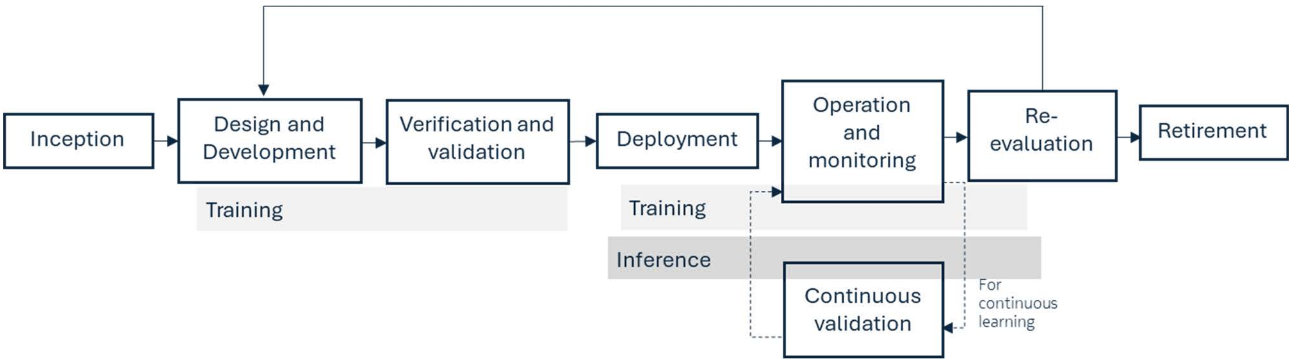

Figure 2: Life cycle stages of an AI system

A life cycle of an AI system consists of inception, design and development, verification and validation, deployment, operation and monitoring, continuous validation, re-evaluation and, finally, retirement as shown in Figure 2. Training and inference are not separate AI life cycle stages according to ISO/IEC 5338 [i.4] but they are central processes in AI systems and therefore indicated in Figure 2, aligned with the AI life cycle stages according to the detailed description given in ISO/IEC 5338 [i.4]. The design and development stage can include several processes like acquiring training data, data preparation, algorithm selection, and model training. Likewise, the deployment can be separated into metrics evaluation, reviews and operationalization.

AI system life cycle stages according to ISO/IEC 22989 [i.3]:

- Inception: Turn an idea into a tangible system by defining a set of requirements for the AI system to be developed.
- Design and development: Creating an AI system that fulfils the original requirements.
- Verification and validation: Checking that the AI system from the design and development stage works according to the requirements set at the inception stage.
- Deployment: Installing, releasing and configuring the AI system in a target environment.
- Operation and monitoring: The AI system is running and available for use. The AI system is monitored for normal operation and possible incidents.
- Continuous validation: If the AI system uses continuous learning, incremental training takes place continuously while the system is running in production. The operation of the AI system is continually checked for correct operation using test data.
- Re-evaluation: Reassessment of whether the AI system still fulfils objectives and requirements, based on the results of the work of the AI system.
- Retirement: The AI system can become obsolete when repairs and updates are not sufficient to meet new requirements, in which case it may be decommissioned and discarded or replaced.

AI systems can also be developed in the open-source community. Some notes from that perspective for the different AI system life cycle stages are described in Annex B.

AI systems can undergo several updates, bug fixes, adaptation to new data sets and improvements including the continuous learning, validation and verification process as part of the same life cycle, as long as these activities do not change the original set of requirements defined for the AI system during the Inception. However, at any point, if the requirements defined during the Inception of the AI system are modified, such fundamental changes or significant alterations to the AI system requirements or functionality qualify as a new AI system, different from the original system. This would result in a different function of the AI system and a separate functional unit might be required considering the new AI system requirements or the function of the AI system to assess the environmental impact.

The main processes are from their environmental impact perspective:

- Training: Training can be expanded over several AI system life cycle stages as shown in Figure 2. Training is not a continuous activity but can be separated into initial training and re-training or continuous learning. Initial training happens in the design and development stage to train the model to be relevant for the intended purpose. Re-training happens during the continuous validation stage while the AI system is in use. Training involves different data sets such as training data, validation data, test data, and data for continuous learning (taken from the production data processed by the AI system in the operation phase). Training data is the input from which the machine learning algorithm extracts its model to address the given task. Validation data is used to validate some algorithmic choices. Test data is used to evaluate that the performance of the AI system fulfils the needs and requirements before its deployment. Data for continuous learning is used during AI system operation to re-train/update the trained model for continued performance to fulfil the intended purpose.

- Inference: During the use of the AI system, inference is the process of running live data through the trained AI model and the generated result, e.g. prediction or conclusions.

Moreover, data handling is closely linked with the AI system. Below are some data related actions which do not necessarily follow a specific sequence, ISO/IEC 5338 [i.4]:

- Acquire or select data: Collecting, recording or purchasing needed data.

- Verification and validation: Checking that data fulfils the needs and quality criteria (including fairness and privacy aspects). Validation of the data source.

- Preparation: Processing of data, e.g. data cleaning or merging, change of format, labelling, metadata preparation, preparing training and validation data, etc.

- Storage: Keeping data on a storage resource.

- Protection: Protecting sensitive data and securing data against malicious actors.

- Transfer/transmission: Moving data from one place to another or from one network to another over a transmission network.

- Update: Acquiring new data.

- Archiving: Intermediate, easily accessible archiving or long-term, permanent archiving (data logging).

- Retirement: At the end of use, data is deleted or archived in a timely manner.

6.3 Classification of AI systems

While all AI systems share the same life cycle, their effects on resources can vary significantly.

AI can be categorized into different types of technology. Figure 3 illustrates some main AI technology types.

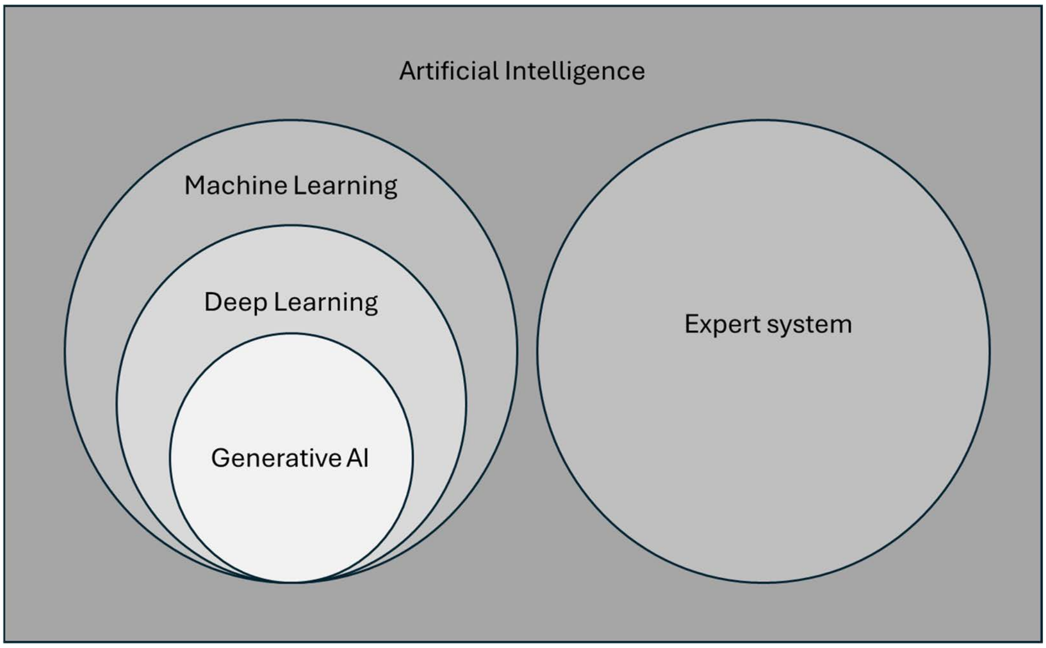

Figure 3: Some main AI technology types

Table 1 proposes a classification of AI technologies into four distinct categories, each reflecting its first order impact on needed resources.

