Responsible procurement of artificial intelligence (AI) solutions

Environmental
Best Practices Guide

ceimia futurearth IVADO

Executive summary

Artificial intelligence (AI) generates significant environmental impacts throughout its life cycle, the main ones being: greenhouse gas emissions linked to energy use, water consumption, depletion of mineral resources, land use, and toxicity linked to poor management of electronic waste. The impacts, both direct and indirect, are growing, and are directly tied to the technology choices made by organizations that acquire or deploy AI solutions. The public sector, as a major buyer, has a concrete lever to steer the market toward more responsible practices.

This document is intended for procurement specialists and teams involved in acquiring AI solutions within public bodies — and, more broadly, for any organization wishing to incorporate environmental criteria into its purchasing processes. It presents 48 best practices organized into six sequential steps, ranging from defining the need through to measuring performance:

1. Define and challenge the need for AI
2. Establish a responsible governance framework
3. Anticipate the potential impacts of AI
4. Prepare the statement of requirements
5. Train teams on the framework for AI use
6. Measure and disclose the solution's performance

The accessibility of these practices varies with each organization's own resources, organizational maturity and digital literacy. From this standpoint, **this document does not aim for perfection but for progress: every practice** implemented represents a real gain. The goal here is to move forward at whatever pace matches each organization's capacity, prioritizing high-impact, low-effort actions **and gradually broadening the approach from there.**

A summary matrix and a checklist are available in the appendix. The matrix presents all the best practices along with, for each one, an ease-of-implementation rating and a potential environmental-impact-reduction rating. Organizations wishing to set priorities are encouraged to consult it to identify the first actions best suited to their context.

In this regard, every step of the process includes practices that offer a particularly favourable effort-to-impact ratio — concrete starting points for organizations that wish to make progress without feeling overwhelmed. Here are a few examples:

Define the need (§ 3.1)

Clearly stating and documenting the problem being addressed (§ 3.1.1) is a simple but foundational action: it prevents unnecessary acquisitions, which are themselves a source of avoidable impact. Assessing the positive and negative effects of different solutions before settling on AI (§ 3.1.4) is also possible and helps avoid deploying a technology where a lighter-weight solution would do.

Establish a governance framework (§ 3.2)

Establishing a clear record of responsibilities — who is responsible for what across the acquisition and deployment chain — (§ 3.2.4) is a practice that is technically undemanding but critical to ensuring consistent oversight over time.

Anticipate impacts (§ 3.3)

Ensuring that the AI solution under consideration is compatible with existing IT equipment in order to avoid premature hardware renewal (§ 3.3.2), is a step within reach of any organization, with high potential for reducing impact. Carrying out a qualitative assessment of environmental impacts as early as the design phase (§ 3.3.1) does not require significant specialized resources and lays the groundwork for informed decision-making.

Prepare the statement of requirements (§ 3.4)

Requiring that the solution be hosted in a region with a low-carbon electricity mix (§ 3.4.5) is a criterion that is simple to formulate in a call for tenders, requires no in-depth technical expertise, and carries among the highest environmental leverage of any practice in this guide.

Train teams (§ 3.5)

Encouraging users to minimize the number of queries submitted to AI (§ 3.5.3), and raising their awareness of the most energy-intensive features—such as image generation or complex reasoning tasks — (§ 3.5.4) are actions that require no prerequisites and can be taken immediately, and whose cumulative effect across an organization can be considerable.

Measure and disclose performance (§ 3.6)

Making sure the AI model remains lean and high-performing once deployed, by defining monitoring indicators with the supplier (§ 3.6.1), and planning a process to periodically re-examine the need over time, to avoid becoming dependent on tools that have become oversized for their purpose (§ 3.6.3), are two moderate-effort practices that anchor the approach for the long term.

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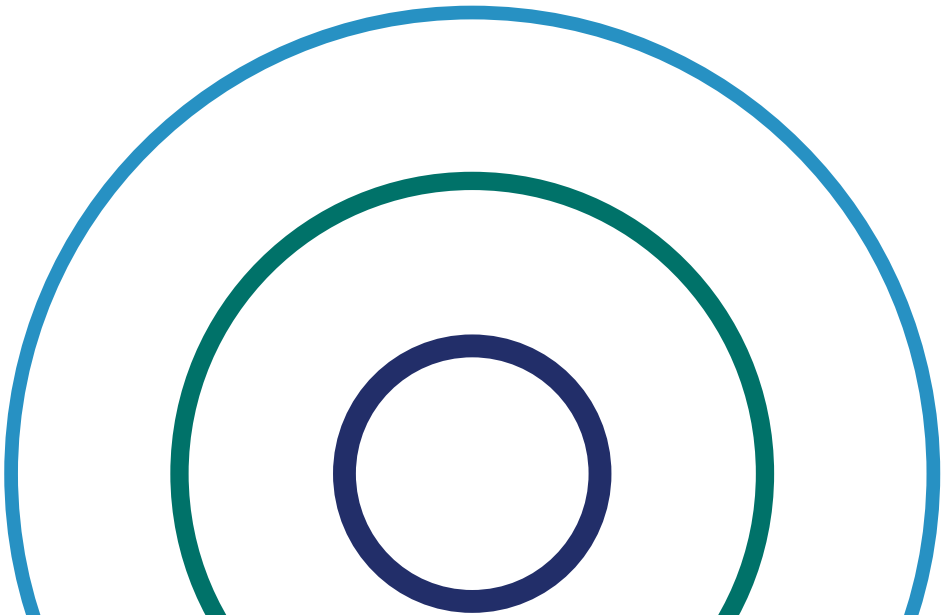
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Abbreviations and acronyms

AI	Artificial intelligence
AIA	Algorithmic impact assessment
CEST	Commission on Ethics in Science and Technology
CNIL	National Commission for Information Technology and Civil Liberties (France)
CPU	Central Processing Unit
CUE	Carbon Usage Effectiveness
GenAI	Generative artificial intelligence
GHG	Greenhouse gas
GPU	Graphics Processing Unit
HDD	Hard Disk Drive
IEA	International Energy Agency
ISO	International Organization for Standardization
IT	Information Technology
ITU	International Telecommunication Union
LCA	Life cycle assessment
LLM	Large Language Model
OECD	Organisation for Economic Co-operation and Development
OQLF	Office québécois de la langue française
PUE	Power Usage Effectiveness
RAG	Retrieval-Augmented Generation
REF	Renewable Energy Factor
SLM	Small Language Model
SME	Small and medium-sized enterprises
SSD	Solid State Drive
UN	United Nations
WUE	Water Usage Effectiveness

Introduction

The ***Énoncé de principes pour une utilisation responsable de l'intelligence artificielle par les organismes publics [Statement of Principles for the Responsible Use of Artificial Intelligence by Public Bodies]*** constitutes the appendix provided for under Order 2025-02 of December 3, 2025 (Gouvernement du Québec, 2025). Under the sustainability principle (#6) set out therein, the responsible use of artificial intelligence (AI) systems must be pursued as part of the search for sustainable development. It specifies that the Statement's principles apply even when a public body relies on suppliers and service providers for AI systems or in connection with them, which makes compliance with the Statement of Principles a procurement issue, since the pursuit of sustainable development must also be ensured by suppliers.

To support public bodies, or any other organization interested in acquiring AI solutions in a sustainable manner, this document presents responsible procurement best practices aimed at mitigating the negative environmental consequences of using AI. Indeed, while this technology offers significant possibilities in terms of technological efficiency — which is why the Gouvernement du Québec adopted its Stratégie d'intégration de l'IA dans l'administration publique 2021-2026 *[Strategy for Integrating AI into Public Administration 2021-2026] (Treasury Board Secretariat, 2021)* — AI also brings environmental risks throughout its life cycle that must be taken into consideration in order to comply with the principle of sustainability. As the Strategy states, "the question of sustainable development is at the heart of the reflection surrounding AI, which must enable better use of resources from a sustainability perspective, whether in terms of factoring environmental impact into AI applications, or the ecological footprint of the necessary technological infrastructure" (Treasury Board Secretariat, 2021, p.9).

The ethical, social, operational and governance risks associated with AI are now well documented, and several reference frameworks offer guidance to steer responsible adoption.

However, the environmental impacts of AI solutions are addressed less often, even though they are significant, growing, and directly tied to the technology choices made by organizations. This document aims to fill that gap. It is intended primarily for procurement specialists and teams involved in acquiring AI solutions developed by external suppliers. Its goal is to provide clear, actionable information to support purchasing decisions that take environmental issues into account across the entire AI life cycle. The social and ethical issues connected to the information provided in this document are addressed briefly.

Although this document is tailored to the public-procurement context, the information it presents is also relevant to the private sector.

The first section of this document is devoted to understanding AI and its environmental and social impacts. The second section provides procurement best practices to adopt in order to reduce these impacts. It can serve as a reference base for subsequently defining concrete responsible-procurement criteria and practices.



1. Understanding AI and its impacts

1.1. Definitions and concepts of AI

The Organisation for Economic Co-operation and Development (OECD) defines AI as "a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions" (OECD, 2025, p.7–8). This is the definition used by the Gouvernement du Québec (2025). The Office québécois de la langue française (OQLF) further specifies that an AI system is designed to simulate the cognitive faculties of human intelligence (OQLF, 2026).

While AI has evolved rapidly in recent years, its origins go back several decades. **Traditional (or symbolic)** AI emerged in the 1960s, based on fixed rules pre-established through programming (statistics, decision trees, expert systems, etc.).

In the 1980s and 1990s, *machine learning* marked a turning point: the system learns from data rather than coded rules, adapting and improving over time. This gave rise in particular to *predictive AI*, capable of forecasting future events by analyzing past trends. In the early 2010s, *deep learning* emerged, based on neural networks organized in layers. This approach transformed many fields, such as computer vision and the processing of natural language, but it also made models increasingly opaque in terms of explainability.

The sector has since undergone rapid development. These advances led, in the 2020s, to the rise of generative AI (GenAI), capable of creating new content (text, images, videos) from existing data (HEC Montréal, 2024). Since the arrival of *generative AI*, AI has seen very significant deployment and adoption. Today, more than half (50%) of internet users in Québec have already used AI, a significant share of them daily (Académie de la transformation numérique, 2025). These trends could continue in the coming years, with the arrival of a new type of AI, agentic AI, capable of reasoning and interacting autonomously with its environment, with little human supervision.

In short, uses of AI keep evolving, and its adoption rate is rising. However, this growth comes with environmental and social impacts that may not be sustainable in the years ahead (The Shift Project, 2025). The rest of this section presents the AI life cycle. Section 2 presents its environmental and ethical issues, focusing on machine learning and deep learning.