Table 1: Classification of AI systems by AI technology

AI technology types	Technologies examples	Use case examples	Hardware resources	Data resources	Energy resources
Expert systems (subset of AI)	Linear regression, logistic regression, SVM, Naive based, Decision trees, Random Forest	Text classification Energy optimization	CPU	Comparatively low	Comparatively low
Machine Learning (subset of AI)	Statistical algorithms	E-mail filtering, product recommendations	CPU + GPU	Comparatively medium	Comparatively medium
Deep Learning (subset of Machine Learning)	Convolutional Neural Network, Recurrent Neural Network, Long short-term memory, etc.	Image recognition	CPU + GPU	Comparatively medium	Comparatively medium
Generative AI (subset of Deep Learning)	Small Language Models, Large Language Models, Specialized models, Multi-modal models	Generation of summaries, videos or images	A significant number of GPU and/or TPU	Comparatively medium to high depending on the use cases	Comparatively high depending on the use cases

It is important to allocate the environmental impact according to the full life cycle of the AI system, whether for general or narrow AIs.

In the case of general AI, allocating the environmental impact associated with the used foundation model may be a complex task because the foundation model may be used to create multiple derived models.

7 General on LCA methodology

LCA methodology is described in Recommendation ITU-T L.1410 (2024) / ETSI ES 203 199 [1]. The present document refers to [1] for further details and requirements. However, in some cases simplified LCA standard can potentially be considered instead, as applicable.

LCA is applicable for AI product systems, but as such it is not applicable for organizations' environmental impact assessment. Other standards should be used for the organization's environmental impact, e.g. Recommendation ITU-T L.1420 [i.7] or [i.8].

8 Framework for assessing the environmental impact of AI systems

8.1 LCA for environmental impact from the AI system

8.1.1 General

Applying LCA methodology to an AI system needs careful consideration as the AI system life cycle stages do not directly align with the four LCA stages in [1]: Raw Material Acquisition, Production, Use and End of Life Treatment (EoLT).

Figure 4 depicts how the AI system life cycle stages and main processes can be mapped to LCA life cycle stages.

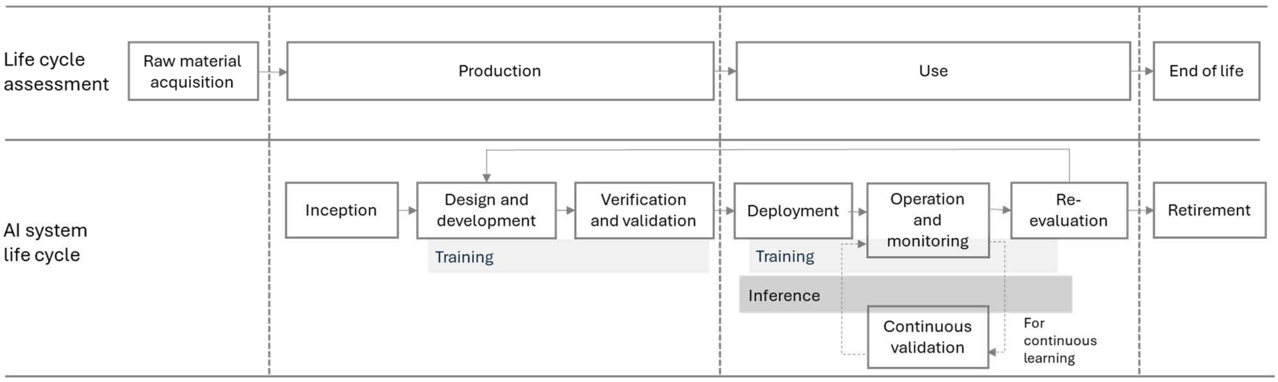

Figure 4: Mapping LCA life cycle stages with AI system life cycle stages [i.6]

The LCA Raw material acquisition stage shall contain the impact from materials for the hardware needed for the AI system.

The Production stage of LCA shall include the impact from hardware production as well as the impact from inception, design and development, and verification and validation stages of the AI system as shown in Figure 4. From the main AI system processes, initial training shall be calculated as part of the LCA Production stage.

LCA Use stage shall include the impact from deployment, operation and monitoring, re-evaluation, and continuous validation stages of the AI system. From the main AI system processes, inference and continuous learning (as part of re-training) shall be calculated as part of the LCA Use stage.

NOTE 1: In some publications, deployment is mapped to belong to the Production stage. Mapping deployment in the Use stage in the present document follows the principles in Recommendation ITU-T L.1410 (2024) / ETSI ES 203 199 [1]. For this reason, it is recommended to mention in the reporting how deployment is mapped in the life cycle stages.

In order not to have any ambiguity in reporting embodied emissions, the LCA practitioner should determine which part of the training impact falls under the Production or Use stage of LCA using the above guidance. It is required that the training impact is also reported separately for full transparency. Since initial training can be measured and an accurate figure provided but continuous learning will be based on estimated figures (using assumptions), these shall be reported separately.

Finally, the End of life treatment stage of LCA shall contain the impact from hardware end of life treatment as well as the impact of the retirement stage of the AI system.

Physical transportation of materials and hardware shall be calculated in each LCA stage as defined in [1].

Data transmission and data storage impact shall be calculated in that LCA stage where the corresponding activity takes place.

AI system installation and maintenance as well as site specific support activities (e.g. cooling systems, lighting, etc.) during use shall be calculated for the LCA Use stage.

In shared infrastructure use, full life cycle impact of the infrastructure shall be allocated to the users according to their usage.

Practitioner shall clearly indicate if multiple AI systems are included in the assessment, when these AI systems together provide the intended functionality.

NOTE 2: Multiple AI systems in the assessment may become very complex with Agentic AI, especially if multiple agents are involved.

8.1.2 Goal and scope definition for AI system

8.1.2.1 Goal and scope of the study

AI is being increasingly integrated into various goods and services, also embedded AI capabilities, requiring a clear definition of the scope and the boundaries of the LCA study of AI systems.