1.2. AI life cycle

The life cycle of an AI system[1] can be described from a technological or a physical standpoint. The technological life cycle refers to the steps required to deploy an AI system, and the physical life cycle refers to the life cycle of the physical infrastructure an AI system relies on.

1.2.1. Technological life cycle

The technological life cycle of an AI system is made up of several stages:

1. planning and design;
2. data collection and processing;
3. building the model(s) and/or adapting existing model(s) to specific tasks;
4. testing, evaluation, verification and validation;
5. release for use/deployment;
6. operation and monitoring; and
7. decommissioning (OECD, 2025).

When looked at from the standpoint of

1. Here, the term "AI system" covers only the life-cycle stages involved in operating the artificial intelligence itself. AI may sometimes be integrated into other digital services, or into non-digital goods. For example, it may be embedded in a website (another digital service) or in a self-driving car (a non-digital good). The life cycle of these other goods and services is not, however, the subject of this document.

environmental impacts, this technological life cycle can generally be summarized in three main stages:

- **Training,** which takes place during model building. Training allows the AI system to build and adapt its model based on the data it learns from. Training methods differ between machine learning and deep learning.
- ***Inference,*** which takes place during the operation and monitoring phase. This refers to use of the AI system by users after it is deployed. During inference, instructions are sent to the AI system so that it generates a response. These instructions are called queries (or prompts).
- **Retraining,** which also takes place during the operation and monitoring phase. To maintain its performance while in use, a model must be retrained on new data. This retraining can happen continuously or at regular intervals while the model is in operation.

For the rest of this document, the term "(re)training" will be used to refer to both training and retraining of the model.

Finally, AI draws on large volumes of data throughout its life cycle: data to develop the model during training, other data to measure its performance, and then new data, gathered while it is in use, to update it regularly. This data often has to be sorted and prepared through human intervention (annotation, deduplication, structuring, etc.) (International Telecommunication Union [ITU], 2026).

1.2.2. Physical life cycle

Carrying out each of the technological life-cycle stages (training, inference, retraining) described in section 1.2.1 relies on a physical infrastructure made up of three layers: data centres, networks, and user devices.

Data centres process and host digital data. This infrastructure brings together various IT equipment that handles computing and data processing, storage, and network connectivity. Computing and processing rely on servers made up of Central Processing Units (CPUs) and/or other specialized components, such as Graphics Processing Units (GPUs), on which (re)training and inference for the AI system take place.[2] Data, for its part, is kept in storage arrays, made up mainly of Solid State Drive (SSD) and Hard Disk Drive (HDD) disks.

To ensure it runs properly, a data centre is also made up of so-called "non-IT" equipment. This includes the cooling system(s), which dissipate heat from the servers, and other auxiliary infrastructure (e.g., the building, backup generators and batteries, video surveillance) (Groupement CLIQ et al., 2026).

Networks, the second layer of digital infrastructure, carry data between data centres and user devices. The main types of networks are fixed networks (cables, Wi-Fi, optical fibre, etc.), which offer localized access through a wired connection, and mobile networks (3G, 4G, 5G, etc.), which rely on relay antennas and cover a wide area (ADEME, 2024).

Finally, user devices (smartphones, computers, screens, etc.) make up the last layer of digital infrastructure. They allow people to access and use an AI service.

Each layer of the physical infrastructure requires IT equipment and hardware. The life cycle of this equipment, including its manufacturing, distribution, use, and end-of-life processing, is responsible for many of the environmental impacts described in section 2.

2. An AI system can be hosted in a data centre and accessed via a separate device, but it can also be hosted and run locally on the device itself (embedded AI). Only the first configuration is examined in this document.

2. Environmental and social impacts of AI

The environmental impacts of AI can be split into direct and indirect impacts. Direct impacts are those associated with the physical existence of the infrastructure that supports AI throughout its life cycle (manufacturing, distribution, use, and end of life). Indirect impacts are tied to the changes in uses, behaviours and economic systems that AI use brings about (Commission de l'éthique en science et en technologie [CEST], 2024).

2.1. Direct environmental impacts of AI

The environmental footprint of an AI system is often dominated by the inference stage, followed by training and retraining (Desroches et al., 2025; Berthelot et al., 2024). The use of AI is responsible for various direct environmental impacts, the main ones being presented in the table opposite and detailed further in the following subsections. These direct impacts are, by definition, negative.

Table: Summary of the direct environmental impacts of AI

Type of direct impact	Consequence
Energy consumption and climate change	Negative
Depletion of mineral resources	
Water consumption	
Land use	
Toxicity of electronic waste	

Several technological factors influence the scale of these environmental impacts. These are discussed in the best practices for procuring AI solutions (section 3).

2.1.1. Energy consumption and climate change

While operating, data centres consume large quantities of electricity. For 2025, global electricity consumption by data centres was estimated at 448 TWh. As the United Nations (UN) notes, "if data centres were a country, their electricity consumption would rank them 11th in the world" (Aczel et al., 2026, p.10). That same year, the share of electricity consumption attributable to AI servers specifically was already significant (about 20%). At the current pace, data centre electricity consumption could double by 2030, with AI accounting for 40% of that consumption (Aczel et al., 2026).

This consumption is mainly explained by the use phase of CPUs and GPUs, which dominates their impact across their entire life cycle (roughly 70 to 90% of their climate-change impact) (Falk et al., 2025).

The cooling systems needed to dissipate heat from the servers also account for a significant share of data centre energy consumption (between 7 and 30%) (International Energy Agency [IEA], 2025). Indeed, the cooling needed to remove heat from the servers is often provided by energy-intensive air-conditioning systems.

Finally, although less energy-intensive (around 5% of a data centre's electricity consumption) (IEA, 2025), data storage could have a significant impact on climate change in the years to come. Indeed, the financial and time constraints involved in collecting and processing data (annotation, deduplication, structuring) mean that it is rarely deleted. Its volume, therefore, keeps growing, further increasing storage and electricity needs (Sveinsdottir et al., 2020).

Today, most data centres are located in regions where electricity is highly carbon-intensive. More specifically, 90% of data centres specialized for AI are concentrated in two countries, the United States and China, which contributes to climate-change-related impacts (Aczel et al., 2026).

Using the carbon intensity of the average global electricity mix, emissions generated by the operation of AI-specialized data centres would amount to about 40 million tonnes of CO_2 equivalent in 2025 (Aczel et al., 2026) — excluding other life-cycle emissions from data centres, as well as those from networks and user devices — which corresponds to nearly half of the greenhouse gas (GHG) emissions of the province of Québec (Environment and Climate Change Canada, 2026).

In addition, the rapid growth in AI-related energy needs could have significant consequences for competition over energy. On one hand, this demand risks drawing on a large share of the available low-carbon electricity, to the detriment of other sectors for which electrification is a key decarbonization lever (e.g., the transportation and industrial sectors). On the other hand, in order to meet rising electricity demand, several countries are massively developing or restarting infrastructure for fossil-fuel-based power generation (gas or coal), to the detriment of their climate commitments (The Shift Project, 2025).

Finally, beyond energy consumption during use, the manufacturing of IT equipment causes significant GHG emissions. At the data centre level, the production of its components (servers, storage arrays, power supplies, etc.) accounts for 20% of a data centre's total carbon footprint (The Shift Project, 2025; Schneider Electric, 2023). This proportion is even more pronounced for user devices: in regions with a low-carbon electricity mix, such as Québec, manufacturing is responsible for the majority (up to 85%) of GHG emissions generated over the life cycle of the device (ADEME, 2025; Istrate et al., 2024). This is mainly explained by the production of the semiconductors that make up electronic chips. Today, Taiwan accounts for 90% of the production of electronic chips intended for AI applications (Venne J.F., 2025). The manufacturing process is particularly energy-intensive, and Taiwan's electricity mix is highly carbon-intensive,[3] leading to substantial GHG emissions. These emissions rise with the growing demand for, and technological complexity of, electronic chips (Oueslati Y., 2026; Roussilhe G., 2024). The manufacturing process also involves the use of fluorinated gases with high global-warming potential (Roussilhe et al., 2024).

2.1.2. Depletion of mineral resources

The manufacturing of IT equipment contributes significantly to the depletion of mineral resources. Many metals go into the composition of IT equipment (servers, processors, batteries, electronic chips, etc.). Some of these metals, called rare metals, are consumed in small quantities but are essential for digital technology, notably cobalt and lithium (in batteries), indium (in screens), gallium and germanium (in semiconductors), and rare earth elements[4] (in magnets).

However, a large share of these metals are considered "critical" (Ollion et al., 2024), as their supply risks becoming restricted in the years ahead (Bureau de Recherches Géologiques et Minières, 2025). The list of metals considered most critical

3. The carbon intensity of Taiwan's electricity mix is about 500 gCO_2eq/kWh, roughly 14 times higher than Québec's (Electricity Maps, 2026). This metric reflects the GHG emissions resulting from producing one kilowatt-hour of electricity.

4. Rare earth elements are a group of 17 metals. They are strategic metals that are essential for manufacturing digital equipment. Despite their name, they are not necessarily rare.

for digital technology varies from one study to another, depending on the criticality factors used (e.g., uncertainty over the longevity of known reserves, availability of the metals, geopolitical risks affecting their supply). The fact that the AI sector, and the digital sector more broadly, uses these critical metals, and that this use is expected to grow in the future, further increases the risk of depleting these resources.

2.1.3. Water consumption

An AI system consumes water at three stages of its life cycle: during the manufacturing of the electronic chips that make up IT equipment (for devices, networks and data centres), during the generation of the electricity that powers data centres, and during the cooling of IT equipment in data centres.[5]

This water consumption is very high. The IEA estimates that in 2023, data centres consumed about 560 billion litres of water[6] worldwide (IEA, 2025), which is roughly the equivalent of 227,000 Olympic-sized swimming pools.

About two-thirds of this consumption is tied to energy production, one-quarter to cooling systems, and the rest to chip manufacturing. This consumption could double by 2030, with a growing contribution from cooling systems (IEA, 2025).

While air-conditioning-based cooling systems have long been favoured, water-cooling technologies are gradually developing[7] because of their significantly lower electricity consumption. However, this reduction in electricity consumption increases pressure on aquifers and the risk of water-use conflicts. Indeed, the water drawn for cooling is often potable and is sometimes drawn from regions where water resources are already under strain. Today, an estimated 45% of data centres worldwide are located in river basins with a high risk of limited water availability (The Shift Project, 2025). In addition, the water used by cooling systems is discharged either as gas, through evaporation, or as liquid. Although some of the discharged liquid water can return to the natural environment, it is often of lower quality (water contaminated by dust, chemicals and minerals, and at too high a temperature [Spindler et al., 2024]), which can affect aquatic ecosystems.