Below three situations are categorized to depict the range of integration of AI with different systems. For each of these situations, the assessment boundaries shall be specified depending on the goal of the assessment (refer to Figure 5):

- **Situation #1:** The AI system is a service designed fully to use AI (e.g. the practitioner aims at assessing the environmental impact of an LLM or a neural network).
- **Situation #2:** AI is embedded into ICT services or ICT goods. This situation refers to an ICT service or ICT good where AI may or may not be necessary to meet the primary functionalities of the ICT service or ICT good (e.g. the practitioner aims at assessing the impact of an AI-embedded ICT service, such as an AI-enabled remote reservation service, AI-enabled geolocation service, AI-enabled conversational phone call service, etc., or the practitioner aims at assessing the impact of an AI-embedded ICT good, such as an AI-capable smartphone, etc.).
- **Situation #3:** AI is embedded in products (goods or services) outside the ICT sector, where AI may or may not be necessary to deliver the primary functionality of the product (e.g. AI is used for controlling the cooling of an intelligent fridge, a group of connected lifts that use AI to optimize distribution of loads / journeys, a connected car with an AI-based assisted driving system that prevents collisions or optimizes journeys, etc.).

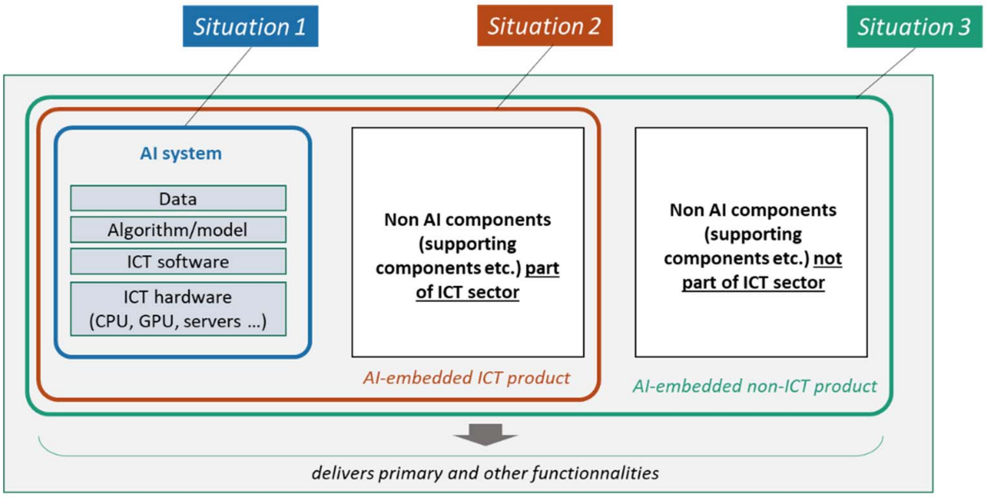

Figure 5: Illustration of the different situations depicting the range of integration of AI systems

Example for Situation 3: One may consider for instance the example of an AI embedded smart fridge which handles two operation modes: a basic mode and an enhanced mode. In the basic mode, the appliance operates as any conventional fridge without using AI capabilities. However, in the enhanced mode, AI supports the functioning of the fridge by implementing a cooling technology that optimizes the energy usage through fine-tuning/adjustments of the cooling temperature based on the fridge's contents and the user's preferences. Compared to the basic mode, the enhanced mode not only extends the freshness of perishable foods but also may generate energy savings. Depending on how the functional unit is defined by the practitioner, the following assessment boundaries could be set:

- If the functional unit refers to "*the supply of 200 L of cooling space (at 5°C) for food storage for 10 years of refrigerator use under the basic mode only*", the practitioner should not consider the AI system in the assessment boundaries.
- If the functional unit refers to "*the supply of 200 L of cooling space (at 5°C) for food storage for 10 years of refrigerator use under the enhanced mode only*", the practitioner shall consider the AI system in the assessment boundaries. In that case, relevant allocations shall be considered in the product system as illustrated in Figure 6.
- If the functional unit refers to "*the supply of 200 L of cooling space (at 5°C) for food storage for 10 years of refrigerator use*", the practitioner should consider an AI system in the assessment boundaries based on the typical profile of usage of the fridge. This typical profile of usage may include a mix between the two operating modes of the appliance.

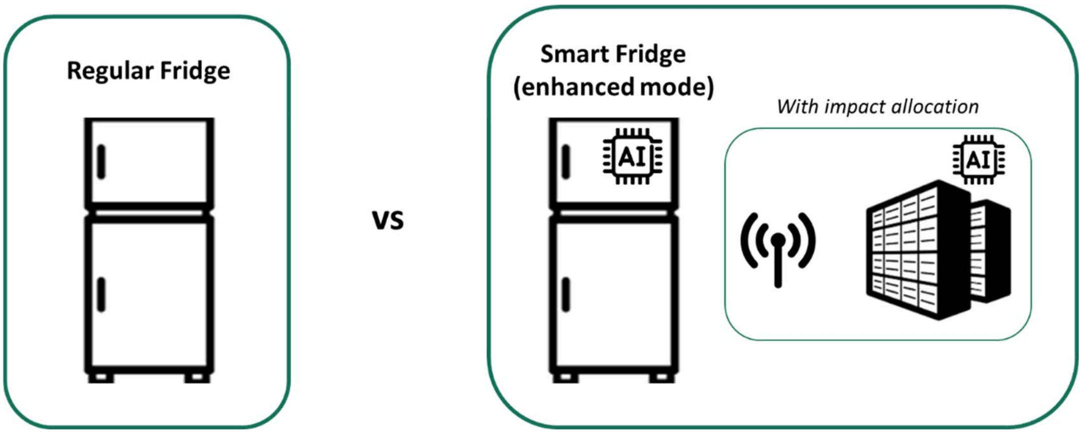

Figure 6: Example of assessment boundaries for a regular fridge and an AI-embedded smart fridge where the functional unit refers to the enhanced (AI-capable) operation mode

8.1.2.2 Functional unit

The functional unit shall be chosen in accordance with the goal and scope of the study. The functional unit defines the performance characteristics delivered by the AI system being studied. The functional unit shall have a function and a quantifiable unit measuring the performance of that function, Recommendation ITU-T L.1410 (2024) / ETSI ES 203 199 [1].

[i.9] gives further guidance that the functional unit(s) shall be identified and specified in detail across all the following aspects:

a) function provided (what);

b) in which quantity (how much);

NOTE 1: Even though the "how long" information is important, the use intensity and resulting overall quantity of the performed function are key to valid comparisons.

c) for what duration (how long); and

d) to what quality (in what way and how well is the function provided).

AI system differs to some extent from a traditional hardware product system. This shall be taken into account when setting the functional unit for LCA study.

Some examples of a functional unit for different kinds of AI systems:

- Text generation: X prompt tokens & Y generated tokens & Z thinking tokens.
- Image generation: X bytes.
- Automatic speech recognition: X bytes of audio recording.
- Video generation: X bytes of video.
- Network management: traffic prediction for network element shut-down/ramp-up.

NOTE 2: Quality is not stated explicitly in the functional unit examples above. Practitioner should include quality in the functional unit according to the set of requirements defined for the AI system under assessment.

NOTE 3: Practitioner should choose a unit that is suitable for comparative analysis as needed.

These examples are analysed against the above criteria in Annex E.