Lastly, water consumption tied to the manufacturing of IT equipment is poorly documented today, despite already-observable consequences. For example, Taiwan experienced a severe drought episode in 2021 due to a lack of rainfall combined with increased water use for semiconductor manufacturing (Conseil national du numérique et al., 2025).

2.1.4. Land use

Although not yet extensively studied, land use associated with AI is also a source of environmental impacts.

On one hand, the extraction of the natural resources needed to manufacture IT equipment causes major effects around mining sites, such as deforestation, groundwater pollution, habitat destruction and biodiversity loss (Government of Canada, 2025).

On the other hand, the rise of AI is driving the construction of more data centres. In 2026, about 11,500 data centres are active worldwide (Data Center Map, 2026), ranging in size from a few dozen to several thousand square metres each. These large buildings contribute to land artificialization, degrading surrounding biodiversity, especially when they are built near sensitive natural areas, such as wetlands (Dugas Bourdon, P., 2024).

Land use associated with data centres also stems from energy-production infrastructure (fuel extraction, renewable-energy infrastructure, etc.). In 2025, globally, 1,400 km^2 of land was occupied by such infrastructure to power AI-specific data centres, or about 23 times the area of Manhattan (Aczel et al., 2026). While renewable energy production reduces the carbon footprint compared with fossil fuels, it often comes with a larger land footprint.

5. Water consumption used by data centre cooling systems is called direct consumption. Water consumed during the generation of the electricity that powers the data centre, and for manufacturing IT equipment, is called indirect consumption (The Shift Project, 2025).

6. This water consumption corresponds to the amount of water withdrawn that is not returned to its original source after use (e.g., through evaporation) (IEA, 2025).

7. There are several types of cooling systems. Some technologies use air (air conditioning), others use liquid (e.g., immersing servers in a dielectric cooling liquid) or water (in an open or closed loop). Free cooling, which uses outside air to naturally cool servers, is also becoming more common (The Shift Project, 2025).

2.1.5. Toxicity of electronic waste

Finally, AI services contribute to the buildup of electrical and electronic waste (processors, GPUs, etc.). Although the environmental impacts of end-of-life disposal are smaller than those associated with manufacturing and use, only about 20% of this waste is properly collected and recycled worldwide (Baldé et al., 2024). As a result, most of this waste is landfilled, incinerated, or processed informally, which poses risks to the environment and human health, since this waste contains toxic substances (lead, mercury, cadmium, etc.) that can contaminate soil and water (Government of Canada, 2025). The new uses made possible by AI, combined with the growing number of devices equipped with AI systems, could accelerate device obsolescence and turnover, and thereby heighten these issues (The Shift Project, 2025).

2.2. Indirect environmental impacts of AI

Artificial intelligence is often presented as a lever for the environmental transition, notably through applications aimed at optimizing resource use, improving energy efficiency, or supporting environmental decision-making. This approach is referred to as AI for sustainability.

However, it is not enough for an AI application to improve a system's efficiency. On one hand, these potential benefits must be weighed against the direct environmental impacts specific to AI systems described in section 2.1. On the other hand, AI's indirect impacts must also be considered, and any negative ones minimized.

AI generates second- and third-order indirect impacts,[8] which are often harder to quantify, and which result from the changes AI brings about in economic systems, modes of production, and consumption behaviours (CEST, 2024). These impacts can be positive (i.e., yield an environmental gain) or negative (i.e., generate additional environmental impacts).

Among indirect impacts, the efficiency effect is the main positive effect: it corresponds to the impact reductions made possible when AI improves the efficiency of a system, a process, or resource use. The substitution effect, which occurs when one technology replaces another, can be positive or negative depending on the nature of the technology being replaced. Induction effects, tied to the creation of new uses made possible by the technology, can likewise be positive or negative: they generally increase demand for digital resources, but can also give rise to new uses that benefit the environment (Lange et al., 2023).

These impacts are, more broadly, accompanied by the direct rebound effect (also called the Jevons paradox). This term originally referred to an economic phenomenon whereby an improvement in a technology's efficiency reduces its cost of use, which leads to an increase in demand and, ultimately, in the overall consumption of resources (Luccioni et al., 2025a). However, the notion of the rebound effect is now understood more broadly and is not limited solely to economic mechanisms. More generally, it refers to the additional negative environmental impacts generated by the introduction of a technology into society, through the intensification of existing practices, which offset the technology's efficiency gains. In the case of generative AI, the rapid growth in usage is not explained solely by a drop in the cost of accessing AI, but also by the emergence of new possible uses (e.g., content generation, conversational assistance, task automation), which encourage more frequent and intensive use of AI. This intensification of use, in turn, places greater demand on digital infrastructure. Beyond data centres, communication networks, particularly mobile networks, must thus cope with rising data traffic and growing technical performance requirements, further heightening their negative environmental impact (The Shift Project, 2025).

The rebound effect can also occur indirectly: it is called the indirect rebound effect and is linked to the reallocation of efficiency gains toward other forms of consumption. For example, savings achieved through AI-driven automation can be reinvested in more emissions-intensive activities, such as travel (negative indirect rebound effect), whereas an AI application aimed at raising awareness of transportation's environmental impact could, conversely, encourage more environmentally friendly behaviour (positive indirect rebound effect). The indirect rebound effect can, in particular, manifest as behavioural, time-related or geographic changes (Luccioni et al., 2025a). For

8. Second-order effects concern the use of digital technologies for environmental purposes, while third-order effects refer to the consequences of digital technology on ways of life (CEST, 2024).

example, the growth of remote work supported by digital tools can reduce certain trips, while at the same time increasing digital infrastructure needs and residential energy consumption.

At a broader scale of analysis, the scale effect refers to the increase in impacts resulting from the mass rollout of a technology: a technology may be more efficient at the individual-unit level, yet its large-scale deployment can nonetheless increase its overall impact because of the growing volume of use. Systemic effects go further, reflecting deeper transformations of economic and social systems (i.e., changes in value chains, and in modes of production or consumption), and remain particularly complex to anticipate and quantify (CEST, 2024).

As such, AI systems can generate both positive and negative indirect environmental impacts, summarized in the table below. The balance between them is difficult to establish. These indirect impacts, just like direct impacts, must be taken into account when assessing the environmental benefits of an AI solution.

Table: Summary of the indirect environmental impacts of AI

Type of indirect impact	Definition	Order	Consequence
Efficiency effect	Reduction in impacts made possible by improving the efficiency of a system, process, or resource use.	2nd	Positive
Substitution effect	Replacement of one technology/activity by another.	2nd	Positive or negative
Induction effects	Creation of new uses made possible by the technology.	2nd	Positive or negative
Direct rebound effect (Jevons paradox)	Drop in the cost of use, linked to an efficiency gain, which leads to an increase in demand and overall consumption.	2nd	Negative
Scale effect	Increase in impacts linked to the mass rollout of a technology, even if each unit is more efficient.	2nd	Negative
Indirect rebound effect	Reallocation of efficiency gains toward other forms of consumption.	3rd	Positive or negative
Behavioural and time-related effects *(a manifestation of the indirect rebound effect)*	Reallocation of time or habits freed up by AI toward other activities.	3rd	Negative (generally)
Geographic effects *(a manifestation of the indirect rebound effect)*	Transformation of the physical organization of activities.	3rd	Positive or negative
Systemic effects	Profound transformations of economic and social systems (value chains, modes of production and consumption).	3rd	Positive or negative

Another dimension, called the *sustainability of AI*, aims to reduce the environmental footprint of the technologies themselves, notably by optimizing models, infrastructure and uses. However, implementing best practices to reduce the environmental footprint of an AI system does not necessarily guarantee that its use is sustainable or aligned with climate and environmental objectives, given the proliferation of uses and the effects mentioned above. Consequently, assessing the sustainability of an AI solution should not focus solely on its relative environmental efficiency, but should also cover the relevance of the need it addresses, the benefits it actually delivers, and the overall impacts likely to occur when it is deployed at scale.

In short, a responsible approach to AI requires considering two dimensions at once (AI for sustainability and the sustainability of AI), to ensure that the negative direct environmental impacts associated with developing and using AI are minimized, justified, and offset by greater environmental benefits.

2.3. Social and ethical impacts of AI

AI, particularly generative AI, raises major ethical and social issues. These issues are summarized in the table below and detailed in the rest of this section.

Table: Summary of the social and ethical impacts of AI

Type of social or ethical impact	Consequence
Bias and concentration of power	Negative
Reliability and accountability	
Privacy and data protection	
Transformation of the labour market	
Ethical issues linked to environmental impacts	

2.3.1. Bias and concentration of power

AI systems can contain biases that risk deepening existing inequalities. On one hand, bias stems from training data that may be incomplete and skewed (Gouvernement du Québec, 2024). In these datasets, marginalized populations (i.e., groups of people facing discrimination based on origin, sex, socio-economic status, etc.) are often under-represented, leading to uneven performance of AI systems depending on the population, and potentially helping to perpetuate systemic bias. On the other hand, bias can also come from algorithms that may favour certain variables over others and produce flawed results (e.g., weighting a factor differently depending on a person's gender, which could lead to varying error rates between genders) (Obvia, 2025).

In the field of generative AI, the high costs associated with developing these systems lead to a concentration of power among a handful of players, who offer algorithms that are often not very transparent.

2.3.2. Reliability and accountability

A second issue concerns the reliability and security of AI systems. Beyond the lack of transparency, AI systems are designed to generate outputs even when those outputs may be wrong or nonsensical, which increases the risk of hallucinations and errors (Gouvernement du Québec, 2024). In certain high-risk sectors (e.g., health care, finance), decisions based on AI systems can have significant consequences when the algorithm errs, which underscores the need to keep humans involved in decision-making processes, and highlights the importance of establishing clear accountability for AI systems when decisions are based on erroneous AI outputs (Obvia, 2025).

2.3.3. Privacy and data protection

A third issue concerns privacy and data protection. Models can sometimes use, reproduce, or reveal personal, sensitive, or confidential data, or data protected by copyright, without the consent of the people concerned. For example, confidential data submitted to an AI system during inference can be reused to retrain it and later resurface in subsequent outputs generated for other users (Gouvernement du Québec, 2024). Data collected could also be resold by the AI solution provider to promote other products or services. It is therefore necessary for AI solution providers to establish explicit, transparent consent policies, and to ensure users are fully informed of the intended uses of their personal data.

2.3.4. Transformation of the labour market

AI also raises issues related to working conditions. The operation of AI can rely on precarious labour (e.g., for data annotation, content moderation), under temporary contracts, with low wages and poor working conditions (Solaiman et al., 2023). Once in use, generative AI can lead to job losses if it replaces staff (e.g., call centres) (Solaiman et al., 2023). Studies show that AI is reshaping the labour market unevenly: in the long run, it will boost productivity for some, while making lower-skilled workers more vulnerable (Qian et al., 2024).

2.3.5. Social issues linked to environmental impacts

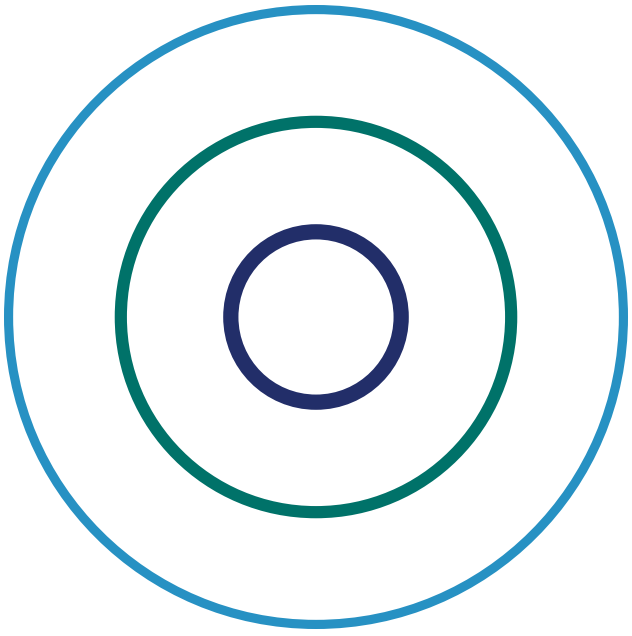
Lastly, certain social issues are tied to the life cycle of digital equipment (user devices, networks, servers). These issues particularly affect countries of the Global South (Solaiman et al., 2023).

First, the extraction of the metals needed to manufacture this equipment often takes place in countries where labour regulation in mines is inadequate, leading to high risks of working conditions that are hazardous to workers' health, of child labour, and of human exploitation (Carr-Wilson et al., 2024).

Next, producing the electronic chips built into digital equipment requires the use of roughly 400 chemical substances. This process generates large volumes of wastewater laden with hazardous chemical pollutants (heavy metals, acids, etc.) capable of causing significant harm to human health (Sandhu et al., 2025).

In addition, manufacturing digital equipment is frequently associated with low wages and precarious employment conditions (Subramanian & Yung, 2018).

Lastly, the management of digital equipment at end of life affects communities involved in the informal recycling of electronic waste, who are exposed to appalling working conditions (Traverso et al., 2024).



3.

Best practices for procuring AI solutions

Building on the environmental risks of AI identified and detailed above, this section presents the procurement best practices to adopt. Broadly speaking, the goal is to assess the environmental impacts of the AI solution and to demonstrate that these factors have been taken into account throughout the procurement cycle in order to comply with the sustainability principle of the *Statement of Principles* (Gouvernement du Québec, 2025).

The best practices are presented following the deployment stages, from defining the need through to continuous improvement:

3.1. Define and challenge the need for AI

3.2. Establish a responsible governance framework

3.3. Anticipate the potential impacts of AI

3.4. Prepare the statement of requirements

3.5. Train teams on the framework for AI use

3.6. Measure and disclose the solution's performance

All the best practices are presented in a summary table in the appendix.[9] Each practice is assigned an ease-of-implementation rating and a rating for its potential to reduce environmental impacts, to help users of this guide prioritize their actions. These are recommendations and assessments drawn from the literature review. It is up to each organization to decide the most appropriate way to incorporate them into its procurement processes, based on its own circumstances and available resources.

3.1. Define and challenge the need for AI

In responsible procurement, a clear definition of the need (the reason for the acquisition) is an important success factor. It provides an opportunity to consider the various alternatives for meeting the identified needs; targets AI use to those needs and avoids unnecessary uses; makes it easier to develop procurement criteria afterward, and serves as a reference throughout the project to ensure decisions stay aligned with the original objectives. The best practices presented below can also apply when the AI purchase is indirect (e.g., included in more general software or in services that use AI).

3.1.1. Clearly state and document the problem or need to be addressed

3.1.1. Clearly state and document the problem or need to be addressed

When adopting new technology, it is especially important to take the time to assess its relevance. The first step in acquiring AI is, therefore, to clearly define the need for the technology. Moreover, given the sensitive nature of an AI-related project and its potential for misuse, thorough documentation can only help build social acceptance of the approach. Doing so supports principle #5 of the Énoncé de principes pour une utilisation responsable de l'intelligence artificielle par les organismes publics [Statement of Principles for the Responsible Use of Artificial Intelligence by Public Bodies] on efficiency, effectiveness and relevance: "The AI systems deployed must be tailored to the actual needs of public bodies, citizens and businesses." (Gouvernement du Québec, 2025)

9. The table was developed based on existing guides, good practice guidelines, and regulatory frameworks, primarily published by AFNOR (2024), GreenIT Association (2026), ARCEP (2024), ARCOM (2024), CESE (2024), INR (2021), Gouvernement du Québec (2025), and UNEP (2024). However, all sources that contributed to its development are indicated in the accompanying table.

3.1.2. Build a multidisciplinary team to support the approach

Surround yourself with people who have the knowledge and experience needed to determine whether AI is a desirable, viable, and suitable solution. Developing, evaluating and implementing AI projects will be more effective with diverse teams able to understand the needs, issues and disciplines that AI technologies involve. This can include expertise in:

- The relevant sector (e.g., health care, transportation), tied to the solution's anticipated use;
- Sustainable development;
- Systems and data engineering;
- Model development (e.g., deep learning);
- Ethics and data protection;
- Information visualization.

If your team lacks expertise, you can draw on professional networks within your organization or the administration to gather important information on the use case you are considering.

3.1.3. Identify solutions (both without and with AI) that can address the identified problem

This helps to better pinpoint the actual need and the range of possible solutions. This exercise can help identify existing solutions or processes that could be improved to address part of the problem without adding unnecessary technology.

3.1.4. Assess the positive and negative effects (environmental, social, economic) associated with these solutions

To make decisions that are informed and aligned with the organization's objectives, potential effects need to be considered to ensure the solution delivers a clear benefit, and mitigation measures for negative impacts should be planned into the choice of solution, its features, and its conditions of use upon deployment (see section 3.3 for more detail).

3.1.5. Consult the market to learn about potential options and their features

A market consultation, at this planning stage, can help determine whether, and to what extent, AI can be part of the solution. Tell suppliers about the problem or challenge and let them propose a solution that meets your needs. Also ask them about their eco-design practices and sustainable management across their solutions' entire life cycle, to gauge their maturity against sustainable-development requirements (see sections 3.3 and 3.4 for topics to ask about). What you learn from this consultation (through a request for expressions of interest or other supplier-consultation methods) will help you better define your problem, the potential options for addressing it, and their features.

Tool: Practical guide for the Responsible Purchasing of Artificial Intelligence (AI) Solutions

The Responsible Purchasing of AI Solutions guide from the French government's Interministerial Mission for Eco-responsible Digital Technology serves as a practical guide for building environmental restraint into an AI project. It first helps verify whether AI is actually necessary, then helps steer the choice of model and architecture toward leaner options. It also provides ready-to-use questions and clauses for structuring a call for tenders or a contract, requiring transparency, energy efficiency and controlled retraining, tailored to the audience involved. It is a reference tool for consulting the market and aligning needs, impacts and requirements for suppliers. (Ministère de l'Économie, de l'Innovation et de l'Énergie [France], 2025)

3.1.6. Determine whether the AI system (or its features) is a relevant solution

After this preliminary research, ask whether the AI solution is right for your problem — rather than looking for a use for an AI solution you already want to acquire or that has been proposed to you. AI should only be deployed if it addresses a genuine need. The organization must demonstrate how AI adds value compared with other, less-impactful digital approaches, and justify the use of advanced techniques (such as deep learning) instead of lighter-weight methods where applicable. AI is not a universal solution; unlike a human being, AI cannot understand a situation in the human sense of the word and can only produce a result from the data fed into the model. It should, therefore, only be deployed when it is the best-suited answer to the identified problem.

To determine whether AI can help you meet the identified needs, ask yourself whether:

- Data containing the information you need exists, even if it is hidden or difficult to access;
- You have enough good-quality data to train the model;
- The use of the data is ethical and safe;
- The target task is broad and repetitive enough;
- Using the solution would provide information a team could act on to achieve concrete results (Government Digital Service, 2023).

3.1.7. Determine the type of AI solution suited to the identified needs

This could be an off-the-shelf AI solution, existing technology with AI elements added, co-creating the AI solution with suppliers, or outsourcing AI development. You could choose to develop all or part of your own technology, but since training your own model from scratch is more environmentally costly, it is recommended to instead opt for an option fine-tuned from an existing model. Consider Retrieval-Augmented Generation (RAG), which reduces the impact tied to training, since if the underlying database changes, the organization can simply update it to keep the model's responses reliable, without retraining it — unlike large models, which must be retrained regularly.

Choosing the AI technology suited to your challenge

(adapted from: Government Digital Service, 2023)

There is no single "AI technology." At present, widely available AI technologies mainly rely on supervised, unsupervised, or reinforcement machine learning. The machine-learning technique that will give you the best results depends on the problem you are trying to solve. The following table presents the different machine learning techniques to help guide your choices.

Table: Machine learning techniques

(adapted from: Government Digital Service, 2023)

Technique	Description	Examples
Classification	Learns the characteristics of a given category, allowing the model to sort unknown data into existing categories.	• Deciding whether a shipment of goods should undergo a border inspection. • Determining whether an email is spam.
Regression	Predicts a value for an unknown data point.	• Predicting a house's market value from information such as its size, location or age. • Forecasting air pollutant concentrations in cities.
Clustering	Identifies groups of similar data points within a dataset.	• Grouping customers to identify sub-groups with particular spending habits. • Grouping smart-meter data to identify clusters of electrical devices.
Dimensionality reduction	Reduces data to its most relevant variables to make models more accurate or to enable data visualization.	• Used by data scientists when evaluating or developing other types of machine-learning algorithms.
Ranking	Trains a model to rank new data based on previously observed lists.	• Returning pages in order of relevance when a user runs a search on a website.