Intensity metrics are sometimes used to indicate environmental impact per individual action, e.g. energy/prompt, GHG emissions/prompt, or water consumption/prompt. When including full life cycle impacts, such an intensity metric may qualify as a functional unit for LCA.

8.1.2.3 System boundaries

The selection of the system boundary shall be consistent with the goal of the study and as required for providing its function defined by its functional unit. The system boundaries define the life cycle stages and the unit processes that shall be considered in an LCA of the AI system.

System boundaries can cover the full life cycle of the AI system, i.e. cradle-to-grave, or partial life cycle stages, e.g. cradle-to-gate.

8.1.2.4 Cut-off rules

Cut-off rules in Recommendation ITU-T L.1410 (2024) / ETSI ES 203 199 [1] apply. Cut-offs can simplify the assessment by excluding processes that will not significantly change the overall conclusions of the study. A cut-off is only acceptable if allowed by all the criteria on mass, energy and environmental significance, and cumulative considerations.

Some AI system processes may be more significant in their impact than others. However, careful consideration is required for the accumulated effects of the not-so-significant processes, to prevent the sum of cut-offs exceeding the targeted share of the total impact which is acceptable for cut-off. For justifying a cut-off, modelled, secondary, or primary data can be used.

8.1.3 Life Cycle Inventory (LCI) for AI system

8.1.3.1 General

The LCI quantifies all material- and energy-flows that occur at every life-cycle stage for an AI system. It rests on three pillars: Data collection, Data calculation, and Data allocation. The requirements in clause 6.3 of [1] apply.

8.1.3.2 Data collection

Data collection for the Life Cycle Inventory (LCI) of AI systems shall encompass all stages of the AI system life cycle (see clause 6.2 for AI system life cycle) and align with the LCA stages outlined in [1]. Specific aspects for comprehensive data collection include:

- **Inception:** Collecting LCI data related to defining the AI system's requirements in line with system boundaries, such as surveys, research activities, initial Proof-of-Concepts (PoCs), and data collection efforts, all of which consume energy and resources.

- **Design and Development:** Gathering LCI data on hardware manufacturing processes for selected environmental impact categories, e.g. energy consumption, material use, water use, etc. Additionally, collect LCI data on AI system activities such as data acquisition, preparation, algorithm selection, and model training. For foundation models, appropriate allocation shall be used.

- **Verification and Validation:** Obtaining LCI data pertaining to testing and validation phases, including energy used for running test data, conducting simulations, and any necessary hardware or software.

- **Use:** Gathering LCI data on the deployment, operation, monitoring, re-evaluation, and continuous validation stages. This includes energy consumption for inference, continuous learning (re-training), data storage, data transmission, AI system installation and maintenance (for computational part), and site-specific support activities. LCI data for the AI system hardware part shall be according to [1]. If additional hardware is in use during the use stage, LCI data for that shall be collected. Primary data from real-world deployments, monitoring systems, and infrastructure providers is preferred when available.

NOTE 1: When relevant, for deployment, collect LCI data related to LLM benchmark leaderboards (such as the Open LLM Leaderboard, Chatbot Arena, etc.), which provide a structured framework for evaluating and comparing large language model performance across diverse tasks like text generation, question answering, summarization, code generation - together with reviews, and the operationalization processes of the AI system.

- **Retirement:** Collecting LCI data related to the decommissioning and disposal or replacement of hardware, as well as data deletion or archiving.

- **Raw Material Acquisition:** Gathering LCI data on the extraction, processing, and transportation of raw materials required for hardware components (e.g. servers, GPUs), including rare earth elements, metals, and plastics. Sources include supplier information, industry databases, and Environmental Product Declarations (EPDs). LCI data for the AI system hardware part shall be according to [1].

- **Production (hardware):** Collecting LCI data on hardware manufacturing processes according to the selected environmental impact categories. LCI data for the AI system hardware part shall be according to [1].

- **End of Life Treatment (EoLT):** Assessing LCI data on the end-of-life treatment of hardware components. LCI data for the AI system hardware part shall be according to [1].

Specific LCI data to collect:

- Energy consumption with associated environmental impact factors: Full life cycle energy consumption impacts shall be covered, such as from training, inference, data handling (storage and transfer), cooling, etc. Energy used in different life cycle stages may come from different sources, and different impact factors may be used, respectively. Primary data shall be collected by measured energy usage (kWh), when available:
  - Energy consumption impact in the value chain can be collected as energy consumption and impact factors or directly in environmental impact figures. In either case, the source of the LCI data shall be described.
  - LCA practitioner shall use the most accurate data representative of the energy mix for the energy consumed [1].
  - When market-based emission data is known, i.e. emissions from electricity that a company has purposefully chosen, e.g. derived from contractual instruments, it should be used for the most accurate results. Location-based emission data, i.e. average grid emission factor data for the given locality or region, can be used when market-based emission data is not available for the use stage. Global average emission data should be used only when nothing else is reasonably available as it provides the least accurate results [1].

NOTE 2: Full emission factors, including distribution and transport losses from electricity generation, should be included as possible and the comprehensiveness of these should be transparently reported [1].

NOTE 3: Compared to typical ICT goods and services, an AI system is also slightly different from an energy consumption point of view. Energy consumption related to some processes, like training, can expand over several AI system life cycle stages (e.g. production and use) as shown in Figure 2. Unlike typical network ICT goods and services, where most significant energy consumption and related emissions are expected during the use stage, AI system energy consumption and related impact on life cycle stages other than the use stage might be significant from an energy consumption point of view.

NOTE 4: Market-based emission data should be prioritized over location-based emission data in the life cycle stages where energy consumption is significant and when data is available. The approach and data used need to be documented and justified by the LCA practitioner.

- Hardware: Collect LCI data related to used server types, GPU models, memory capacities, and other relevant hardware components.
- Data centre infrastructure: Assess data centre site specific auxiliary impact from Power Usage Effectiveness (PUE) and other site specific information.
- Transportation details: Track transportation distances and modes of transportation for materials and hardware transportation.
- Data storage: Assess data storage capacity and utilization rates for all processes during the full life cycle. Collect related environmental impact information.
- Data transmission: Assess data transmission volume and utilization rates for all processes during the full life cycle, covering the end-to-end connection. Collect related environmental impact information.
- End user device: AI related data when the end user device is included within system boundaries.

Possible data sources:

- Cloud Service Providers: Utilize cloud platforms or APIs from service providers for data on energy consumption and resource utilization with associated environmental impact factors.
- Hardware manufacturers: Refer to EPDs and technical specifications provided by the hardware manufacturers.
- Energy monitoring systems: Access data centre energy monitoring systems for measured energy usage metrics.
- Logistics providers: Obtain transportation data from logistics and transportation service providers.
- LCI databases: Use the most relevant and latest databases for secondary data.

- Literature and reports: Incorporate information from scientific literature and industry reports to supplement data collection.

Annex C describes some examples of LCI data with some representative parameters and their units.

8.1.3.3 Data calculation

The general requirements for data calculations in [1] shall be applied. Especially, all calculation procedures shall be explicitly documented and the assumptions made shall be clearly stated and explained.