Common applications of machine learning

Certain categories of problems are frequently addressed using machine learning. For many of them, it is possible to purchase or adapt existing commercial products. The following table presents different applications to help guide your thinking.

Table: Applications of machine learning
(adapted from: Government Digital Service, 2023)

Application	Description	Examples
Natural language processing[10]	Processes and analyzes natural language, recognizing words, their meaning, context and narrative structure.	• Converting speech to text to automatically generate subtitles. • Automatically generating a reply to a customer email.
Computer vision	The ability of a machine or program to mimic human vision.	• Identifying road signs for self-driving vehicles. • Facial recognition for automated passport checks.
Anomaly detection	Identifies abnormal data points within a dataset.	• Spotting fraudulent activity in a user's bank account.
Time-series analysis	Understanding how data changes over time in order to make forecasts and track trends.	• Carrying out budget analyses. • Forecasting economic indicators.
Recommendation systems	Predicts how a user will rate a given item in order to offer new recommendations.	• Suggesting relevant pages on a website based on articles the user has already viewed.

3.2. Establish a responsible governance framework

Building a framework for trustworthy AI within public administration is essential to the project's success, to respecting stakeholders, and to mitigating risk. Below are broad guidelines for establishing such a framework in the context of acquiring or using an AI solution. These are high-level recommendations, which may be more or less attainable depending on organizational context, but which should be implemented as fully as possible. At a minimum, the principle of proportionality must be applied, whereby the resources deployed to mitigate identified risks must be commensurate with those risks. Under principle #9 on accountability in the Statement of Principles, public bodies remain fully accountable for the decisions, actions and impacts generated by AI systems, even when those systems operate autonomously. Therefore, they must put in place adequate governance along with clear, traceable accountability mechanisms, so as to foster public trust in the use of AI systems (Gouvernement du Québec, 2026).

For more information on trust-related risks and safeguards to consider, see the OECD's work (Governing with Artificial Intelligence; OECD, 2025) as well as the Énoncé de principes pour une utilisation responsable de l'intelligence artificielle par les organismes publics (Gouvernement

10. For more potential use cases for generative AI, see the *Mesures applicables lors de l'utilisation de l'intelligence artificielle générative* and their *Guide d'application* (in French). To document and analyze GenAI use cases, ministries and organizations subject to the Loi sur la gouvernance et la gestion des ressources informationnelles des organismes publics et des entreprises du gouvernement (LGGRI) may also use the template from the Gouvernement du Québec's (2026) *Portefeuille des occasions porteuses en IA*, which is currently reserved for public administration use and is not publicly available.

du Québec, 2025). The Mesures applicables lors de l'utilisation de l'intelligence artificielle générative (Gouvernement du Québec, 2025) and their Guide d'application (Gouvernement du Québec, 2026) set out, for their part, the guidelines for good organizational governance of GenAI systems.

3.2.1. Establish a multi-stakeholder governance framework

This framework must involve internal and external stakeholders to support decision-making on the solution's acquisition and deployment. This can include the internal multidisciplinary team (see § 3.1.2), subject-matter experts, representatives of beneficiary groups, local authorities, affected communities, and any other relevant external stakeholder.

3.2.2. Determine a process for consulting and informing the public about the AI system's implementation when the solution may affect them

The AI Now Institute proposes disclosure in four sections: 1) Scope, 2) Public notice, 3) Self-assessment, and 4) Access plan (see box below). It is necessary to collaborate actively with key stakeholders through open, transparent mechanisms, such as citizen assemblies, engaging public-service staff, or involving users in decision-making.

TOOL/REFERENCE:
Algorithmic Impact Assessments Report: A Practical Framework for Public Agency Accountability - AI Now Institute (Reisman, Schultz, Crawford & Whittaker, 2018).

- → **SCOPE:** define the automated decision-making system to be put in place in a practical manner appropriate to the context.
- → **PUBLIC NOTICE:** inform communities of systems likely to affect their daily lives.
- → **SELF-ASSESSMENT:** strengthen public bodies' capacity to assess fairness, justice, due process, and discriminatory effects. "In their self-assessments, agencies must identify potential impacts on the public and proactively involve affected communities. […] **An agency should involve its communities from the outset, even before the formal notice-and-consultation process."**
- → **MEANINGFUL ACCESS PLAN:** Allow researchers and auditors to examine the systems once implemented.

3.2.3. Put in place monitoring mechanisms for the AI system

The Mesures applicables lors de l'utilisation de l'intelligence artificielle générative and their Guide d'application (Gouvernement du Québec, 2026) propose monitoring mechanisms for these systems, including establishing and applying a structured feedback process to encourage users to report their needs, any obstacles encountered (e.g., hallucinations, bias), and their concerns.

3.2.4. Establish a record of responsibilities specifying who is responsible for the various aspects of the AI solution

It is worth checking, among other things, whether the models meet their objectives, whether a clear testing and monitoring framework exists, whether the algorithms are robust, unbiased, fair and explainable, and whether the project matches how citizens and/or users expect their data to be used.

3.3. Anticipate the potential impacts of AI

Using AI comes with several issues, as documented in section 2. It is therefore essential to estimate potential impacts and to develop procurement clauses and criteria that make it possible to manage them.

According to the United Kingdom government's AI procurement guidelines (Government Digital Service, 2020), an AI impact assessment should include:

- Your user needs and the public benefit of your AI system;
- The human and socio-economic impacts of your AI system;
- The effects on your existing technical and procedural landscape;
- Data quality and any potential inaccuracies or bias;
- Any potential unintended consequences;
- Cost considerations across the entire life cycle, including ongoing support
- and maintenance requirements.

In addition, the solution's environmental benefits and impacts are to be assessed both qualitatively and quantitatively. One such assessment, for solutions involving automated decision-making systems, is the algorithmic impact assessment (see box opposite).

3.3.1. Qualitatively assess AI's environmental impacts across its entire life cycle, from the design phase onward

More specifically, provide a qualitative list of potential direct and negative indirect (2nd- and 3rd-order) environmental impacts, covering every stage of the life cycle as thoroughly as possible. Where applicable, demonstrate how the solution contributes to environmental ends (e.g., raising sustainable-development awareness among students, optimizing bus routes, reducing food waste). This is a brief upfront analysis, for the market study, to be supplemented later by a full life-cycle assessment where available (see § 3.4.3).

Without knowing the specifications of the AI system you will be acquiring, it is not possible to conduct a complete assessment on the first try. This means the initial assessment must be repeated when more information on the selected solution and supplier becomes available, and before the system is put into operation.

Algorithmic impact assessments for automated decision-making systems

Algorithmic impact assessments *(AIAs)* draw on impact-assessment frameworks in the fields of environmental protection, data protection, privacy, and human-rights policy, to allow an automated decision-making system to be assessed before the administration commits to using it. This lets the administration and the public identify concerns that may require negotiation or other handling before a contract is signed. This is also the stage at which the public and elected officials can oppose deployment before potential harms occur.

Before starting the AIA, you should obtain information on:

- → The algorithm, including its parameters, data-processing techniques, and outputs;
- → The data used by the system, along with information on its type, source, collection method, and security classification;
- → Measures planned or in place to ensure quality;
- → Measures planned to ensure transparency and communicate information about the initiative to clients and the public.

TOOL/REFERENCE

The Algorithmic Impact Assessment tool (Government of Canada, 2026), part of the Directive on Automated Decision-Making of the Government of Canada (2025)

The AIA tool is a risk-assessment tool designed to support the Treasury Board's Directive on Automated Decision-Making, and shared as open-source software. The AIA is available as an online questionnaire on the Open Government Portal. Once the questionnaire is completed, an impact level is established based on the results. The AIA is used to identify risks and assess their impact across a wide range of areas, including:

- → The rights of individuals or communities;
- → The health or well-being of individuals or communities;
- → The economic interests of individuals, entities or communities;
- → The sustainability of ecosystems.

3.3.2. Analyze the impact of AI solutions on IT equipment

Make sure the AI model can run on existing hardware and, where relevant, over a low-bandwidth or offline connection, so as to avoid premature hardware renewal. This includes devices, operating systems, and web browsers.

3.3.3. Determine decision points and thresholds tied to the impact assessment

The associated risks and their respective mitigation strategies must be provided and approved as part of the impact assessment, and should include key "go/no-go" decision points where applicable. Plan decision points to review the impact assessment, both on a regular basis and whenever a substantial change is made to the AI system's design.

3.3.4. Check that deploying the technology does not compromise the organization's climate and sustainable-development commitments

The AI deployed must be consistent with public climate and sustainable-development strategies, including climate-change mitigation and adaptation targets. Local, national and international strategies must not be undermined by the uncontrolled growth of AI and, in particular, of its energy demand. Using the GHG emission estimates produced (and the underlying energy consumption), check whether this consumption and the resulting additional emissions are consistent with the decarbonization targets that apply to your organization.

3.4. Prepare the statement of requirements

Adding environmental and social criteria to the specifications helps lock in suppliers' commitments on sustainable development. The goal is for the procurement process to be responsible, so as to mitigate the main risks tied to AI use. This section, like the rest of the document, focuses on environmental criteria, but two boxes at the end offer additional social and ethical considerations.

3.4.1. Consider agile and innovative public-procurement methods

If you are purchasing the development of the AI solution, prioritize an iterative approach to product development and reflect this accordingly in the call for tenders. Be sure to adopt an approach that does not impose unnecessary burdens that would discourage suppliers — including start-ups, small and medium-sized enterprises (SMEs), non-profit and community-sector suppliers, and those belonging to under-represented groups — from bidding. Clearly state, in your procurement documentation, why you consider AI relevant to the problem, while remaining open to other solutions.

Whatever strategy is chosen, keep in mind that AI technologies are evolving quickly and that new technologies and new products keep appearing on the market. In your calls for tenders, **define outcome-focused criteria**, emphasizing the description of the challenges and opportunities you face. This will let suppliers determine which technologies are best suited to your needs (see box opposite).

Key elements to consider when preparing your statement of requirements (Government Digital Service, 2020):

1. Start by defining your problem;
2. Highlight your data strategy and requirements;
3. Focus on data quality, bias, and limitations;
4. Ask questions to stress the need for you to understand the supplier's approach to AI (algorithms, models, data sources, etc.);
5. Consider strategies to avoid vendor lock-in and "black-box" AI systems;
6. Emphasize the importance of intellectual property;
7. Note any integration with related technologies or services;
8. Take your long-term support and maintenance needs into account;
9. Include considerations related to accountability and risk.