8.1.3.4 Allocation procedure / allocation of data for AI system

Allocation is important when inputs or outputs are shared among multiple products or systems. For AI systems, this is particularly relevant for shared infrastructure like data centres and cloud computing resources.

- **Shared infrastructure:** Allocate environmental impacts based on the AI system's usage of shared infrastructure. Usage allocations should be suitable, e.g. energy or time-based allocation.
- **Data transmission and storage:** Allocate impacts based on the volume of data transmitted and/or stored by the AI system, considering the specific characteristics of the network and storage infrastructure.
- **Foundation-model:** Allocate its embodied and pre-training impacts by estimated inference volumes and number of derived models where available. If widely deployed foundation model is used, best estimates for allocation should be sought from secondary data or literature and assumptions should be documented.
- **Non-foundation model:** In general, allocations should be applied whenever knowledge transfer, optimization or refinement techniques are used to feed the design of a new model. Any non-foundational model, which is used as an input into another model should have its impacts allocated by the estimated inference volumes of the downstream model.

NOTE 1: Allocation for models and training is to be followed with caution since the ever-growing number of AI use and users will affect the volume of inference significantly.

NOTE 2: The practitioner should consider aspects like the popularity of the model in terms of downloads, its lifetime since creation, etc. This would benefit from further guidance in the future.

8.1.4 Life Cycle Impact Assessment (LCIA) for AI system - Selecting environmental impact categories

[1] provides guidance for LCA practitioner for the selection of impact categories that reflect a comprehensive set of environmental issues related to the product system being studied.

The midpoint category Climate change is mandatory. The LCA practitioner shall decide which other impact categories to include and how to calculate them, based on the studied AI system and the purpose of the LCA study. It is recommended to use a broad approach, including multiple environmental impacts, to get a wide enough understanding of the environmental impact of the studied AI system.

Depending on the AI system and the goal and scope of the assessment, impact categories such as land use, resource use, and water use could give a complementary understanding of the environmental impact from the AI system, in addition to the GHG emissions.

Some AI system aspects for different environmental impact categories include:

1) Climate Change: AI system's full life cycle, including data processing and model training, has high energy demands that result in associated GHG emissions.

2) Water Use: The production and cooling of AI hardware consume water resources, impacting local water availability and quality. This includes both direct (e.g. for cooling) and indirect (e.g. energy generation) water usage.

NOTE: It may be difficult to measure indirect water usage since that would need information about power generation in use at that time in that region which is not always readily available.

3) Resource Use, minerals and metals: AI hardware relies on various rare minerals and metals. The extraction and processing of these materials can lead to resource depletion.

4) Resource Use, fossils: The energy consumption of AI systems to some extent relies on the use of fossil fuels, contributing to the depletion of this non-renewable resource in addition to the climate change impact.

Additional consideration on Biodiversity: AI system's full life cycle can have an impact on biodiversity due to the pressure generated by e.g. the extraction of materials used for the hardware and by GHG emissions occurring in all stages of its life cycle.

8.1.5 Life cycle interpretation for AI system

Findings from the Life Cycle Inventory (LCI) analysis and the Life Cycle Impact Assessment (LCIA) are considered together according to [1].

Uncertainty analysis and Sensitivity analysis shall be conducted according to [1].

8.1.6 Reporting and Critical review of LCA results for AI system

Reporting and critical review of Life Cycle Assessment (LCA) results are important to ensure transparency, reliability, and validity. This clause provides guidelines for reporting and reviewing LCA results specific to AI systems, in alignment with [1]:

- System description: Provide a comprehensive description of the AI system assessed, including its architectural components, functionalities, and operational context.
- Functional unit: Define the functional unit specific to the AI system, such as "per inference operation" or "per training cycle," ensuring clarity in the unit of analysis. See further guidance for setting the functional unit in clause 8.1.2.
- System boundaries: Report the system boundaries, specifying which part of the LCA life cycle stages are included (e.g. cradle-to-gate, cradle-to-grave) and which components of the AI system are within the system boundaries.
- Data sources and quality: Report the sources of data used in the LCA, including primary and secondary data, and assess the quality and reliability of these data sources. Justify and report any assumptions, allocations and/or cut-offs made. For GHG emissions, specify the emission factors applied, including their sources, particularly for energy sources powering AI operations.
- Energy consumption metrics: Report energy consumption specific to the AI system, reporting training and inference processes separately.
- Life cycle stages: It is recommended to provide a breakdown of environmental impacts for different LCA life cycle stages (raw material acquisition, production, use and end-of-life).

The report shall contain a compliance statement indicating either full or partial compliance with the present document, with transparent justification for any exceptions to partial compliance.

8.2 General description of comparative LCA for AI system footprint (first order effects)

8.2.1 General

Comparative analysis aims to provide the difference in environmental impact between two product systems that offer the same or similar functionality. This analysis can be used to compare existing product systems or comparing possible scenarios in the design and planning phase.

8.2.2 Target systems for comparative analysis for AI system

Two different applications for comparative analysis are covered by the present document:

Case 1: Comparison between an AI system and a reference non-AI system.

Case 2: Comparison between two AI systems.

In comparative analysis between two or more product systems, the functional unit shall give an unambiguous definition of the service or function that the compared product systems are providing.

8.2.3 Principles of comparisons between systems (comparative analysis)

In line with [1], in a comparative analysis between two AI product systems or an AI product system and a reference non-AI product system, the scope of the LCA study shall be defined in such a way that the two product systems can be compared. The functional unit shall be defined so that it is applicable to both product systems being compared. The two product systems shall be compared using the same functional unit and equivalent methodological considerations, such as performance, system boundary, data quality, allocation procedures and cut-off rules. Any differences between systems regarding these parameters shall be identified and reported.

The comparative LCA study is based on the selected functional unit which refers to the intended use case or intended output. For this functional unit, the system boundaries shall encompass all applicable life cycle stages and all components which are needed for providing the functionality as defined by the functional unit.

NOTE: The functional unit may refer to any attribute/function of the product system, not necessarily the primary functionality of the product system.

When the goal of the comparative analysis is to assess the difference of impacts between the two product systems, rather than the total impact of each product system, processes or input/output data may be excluded if they are the same in both product systems.

Depending on the situation (as described in clause 8.1.2), the system boundaries in a comparative LCA involving an AI product system could be set according to the examples in Table 2.