3.4.2. Identify and plan for strategies that mitigate the main risks identified throughout the life cycle

The findings of the initial impact assessments must inform procurement and be reviewed at key decision-making moments.

The best practices below, transformed into mandatory or evaluation responsible-acquisition criteria, aim to reduce the environmental impact of the AI solutions acquired.

ENVIRONMENTAL TRANSPARENCY

3.4.3. Favour a supplier that has carried out a multi-criteria life cycle assessment (LCA) of the AI solution

This LCA must be based on recognized standards, or have been reviewed by a credible third party. Otherwise, ask the supplier to estimate the environmental impact of its AI solution using existing estimation tools. The results should be transparent about the type of data used and the life-cycle stages included.

The box below proposes a hierarchy of approaches that can be requested.

Recommendations for quantitatively measuring AI life-cycle impacts

Ideally, carry out an LCA of the AI solution, following internationally recognized norms and standards (*ISO 14040/44* [ISO, 2022; ISO 2006], *Product Environmental Footprint* [Damiani et al., 2022], *Référentiel général pour l'IA frugale* [AFNOR, 2024], etc.) The environmental indicators assessed should at minimum include the contribution to climate change (GHG emissions), water consumption, and the depletion of resources (mineral and fossil).

If carrying out an LCA is not possible, estimate the environmental impacts using existing estimation tools: CodeCarbon (Courty et al., 2026), Green Algorithms (Lannelongue et al., 2021), or Ecologits (online calculator) (Rincé et al., 2025). These tools can, at minimum, estimate energy consumption and contribution to climate change. However, their estimates are less precise than LCA results, which is why they should be considered a second-choice option.

In both cases, quantifying impacts should ideally be done using measured data (e.g., energy consumption, training duration, etc.) or figures calculated from it; otherwise, from estimates and theoretical calculations.

If the entire life cycle cannot be covered, include at minimum the training and inference stages in the study.

In all cases, transparently state the type of data used (measured, estimated) and the life-cycle stages included in the assessment, for both the technological life cycle (training, inference, etc.) and the physical life cycle (hardware production, transport, use, end of life).

For example, the French company Mistral AI carried out an LCA of an AI model (Mistral AI, 2025). This study assesses the impact of training the Mistral Large 2 model, and of an average inference associated with generating one page of text, based on three environmental indicators (climate change, water use, and the depletion of resources (minerals and metals).

3.4.4. Require the data needed to measure environmental performance

Depending on the metrics you want to track (see section 3.6.2 on sustainability indicators), the supplier must commit to providing information on the AI model's use and performance throughout its life cycle. Model developers rarely publish their environmental data on their own, so it must be required. This includes energy and water consumption and other life-cycle impacts.

HOSTING

3.4.5. Favour data centres located in a region with a low-carbon electricity mix or a high Renewable Energy Factor (REF)

The REF should be as close to 1 as possible, for training and inference. When using a large-scale cloud service (e.g., Google Cloud, AWS, Microsoft Azure), it is possible to choose the region where processing takes place. The Electricicy Maps platform (2026) can be used to visualize the carbon intensity of the electricity mix around the world.

3.4.6. Favour data centres with strong environmental performance

PUE, WUE, CUE, REF and ERF are indicators that can be used to measure data centre performance. The following table presents these indicators, specifying their equations, their units, the standard governing their calculation (which should be followed when calculating these indicators, or an equivalent one), as well as the target value to achieve for strong environmental performance. These are, however, site-level indicators and not a complete measure of an AI solution's impact. In practice, improving one indicator can lead to a decline in another, which is why these indicators need to be tracked together.

Table: Hosting performance indicators

Indicator name	Equation	Calculation standard	Target value
PUE (Power Usage Effectiveness) [1]	$PUE = \frac{\text{Total data centre energy [kWh]}}{\text{Energy of IT equipment [kWh]}}$	ISO/IEC 30134-2	Below 1.5 (Arcep and Arcom, 2024). The global average is 1.54 (Taylor, P., 2026).
CUE (Carbon Usage Effectiveness) [2]	$CUE = \frac{\text{Total } CO_2 \text{ emissions of the data centre}}{\text{Energy of IT equipment [kWh]}}$	ISO/IEC 30134-8	As low as possible.

Table: Hosting performance indicators (continued)

Indicator name	Equation	Calculation standard	Target value
WUE (Water Usage Effectiveness) [3]	$WUE = \frac{\text{Total water consumption of the data centre [L]}}{\text{Energy of IT equipment [kWh]}}$	ISO/IEC 30134-9	Below 0.4 L/kWh (Arcep and Arcom, 2024), including only on-site (direct) water consumption.The US average is 0.36 L/kWh (Shehabi et al., 2024).
REF (Renewable Energy Factor)	$REF = \frac{\text{Renewable energy of the data centre [kWh]}}{\text{Total energy of the data centre [kWh]}}$	ISO/IEC 30134-3	As close to 1 as possible. The global average is 27% (IEA, 2025).
ERF (Energy Reuse Factor) [4]	$ERF = \frac{\text{Waste energy reused [kWh]}}{\text{Total energy of the data centre [kWh]}}$	ISO/IEC 30134-6	As close to 1 as possible

Note: For data centres more than 2 years old, these indicators should reflect "actual" values rather than theoretical "design" values, where possible. They should be assessed over a minimum period of one year, but ideally over several years.

[1]: PUE measures a data centre's energy efficiency, particularly that of its cooling system, but does not reflect the efficiency of the IT equipment itself: a site can have a low PUE while under-utilizing its servers and consuming a lot of energy. On the energy side, PUE says nothing about the GHG emissions associated with electricity generation — so it should be paired with CUE and REF — nor about energy recovery (e.g., recovering waste heat from servers to heat buildings). Lastly, PUE does not account for water consumption. In fact, replacing an air-conditioning cooling system with a water-evaporation system often lowers PUE while increasing water consumption, highlighting the importance of tracking WUE alongside PUE.

[2]: The ISO/IEC 30134-8 standard defines two CUE categories. Category 1 counts only the CO2 emissions tied to the data centre's electricity consumption (expressed in kg CO2/kWh). Category 2 counts the emissions of all GHGs tied to the consumption of all forms of energy (expressed in kg CO2 eq./kWh).

[3]: In calculating WUE, water consumption corresponds to water withdrawn that is not returned to its original source (including, notably, water lost during the operation of cooling systems and the humidification of server rooms). This indicator has several limitations. First, it does not distinguish the source of the water withdrawn (potable water, recycled water, surface water, etc.), nor the region it was drawn from, even though the environmental impact of withdrawing the same volume of water varies greatly depending on local water stress. In addition, the WUE type 1 defined by ISO/IEC 30134-9, the one most commonly assessed, is limited to direct on-site water consumption, and does not include the indirect water consumption tied to generating the electricity the data centre consumes, or to manufacturing IT equipment. Lastly, WUE does not account for volumes withdrawn and then discharged into the natural environment, nor the quality of those discharges, which limits its ability to assess the ecological impacts of discharge.

[4]: Not every site is technically or economically suited to recovering and using the waste heat generated by servers, especially in smaller or decentralized data centres. Since ERF depends heavily on local conditions and measurement parameters, comparisons in isolation are of limited use.

3.4.7. Favour a host committed to reducing environmental impact

Several criteria can apply:

- Having completed a GHG inventory following the GHG Protocol or a recognized methodology, and having a GHG-emission reduction plan;
- Having carried out a climate-change risk assessment of the service, and having a plan to reduce and adapt to climate-related risks;
- Having a responsible-purchasing program for IT equipment (servers, storage arrays, etc.);
- Having a sustainable end-of-life equipment management program that follows
- the 3RV hierarchy (reduction, reuse, recycling and recovery);
- Holding one or more sustainable-management certifications: *ISO 14001, ISO 50001,* TCO Certified cloud certification, or similar.

TOOL/REFERENCE

ECPAR's responsible cloud-services procurement guide (ECPAR, 2024) proposes clauses for reducing the environmental footprint of hosting.

DATA COLLECTION AND MANAGEMENT

3.4.8. Limit data to only the information necessary across AI's life cycle

This involves identifying, from the design phase onward, the data that is genuinely essential to achieve the expected performance (Commission Nationale de l'Informatique et des Libertés [CNIL], 2024; CNIL, 2025). This avoids collecting or processing irrelevant or personal data and helps reduce the environmental footprint (and other risks) (Gouvernement du Québec, 2025). The supplier should explain what types of data are used (text, image, audio, etc.), justify their use, and how relevant data is selected, throughout the system's life cycle (training, testing, inference).

3.4.9. Favour data quality over quantity

Reliable data, well sorted and annotated, allows a model to be trained on a smaller volume of data (Sajith & Kathala, 2024; AFNOR, 2024) while maintaining a good level of performance. As a result, fewer resources are consumed and fewer impacts are generated. Open-access datasets should be the first source considered, since they have often already been sorted and cleaned. The supplier should justify the provenance of the data across AI's life cycle and explain why these sources were chosen.

3.4.10. Optimize data cleaning, annotation, and preparation

Sound upfront processing (removing duplicates, correcting inconsistencies, annotation suited to the purpose, etc.) improves model performance and avoids excessively long training. This rigour should extend across the supplier's entire data infrastructure, not just training datasets: keeping a thorough, up-to-date inventory of the data used, including its metadata, makes it possible to spot and eliminate outdated versions and duplicate data across the system's full life cycle, correspondingly reducing the volume of data stored (Gouvernement du Québec, 2025). The supplier should document its data-preparation procedure, including maintaining this inventory, and explain how it ensures the quality of the prepared data.

3.4.11. Adapt storage strategies based on how the data is used

Frequently accessed data requiring fast retrieval (sometimes called "hot" data) should be stored on high-performance storage media (e.g., SSD drives, volatile memory), which are energy-intensive, while rarely accessed data (sometimes called "cold" data) can be stored on other, lower-performance media (e.g., HDD drives) (Seagate, n.d.) that consume less energy. A good practice is to reduce the volume of cold data (e.g., through compression or reduced precision). The supplier should be able to explain its storage strategy and technology choices.

3.4.12. Limit the retention of data collected across the AI system's life cycle, particularly while the model is in use

Put in place a regular process to check the relevance of this data, set a data-retention period, and delete data that is no longer needed (CNIL, 2024; CNIL, 2025). The supplier should have such a process in place. In Québec, this obligation is based in particular on the retention schedule set out in the Loi sur les archives [Archives Act] (RLRQ, c. A-21.1), which public bodies must comply with in establishing their data retention and deletion processes (Gouvernement du Québec, 2025).