Table 2: Assessment boundaries for example comparative analysis cases in different situations 1 to 3

<table>
<tr><th>Situation</th><th>Product system 1</th><th>Product system 2</th><th>Parts to be included in full comparative analysis</th></tr>
<tr><td>1</td><td>Full AI system, e.g. LLM system</td><td>Full AI system, e.g. another LLM system</td><td>AI components (ICT hardware and software)</td></tr>
<tr><td rowspan="4">2</td><td>AI-embedded ICT service, e.g. AI enhanced video conference</td><td>Non-AI-embedded ICT service, e.g. regular video conference</td><td rowspan="4">AI components (ICT hardware and software) and
non-AI ICT components (note 1)</td></tr>
<tr><td>AI-embedded ICT service, e.g. LLM enhanced video conference services or Web search with non-generative AI</td><td>AI-embedded ICT service, e.g. another LLM enhanced video conference services or Web search with generative AI</td></tr>
<tr><td>AI-embedded ICT good, e.g. AI capable smartphone</td><td>Non-AI-embedded ICT good, e.g. regular smartphone</td></tr>
<tr><td>AI-embedded ICT good, e.g. AI capable smartphone</td><td>AI-embedded ICT good, e.g. another AI capable smartphone</td></tr>
<tr><td rowspan="2">3</td><td>AI-embedded non-ICT good, e.g. AI smart washing machine</td><td>Non-AI-embedded non-ICT good, e.g. regular washing machine</td><td rowspan="2">AI components (ICT hardware and software),
non-AI ICT component and
non-AI non-ICT components according to non-ICT LCA (notes 1 to 3)</td></tr>
<tr><td>AI-embedded non-ICT good, e.g. AI smart washing machine</td><td>AI-embedded non-ICT good, e.g. another AI smart washing machine</td></tr>
<tr><td colspan="4">NOTE 1: AI components are included as long as AI is needed to provide the functionality as defined by the functional unit in the comparative assessment.
NOTE 2: For non-ICT LCA, sectoral specific LCA guidance is privileged if available, otherwise, the practitioner may consider simplified assessments (e.g. using physical proxies such as the weight, using economic input output approaches).
NOTE 3: For the example of the (AI smart or regular) washing machine, non-ICT components include for instance water pumps, drain-pipes, valves, motor, agitator/impeller, etc.</td></tr>
</table>

Another example of Situation 3 is a comparative assessment between an AI-embedded smart fridge (see example description in clause 8.1.2) and a regular fridge. In this comparative assessment example, AI components and non-AI ICT components would be included in the assessment depending on how the functional unit is defined by the practitioner. See clause 8.1.2 for different example alternatives for the functional unit for this example and whether AI components would be considered within the assessment boundaries. The comparative assessment setup is shown in Figure 6.

8.2.4 Methodological framework of comparative analysis for an AI system

The procedures for comparison between two product systems contain the steps defined in clause 12.4 of [1]. These are:

- Definition of goal, functional unit and scenarios.
- Definition of system boundaries for each product system.
- Life cycle inventory including data collection for each product system.
- Life cycle impact assessment for each product system.
- Life cycle interpretation including comparison.

8.3 Evaluation of second- and higher-order effects coming from the use of AI

8.3.1 Scope of this clause: clarification of the term "use"

The term "use" of AI as considered in [1] on life cycle assessments, taken up in the previous parts (see clauses 8.1 and 8.2) of the present document are about the AI system (or the various AI systems used to provide a service) itself during its use: deployment, energy consumption, monitoring, re-evaluation and improvements, etc.

The aim of clause 8.3 is to assess the GHG emission impact of the consequences of this AI system use on the user's third-party processes, using the methodology described in Recommendation ITU-T L.1480 [2], which is based on the study of the consequences of AI system use by the user under study (these consequences are usually represented by drawing up a consequence tree). It therefore does not concern the carbon footprint of the AI system solution itself, which is a first-order effect whose assessment is described in clauses 8.1 and 8.2, but rather focuses on the consequences of its use in relation to a reference situation (second- and higher-order effects).

NOTE: At the time of writing the present document, the methodology in Recommendation ITU-T L.1480 [2] gives guidance on GHG emissions. Expansion to other environmental impact categories is left for the practitioner or for future development.

Annex E describes one example of a consequence tree for a specific AI use.

8.3.2 Specific elements of the assessment of the GHG impact of AI system use

8.3.2.1 General

The evaluation of the use of an AI system by a user shall follow the steps described in clause 10, Figure 1 of [2].

When carrying out this assessment, attention should be paid to the following points in clauses 8.3.2.2 to 8.3.2.7 of the present document.

8.3.2.2 Identifying the user and specifying the intended use

A user (or users) shall be clearly identified, so that analysis of usage (second-order effects) and changes in behaviour including rebound effects (higher-order effects) can be carried out to provide the data required for evaluation.

8.3.2.3 Precise knowledge and description of the AI system use case studied

It is also advisable to be precise about the AI system use evaluated, which should be sufficiently circumscribed to carry out an evaluation based on actual observation of the user behaviour for this use.

In particular, it is recommended to consider a typology of different services provided by an AI system, in terms of how they are used (e.g. a Chatbot to advise customers, or do automatic dubbing in real time, replace voices, generate "deepfakes", analyse code, summarize documents, etc.) in order to precisely describe the type of usage studied with the identified user.

8.3.2.4 Identifying consequences unrelated to GHG emissions (i.e. non-GHG consequences)

If the use of an AI system has consequences that change GHG emissions, this use is also likely, probably more than with many other categories of ICT solutions, to generate non-carbon consequences, whether environmental (biodiversity or mineral or water resources, etc.) or of a different type, such as societal or economic (health, safety, employment, etc.).

It is therefore advisable to identify them, whatever their type, in the consequence tree (see clauses 11.2.6 and 11.2.7 of Recommendation ITU-T L.1480 [2]: "*Each identified consequence that has a GHG effect should be included. Moreover, non-GHG environmental consequences should also be added to the consequence tree(s)*").

8.3.2.5 Definition of the reference situation

The reference situation (see clause 10.2.5 in [2]) used as a baseline shall be credible and up-to-date.

In particular, in the case of a historical reference situation, the definition of the reference situation shall be based on actual observation of the AI system user's usage before they start using it.

This may involve, for example, the use of conventional computer search methods based on search engines or chatbots, or the previous use of another AI system or another type of AI (switching from non-generative to generative AI, for example).

The user's sector of activity shall be specified (agriculture, mobility, energy, construction, household, etc.) and the observation of impacts shall be justified, in particular the absence of cherry picking.

8.3.2.6 Assessing the second-order effects of AI system use

When observing and measuring the usage data required for the assessment, it is important to specify the types of application concerned, in particular whether they are intended to replace digital services or generate new uses.

Particular attention needs to be paid to the immediate organizational effects, linked to the implementation of an analysis level offering a degree of autonomy to the AI system. For example, the analysis of a medical X-ray by an AI system replaces a first-level (doctor) specialist and is then confirmed and checked by a second-level (human) specialist.

Each consequence shall be analysed from the point of view of the evolution of the service provided compared to the previous situation.

8.3.2.7 Assessing the higher-order effects of AI system use

These higher-order effects of AI system use include deferred effects, not directly linked to the implementation of the AI system solution, albeit resulting from the adaptation of third-party processes to the presence of the AI system in the causal chain.

In this respect, particular emphasis should be placed on the impacts of the AI system on the organization of this entire causality chain (suppliers, raw material producers, reorganizations, social changes, etc.) and then identify those with GHG consequences so that they can be submitted for assessment.

This part of the assessment dealing with higher-order effects should, perhaps more crucially than with other ICT solutions, be monitored over time, partly because of its rapid evolution, and partly because of the potential magnitude of its effects on social organizations and their relationship with the environment.