MODEL CHARACTERISTICS

3.4.13. Favour existing, fine-tuned models rather than building one from scratch

Fine-tuning is the "process by which an artificial intelligence model pre-trained on a large, general dataset is adapted to a more specific task, domain, or context by further adjusting its parameters" (OQLF, 2025). This allows training costs and other impacts to be shared with other user organizations.

3.4.14. Choose the lightest possible model (i.e., with the fewest parameters)

Compared with Large Language Models (LLMs), Small Language Models (SLMs) have fewer parameters — ranging from one million to 10 billion parameters (Johnson, J., 2025), although this definition varies by source — and therefore consume fewer resources, but can be just as effective as LLMs thanks to fine-tuning. This choice is also recommended by the Gouvernement du Québec (2024).

However, SLMs are dedicated to performing limited tasks, and are not intended for diverse, complex and varied tasks (Jeanquartier et al., 2026). Where possible, choose a model specialized for the type of task at hand rather than a general-purpose one. Favour models that are transparent about their number of parameters.

TOOL/REFERENCE

The French platform Compar:IA (Ministère de la Culture [France], n.d.) provides information on the size of large models to inform decision-making.

TOOL/REFERENCE

To help choose a small model, SLM-Benchmark (Pham et al., 2025) is an open-access benchmark that evaluates SLMs on accuracy, efficiency and sustainability across different tasks. According to this benchmark, Mistral-7B is the model with the best score on these three indicators, making it a strong candidate for many applications.

3.4.15. Favour energy-efficient models

Recommended by the Gouvernement du Québec (2024), existing benchmarks and comparative rankings on model energy efficiency can be used (e.g., AI Energy Score [2025b], Compar:IA, ML.ENERGY Leaderboard [Chung et al., 2025]). These benchmarks help identify the energy consumption of models offering the same service, making it possible to choose lower-energy-consumption models.

3.4.16. Optimize model performance through compression techniques

The most common and effective techniques are: *pruning*, which removes redundant or barely useful connections or neurons; knowledge *distillation*, which trains a smaller model that mimics a larger, more complex one; and *quantization*, which reduces the numerical precision of the parameters (Berenstein & Charpentier, 2025). These aim to lower computing and memory resource needs, though other techniques also exist.

3.4.17. Reduce inference energy consumption by favouring batch inference

Batch *inference* means grouping several queries together and processing them together, rather than one at a time and in real time (which corresponds to *continuous inference*). This reduces how often the IT hardware (GPUs and/or CPUs) is called on, uses it more efficiently, and thereby lowers energy consumption (Hugging Face, n.d.). This approach is especially useful when queries do not require an instant response.

3.4.18. Cache repeated query fragments to avoid unnecessary computation

Prompt caching means storing the parts of queries that recur often (e.g., a long context sequence repeated in every query) (Association GreenIT, 2026). This avoids calling on the IT hardware repeatedly to process identical prompt elements, thereby reducing the computational load, particularly for generative AI models. The supplier should explain the caching strategies applied and give an approximate share of query sequences that are cached (Association GreenIT, 2025).

(RE)TRAINING

3.4.19. During (re)training, find the balance between the resources devoted to training, to improve the AI model's efficiency, and the performance gains achieved

In other words, the model's optimal performance level should be determined, to avoid wasting resources training a model whose performance has already plateaued. The supplier can explain the techniques or approaches used to assess this balance and to stop training the model once it reaches its optimal performance level.

For training, the optimal amount of training data to collect can be determined relative to the size of the model. The "Chinchilla scaling law" states that a model reaches its optimal performance when the number of training tokens is about 20 times the model's number of parameters (Hoffmann et al., 2022). This law suggests that some existing large models (e.g., GPT-3) may have been trained sub-optimally, having too many parameters relative to the volume of training data. It also shows that increasing a model's number of parameters does not necessarily improve its performance. A model with fewer parameters can perform better, if the model size and data volume are well balanced.

3.4.20. Favour training during periods of infrastructure under-use, or during periods when the electricity grid's carbon intensity is low

Since the carbon intensity of electricity varies by day and time of day, significant computing loads (e.g., training) should, where possible, be carried out or scheduled to run during periods when electricity is less carbon-intensive. One option is to start model training when the carbon intensity of electricity in the data centre region falls below a certain threshold, then to pause training once carbon intensity exceeds a certain threshold. The Electricity Maps platform provides real-time carbon-intensity estimates for most countries.

3.4.21. Minimize the number of model retrainings

The need for retraining phases must be justified, and non-essential retrainings avoided. The assessment process and the criteria justifying the need for retraining must be explained (e.g., user feedback indicating that the generated content no longer meets requirements), by the organization or by the supplier (in the case of the acquisition of an AI solution). The expected number of model retrainings over its entire service life must also be stated (a range may be given), and should be as low as possible, along with reports on the improvements delivered by retraining (qualitative and quantitative) and the associated environmental impacts.

INFERENCE (QUERIES)

3.4.22. Favour models that can run locally on user devices

This mainly avoids transferring data over networks, thereby reducing their associated impact, provided these models are small (notably SLM-type) and do not lead to the obsolescence and replacement of user devices. In this context, the supplier should guarantee the AI solution's compatibility with devices already deployed, including when improvements are introduced to the model. It should also offer the option of keeping an earlier version, so as not to force a device upgrade or replacement.

3.4.23. Provide the option to turn the AI call on or off

This makes it possible to limit the number of non-essential queries. A user may also be asked to confirm their need to use AI before submitting a query (Association GreenIT, 2026). This may involve changing default display options, so that the AI system is not activated without the user's action (opt-in).

3.4.24. Configure the model to limit the size of generated responses

This helps reduce the impacts, since response size (output tokens) has a major influence on the amount of resources used (Luccioni et al., 2024).

OTHER ECO-DESIGN PRACTICES

3.4.25. Adopt or require other eco-design practices

Consult the Référentiel général de l'écoconception des services numériques [General Framework for the Eco-design of Digital Services] (Arcep & Arcom, 2024) to find additional measures suited to your context and use case, and to frame potential requirements for suppliers. These practices go beyond AI models and apply to digital solutions generally.

Additional social considerations

On the social side, it is worth asking suppliers for information on their supply chain and their socially responsible digital practices, for example:

- → Can you provide information on the production chain of your AI solution (design, training, testing, deployment, continuous improvement), including the companies involved and their location?
- → Is your company committed to a responsible-digital approach on the social front (respect for human and labour rights, algorithmic ethics and non-discrimination, accessibility, personal data protection, etc.)?
- → What measures are in place to minimize your solution's negative social impact (on human and labour rights, algorithmic ethics and non-discrimination, accessibility, personal data protection, etc.) across the different stages of its life cycle (design, training, testing, deployment, continuous improvement)?

These elements are consistent with the principles of respect for persons and the rule of law, as well as inclusion and equity, in the *Gouvernement du Québec's Statement of Principles* (2025).

Additional ethical considerations

On the ethical side, it is important to question, take into account, and include contractual clauses on supplier practices to ensure model transparency, data governance, human oversight, accuracy and robustness levels, etc. To that end, the European Union contractual clauses presented below are very useful. The model clauses for technical documentation are ideal for including information on the AI system's environmental footprint.

TOOL/REFERENCE

Updated EU standard contractual clauses for AI models (European Commission, 2025).

On June 13, 2024, the European Union adopted the Artificial Intelligence Act (the EU AI Act), the first legislation in the world to regulate AI comprehensively. To promote responsible AI procurement, the Community of Practice published, on September 29, 2023, EU standard contractual clauses, updated in March 2025.

This resource contains contractual clauses for the following topics:

- → Essential requirements applicable to the AI System
  - o Risk management system
  - o Data and data governance
  - o Technical documentation* and instructions for use
  - o Record-keeping (of events)
  - o Transparency
  - o Human oversight
  - o Accuracy, robustness and cybersecurity

- → Supplier obligations regarding the AI System
  - o Compliance
  - o Quality management system
  - o Fundamental rights impact assessment
  - o Corrective measures
  - o Obligation to provide an explanation for individual decisions
- → Rights related to the use of datasets
- → AI System registry and audit
- → Costs

Additionally, open access to models can also be an ethical criterion to factor into the choice or development of the AI solution.

TOOL/REFERENCE

The Compar:IA site (Ministère de la Culture [France], n.d.) indicates whether existing large models are open-source or proprietary.

3.5. Train teams on the framework for AI use

Organizations must treat mastery of responsible AI as a long-term commitment, building it into their human-resources development strategies (training) and putting in place appropriate monitoring mechanisms to enable rigorous oversight of AI systems throughout their life cycle.

3.5.1. Include, in user training, concepts related to sustainable development and AI's environmental, social and ethical risks

Operational or service staff must have sufficient knowledge of the AI system to understand how to use it responsibly and act on its outputs. This supports principle #10 of the Statement of Principles, namely competence: "Public-body staff must be made aware of the use, best practices and issues that may arise throughout the life cycle of AI systems […]" (Gouvernement du Québec, 2025). It is important to ensure that knowledge transfer and training are part of the contract requirements, and that explanations are accessible to non-specialists who may need to understand the AI system. The Mesures applicables lors de l'utilisation de l'intelligence artificielle générative and their Guide d'application provide sample training plans for GenAI (Gouvernement du Québec, 2026). The Gouvernement du Québec also makes available to public bodies, on the BRIO and Agora platforms, six training programs that support the responsible use of AI, including Introduction à l'intelligence artificielle pour l'administration publique and Intelligence artificielle générative : opportunités, risques et défis (parties 1 et 2) [Generative Artificial Intelligence: Opportunities, Risks and Challenges (Parts 1 and 2)].

3.5.2. Specify the profiles and use cases that are authorized, to avoid non-essential uses

The Mesures applicables lors de l'utilisation de l'intelligence artificielle générative and their Guide d'application ask public bodies to adopt such internal rules, and provides examples of use cases that may be authorized or prohibited (Gouvernement du Québec, 2026). Internal information technology (IT)

departments should define AI usage profiles and grant access only to staff who genuinely need it, based on the needs identified during the planning phase.

3.5.3. Encourage users to minimize the number of queries submitted to AI

Group tasks together to submit a minimum number of queries (*prompt engineering*).

> HEC Montréal created a prompt catalogue to help its community write high-quality prompts. This makes it possible to get a satisfactory answer with fewer iterations.