Annex A (informative):
Other initiatives on environmental impact of AI

Some other initiatives on this topic include the following (list is not exhaustive):

- ISO/IEC JTC1 SC42 published in 2025 a technical report ISO TR 20226 "Information technology — Artificial intelligence — Environmental sustainability aspects of AI systems". This report describes aspects that cause environmental impact in AI systems.
- CEN/CENELEC JTC21 has been drafting a standard on "Sustainable Artificial Intelligence – Guidelines and metrics for the environmental impact of artificial intelligence systems and services". This is called on the shorter name "Frugal AI". Work has been ongoing since autumn 2024, and the official WI was approved in autumn 2025.
- IEEE™ P7100 is working on a framework for the environmental impact of AI. The title is "Standard for Measurement of Environmental Impacts of Artificial Intelligence Systems". The work is ongoing in autumn 2025.
- Other organizations have published frameworks for AI. One example of such is UNESCO's framework on AI: https://www.unesco.org/en/artificial-intelligence/recommendation-ethics.
- France organized a Summit on AI in February 2025. The Coalition for Sustainable AI was announced in that event with three co-founders: France, ITU and UNEP. https://www.sustainableaicoalition.org/.
- Green Software Foundation: Software Carbon Intensity for AI - A proposed specification that extends the existing Software Carbon Intensity (SCI) standard to help AI practitioners measure, understand, and reduce the carbon footprint of AI systems through informed choices about model design, computational efficiency, and deployment. https://greensoftware.foundation/articles/sci-for-ai-workshop-report.

Annex B (informative): Examples of impacts from Open-source development of AI systems

Open-source AI systems follow the same AI system life cycle stages but exhibit distinctive patterns due to transparency, community collaboration and public model weights.

Stage-specific remarks:

- Inception: requirements are crowdsourced through mailing lists, issue trackers and community RFCs, often leading to broader societal objectives.
- Design & development: code, data-cards and training scripts are public; contributors propose pull requests that may optimize compute efficiency. Energy-profiling logs are typically published.
- Verification & validation: transparency enables external audits: community benchmarks and red-team bug bounties reduce hidden defects.
- Deployment: model weights are released on open hubs. Mirror downloads and torrent seeding create significant network traffic that should be inventoried.
- Operation & monitoring: down-stream users fine-tune or quantize the base model for edge or on-device inference. Hardware diversity requires collecting device-specific power data.
- Continuous validation: community submits evaluation reports and patch releases; popular repositories run nightly CI that re-tests bias, toxicity and accuracy, constituting additional compute load.
- Re-evaluation: foundation-model stewards periodically assess whether refreshed datasets or new guard-rail techniques are required.
- Retirement: even when the original maintainers stop, forks may continue. Responsibility for data deletion and hardware disposition should be clarified; IT asset disposition certificates should reference both the original and forked projects.

Additional remarks for allocation:

- Distributed Compute: Community pre-training and fine-tuning may span over multiple cloud regions. Record region-specific grid emission factor values and avoid double-counting upstream impacts.
- Checkpoint Distribution Traffic: For large language models publicly released, include network energy for every download from model hubs or mirrors; model cache layers separately where data exists.
- Transparent Logs: Open repositories often publish training durations, hardware types and energy logs. Treat these as preferred primary data sources.
- Hardware Heterogeneity: Community fine-tuning may use consumer GPUs, TPUs or CPUs. Collect device-specific power data.

Annex C (informative): Example of LCI data for an AI system

Table C.1 lists some example parameters to collect in addition to the generic ICT data required by Annex B of [1].

Table C.1: Example of an AI system -specific data to collect

AI life cycle stage	Parameter (unit)	Typical source
Inception	CPU/GPU-hours (h), PoC energy (kWh)	Cloud usage export, local meters
Design and development	• GPU/TPU-h, avg power (W) • Training FLOPs • Data processed (TB), CPU-h	Scheduler logs, power distribution unit logs, foundry EPD (e.g. EPD published by a semiconductor foundry covering the fabrication of silicon wafers or dies produced at a given technology node)
Verification and validation	Validation runs (-), simulation core-h, test-set size (TB), kWh	CI/CD pipeline
Deployment	Container/VM image (GB), data transfer (GB), staging-cluster kWh, throughput (tokens/second), latency (response time), tokens processed (input + output)	DevOps pipeline
Operation and monitoring - Data centre	Inference requests h^{-1}, accelerator utilization %, IT-kWh; PUE, WUE, renewable %	Data centre management systems, cloud APIs
Operation and monitoring - edge	Device count, Pactive & Pidle (W), active time (h), update size (MB)	Device telemetry
Continuous / federated learning	Update frequency, re-training kWh, client kWh	Server & client logs
Retirement	Mass of servers/GPUs/edge devices by fate; data sanitization kWh	IT asset disposition certificates

Annex D (informative): Analysis of the functional unit examples against the set criteria

The examples for AI system functional unit in clause 8.1.2.2 are analysed in Table D.1 against the criteria in clause 8.1.2.2.

Table D.1: Functional unit examples analysed against defined criteria

Criteria\Example	Text generation: X prompt tokens & Y generated tokens	Image generation: X bytes	Automatic speech recognition: X bytes of audio recording	Video generation: X bytes of video	Network management: traffic prediction for network element shut-down/ramp-up
Defines the performance characteristics delivered by the AI system being studied [1]	Yes: X prompt tokens & Y generated tokens	Yes: X bytes	Yes: X bytes of audio recording	Yes: X bytes of video	Yes: traffic prediction for network element shut-down/ramp-up
To have a function [1], (what) [i.9]	Yes: Text generation	Yes: Image generation	Yes: Automatic speech recognition	Yes: Video generation	Yes: Network management
To have a quantifiable unit measuring the performance of that function [1], (how much) [i.9]	Yes: X prompt tokens & Y generated tokens	Yes: X bytes	Yes: X bytes of audio recording	Yes: X bytes of video	N/A, see note 1
For what duration (how long) [i.9]	N/A, see note 2	N/A, see note 2	N/A, see note 2	N/A, see note 2	N/A, see note 2
To what quality (in what way and how well is the function provided) [i.9]	N/A, see note 3	Yes: X bytes (contains also the quality of the image)	Yes: X bytes of audio recording (contains also the quality of the automatic speech recognition)	Yes: X bytes of video (contains also the quality of the video)	N/A, see note 3
NOTE 1: In network management, it is difficult to set a numeric value for targeted shut-down & ramp-up since it depends on the traffic profile of the network. NOTE 2: The criteria for duration (how long) are not fulfilled with the current examples. However, it does not seem relevant for image generation of X bytes or the other examples, since the time spent is not the most critical aspect in these tasks. They take the time that they take to complete the task. For network management example, duration would add the tasks comparability in case of comparative analysis. NOTE 3: Some of the examples contain quality implicitly in the number of bytes. For text generation, quality is not included in the functional unit, but it is also difficult to define what qualifies as a quality for text generation. Would it be easy to read, without grammatical errors, interesting to read, or no hallucination? Also, for network management, the quality of the function is tricky to define. An accurate enough traffic prediction could be considered as being implicitly in the functional unit. Another quality could be some percentage level of correct shut-down & ramp-up decisions.					

Annex E (informative): Example of a consequence tree for a specific use of an AI system

The example presented here illustrates a consequence tree in Figure E.1 resulting from a specific use of an AI system, namely:

- Assessing the GHG effects of the use of AI by developers (coders) who create ICT solutions for the company and the industry that employs them.

NOTE 1: This tree is generic in that it does not specify the consequences which vary depending on the sector of activity and the company for which the developers work, particularly those linked to the use by the company in that sector of the code produced using AI.

In particular, using AI for coding could enable certain sectors and companies to offer products and services that would otherwise be inaccessible without the use of AI for coding, such as optimized autonomous vehicles traveling at high speeds or in hostile or difficult environments, on-the-fly production of high-definition 3D videos, or real-time generation of digital twins or digital terrain models.

These consequences, which depend on the sector in which the code generated with the help of AI is used and on the actual use made of it by the company employing the developers, are described in general terms in Consequence 3b1d.

NOTE 2: The section relating to the GHG impacts associated with the existence and operation of the AI system itself, the impacts of which are independent of the actions of its users but include the maintenance phase during its use (see clause 8.1, Figure 4), has been summarized by its mention in Consequence 1a.

Figure E.1: Example of a consequence tree: use of AI by developers (coders) who create ICT solutions for the company and industry that employs them

Tables E.1 to E.4 describe the effects shown in the consequence tree in more detail.

Table E.1: First-order effects

Name of the consequence	Description
1a. Part allocated, according to usage, of the AI life cycle (see clauses 8.1 and 8.2).	Share of the life cycle footprint of the AI system used by developers, allocated according to its use by these coders. See note 1.
1b1a. Change in local hardware configuration (terminals, LAN, etc.)	Changes made necessary by the use of AI in the physical environment of coders, for example, modifications to the power of terminals and servers, or changes in the capacity of access networks, including local ones.
1b1b1. Purchasing, downloading, and installing the AI application in the code editor	Developments in AI integration into code editors, necessary for using AI to code.
1b1b2. Creating libraries, wizards, and inserting the project context	Changes in project preparation operations are required for coding due to the use of AI.
1b1b3. Auto-completion: interaction with the Chatbot	Change in requests for the use of the Chatbot used by developers. See note 2.
1b2. Change in network usage to access AI resources	Changes in transmission network usage due to the use of AI resources.
1b3. Change in the use of data centres for coding with AI	Proportion of data centre usage where AI is operated and maintained, based on usage by company coders for the project studied in these data centres.
NOTE 1: The various elements of this GHG footprint are not detailed in the tree. NOTE 2: A dedicated Chatbot may not be available in some companies employing developers.	

Table E.2: Second-order effects

Name of the consequence	Description
2a1a1. Changes in forum traffic and questions	Changes in the use of developer forums, both in terms of how they are consulted and the type of questions asked and how they are handled.
2a1a2. Evolution in requests made from a browser	Changes in the use of "traditional" information search queries.
2a1a3. Changes in visits to documentation libraries for software	Changes in the report and use of library documentation intended for coding, both in terms of volume and time spent, as well as the type of information sought.
2a1b. Evolution of the reuse of pre-existing code	Change in developers' habits regarding the reuse of existing code, both in terms of purpose and the level of trust placed in them.
2a2a1. Changes in posted messages	Changes in the volume and content of messages posted and exchanged between developers, and between them and the client of the company that employs them.
2a2a2. Connection trends	Modification of the use between developers of network exchange resources.
2a3a1. Changes in how code is tested	Changes in the test grids used to test AI-generated code versus conventionally generated code, and in error detection mechanisms and practices, particularly the search for errors of a different or new nature, which are often detectable at a later stage.
2a3a2. Change in how to debug and correct code	Evolutions in reflexes and techniques to correct identified errors and in the search to prevent the spread of new errors before the code is put into operation.
2a3b1. Change in time and activities spent generating code	Changes in the raw code generation for a defined task, before verification and corrections.
2a3b2. Changes in code execution time	Changes in the execution time of the finalized code, once it is put into operation at the customer's site or in the company employing the developers.
2b1. Evolution of security breach risks	Change in errors (flaws) discovered late, after the ICT solution based on AI-generated code was put into operation.
2b2. Changes in the choice of whether (or not) to use AI for coding by certain developers	Changes in developers' behaviour in their use of AI for coding, including, for some, a return to "AI-free" coding.

Table E.3: Higher-order effects

Name of the consequence	Description
3a1. Evolution of awareness and training in the use of the AI tool	Changes in developer training to incorporate specific requirements related to AI code generation.
3a2. Use of AI tools other than the one initially used in the company	Changes in developers' behaviour in their quest for efficiency, particularly the use of different AI systems and tools, and various sources other than those recommended by the company that employs them.
3b1a. Change in the nature of coded elements	Using AI to encode information enabling services that were not previously coded or were built differently.
3b1b. New products made possible in the industry sector in which the developer works	Developments in the products and services offered by the company that employs the developer to its customers, made possible by the use of AI for programming, whether in terms of the number of services (volume) or the type of services (new products).
3b1c. Modified exploration of code application domains	A shift in the developers' habits, who are testing coding capabilities in areas and dimensions that were previously unused or inaccessible, particularly to less experienced coders.
3b1d. Etc.: depending on the industry sector in which the developer using AI works	This consequence depends on the sector of activity, the business, and the product catalogue of the company employing the developer. It should be developed and adapted based on observation of the actual uses of the code once it is put into operation, and the effects of these uses, including the financial gains (or losses) of the user of the coded solution.
3b2. Evolution of continuing education for developers (professional skills) through AI-based learning	Changes in the training of developers from AI training itself to programming using this AI.
3b3. Change in customer requirements (specifications) to integrate AI into projects	Changes in the demands of the company's clients employing the developers, both in terms of volume and financial requirements, as well as the nature of the services and, consequently, the coding required.
3b4. Financial effects of developers' use of AI on the companies that employ them	Consequence of financial gains or losses of the company employing the developers, resulting from their use of AI. See note.
NOTE: The financial gains or losses of the user of the AI-programmed product are assessed in consequence 3b1d.	

Table E.4: Other effects, non-carbon effects

Name of the consequence	Description
4a. Gradual decline in expertise in coding without AI and decline of the recognition of this expertise within the company	Changes in the company's personnel management policy, which will place less value on coding skills without AI; correspondingly, a decline in these skills, which will become less sought after and less valued in favour of, for example, sharp code correction skills that are different in nature than before.
4b. Evolution of autonomy and skill acquisition among junior developers	Changes in the integration of young developers and in their uses and capabilities: for example, AI-facilitated use to code different (e.g. more ambitious or complex) projects than previously. See note.
4c. Changes in workload and its effects	All changes to working conditions resulting from the use of AI.
4d. Evolution of interaction and sharing of best practices on AI among developers	Any change brought about by the use of AI in developer relations, with no impact on GHG emissions.
NOTE: The GHG effect of this evolution itself of programs generated using AI is measured among the higher-order effects of category 3b.	

History

Version	Date	Status	
V1.1.0	April 2026	MAP process	MV 20260607: 2026-04-08 to 2026-06-08