3.5.4. Raise staff awareness of resource-intensive features

Generation tasks (text generation, summarization, text correction, etc.) are more energy-intensive and higher-impact than discriminative tasks (classification, error detection, etc.) (Luccioni et al., 2024), and tasks involving images are likewise higher-impact than tasks that handle only text. As a result, the most energy-intensive tasks should be reserved for situations where they provide real added value. In addition, complex tasks requiring precise reasoning steps should use the chain-of-thought approach, to identify and correct potential errors while keeping the number of queries limited — but this more energy-intensive approach should not be used for simpler tasks.

3.5.5. Inform the user of the environmental impact of their query

Inform them, at a minimum, of the energy consumption and contribution to climate change. Some tools integrate into the codebase, directly measuring energy consumption while the query runs, then estimating the carbon footprint (e.g., CodeCarbon, Ecologits (Python library)). When using certain large AI models (Claude, Gemini, ChatGPT, etc.), the average environmental impact of a query can be estimated using Ecologits (online calculator). Informing users of their query's environmental impact enables more informed choices about AI use.

3.6. Measure and disclose the solution's performance

For AI-powered solutions, implementation plans, ongoing sustainability-assessment methods, and the mechanisms for feeding information back into the data model are crucial to ensuring responsible use. Moreover, the operation and consequences of AI systems may not be apparent during the procurement process and often only become clear at the time of deployment, requiring sustained communication and information-sharing between buyer and supplier, which must be built into the contract terms.

3.6.1. Make sure the model remains effective, accurate and lean once deployed, and that operating practices keep evolving in the right direction

The model must be tested continuously to guarantee its accuracy, since an inaccurate model can lead to flawed decisions with negative consequences. Require certain performance indicators, or work with the supplier to define how the model's efficiency will be monitored once deployed. Some indicators are proposed in the following table.

Table: AI solution performance indicators

Element measured	Life-cycle stage	Indicator	Tool/source
Computing effort per use	Inference	Number of tokens processed per query	Supplier logs / API
Volume of data stored	Storage	Gigabytes stored (hot/cold)	Host logs
Retraining frequency	Training	Number of retrainings per month or per year	Supplier
Prompt reuse rate (caching)	Inference	% of tokens avoided thanks to caching	Supplier logs

3.6.2. Put in place monitoring and reporting on sustainability indicators

As recommended by the Gouvernement du Québec (2025), this tracking of sustainability indicators must be put in place and built into project governance. Put in place tools to measure performance throughout the AI systems' life cycle and report on this publicly. Indicators that can be included in the specifications are presented in the table below.

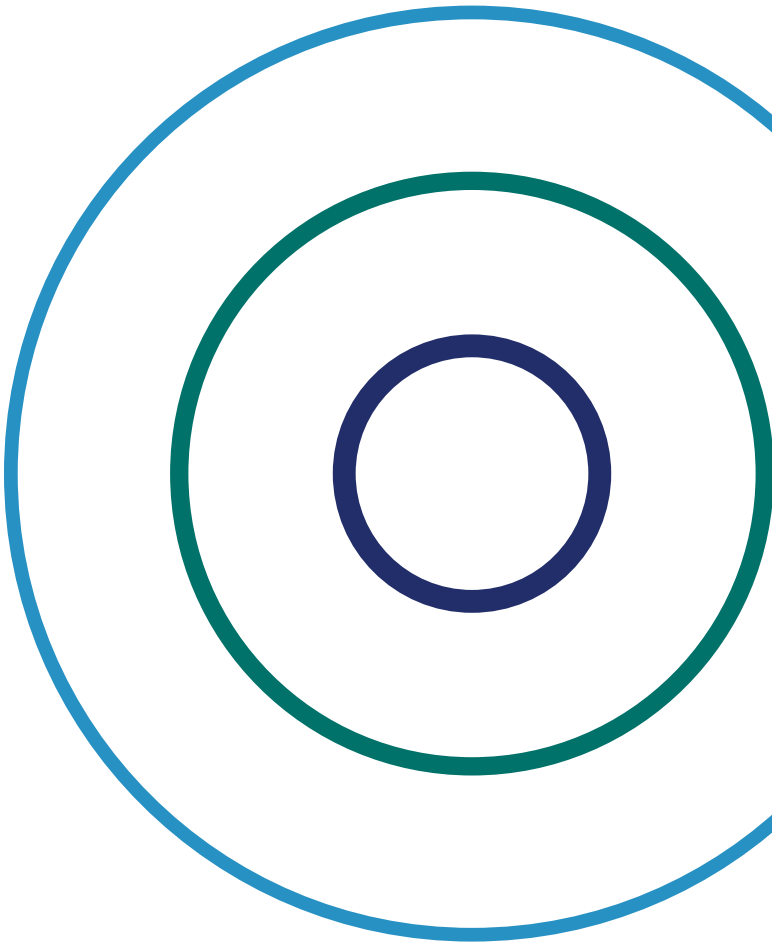


Table: Environmental performance indicators for the AI solution (adapted from: Ministère de l'Économie, de l'Innovation et de l'Énergie [France], 2025)

Element measured	Life-cycle stage	Indicator	Tool/source
Energy cost of retraining	Retraining	kWh per retraining	CodeCarbon Green Algorithms
Energy efficiency per token	Inference	kWh/1,000 tokens	Internal estimate EcoLogits
GHG emissions	Training and inference	CO_2 eq. emitted per training run or query	CodeCarbon Green Algorithms
Impact per query (external APIs)	Inference	Energy, emissions, water, hardware used	EcoLogits
Carbon intensity of the electricity mix	Hosting	gCO_2/kWh	Host
Data centre efficiency	Hosting	PUE, CUE, WUE, ERF	Host
Renewable energy rate	Hosting	% of renewable energy used (REF or national mix rate)	Host

3.6.3. Avoid becoming dependent on overly heavy models, and periodically re-examine the need to keep maintaining AI tools over time

The initially identified need may change, and a model that was appropriate at the outset may become oversized—particularly if actual usage is more limited than anticipated or if a lighter model now meets the same need. It is therefore advisable to include, right from the specifications stage, a provision for periodically reviewing the relevance of the solution and its benefits in light of its impacts, in order to migrate to a more streamlined model if necessary or to discontinue its use.

3.6.4. Put in place a strategy for reusing and extending the service life of the AI model internally and/or within the community

AI models can be added to an internal library shared among collaborating organizations, or shared as open source with the community, in order to avoid costly, energy-intensive retraining. These arrangements must be provided for in the call for tenders. The reuse and pooling of GenAI systems and queries are recommendations of Gouvernement du Québec (Mesures applicables lors de l'utilisation de l'IA générative, 2025) that must be provided for in the statement of requirements from the outset.

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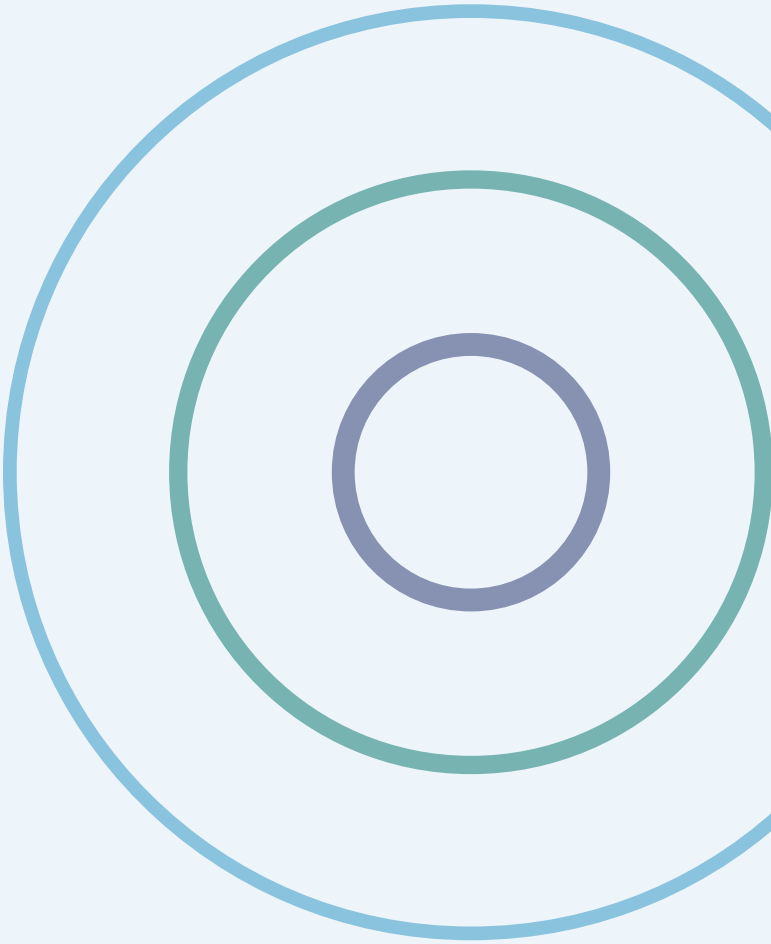
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Appendices

Matrix



Best-practice scale

Section no.	Best practice	Effort implementation	Potential environmental impact reduction	Total
3.1.	**Define and question the need for AI**			
3.1.1	Clearly state and document the problem or need to be addressed.	5 (Easy)	4 (Moderate-high)	9
3.1.2	Build a multidisciplinary team to support the approach.	4 (Fairly easy)	3 (Moderate)	7
3.1.3	Identify solutions (both without and with AI) that can address the identified problem.	3 (Medium)	5 (High)	8
3.1.4	Assess the positive and negative effects (environmental, social, economic) associated with these solutions.	4 (Fairly easy)	5 (High)	9
3.1.5	Consult the market to learn about potential options and their features.	3 (Medium)	n/a	n/a
3.1.6	Determine whether the AI system (or its features) is a relevant solution.	3 (Medium)	5 (High)	8
3.1.7	Determine the type of AI solution suited to your needs.	4 (Fairly easy)	4 (Moderate-high)	8
3.2.	**Establish a responsible governance framework**			
3.2.1	Establish a multi-stakeholder governance framework.	2 (Fairly difficult)	4 (Moderate-high)	6
3.2.2	Determine a process for consulting and informing the public about the AI system's implementation.	3 (Medium)	3 (Moderate)	6
3.2.3	Put in place monitoring mechanisms for the AI system.	3 (Medium)	4 (Moderate-high)	7
3.2.4	Establish a record of responsibilities specifying who is responsible for the various aspects of the AI solution.	4 (Fairly easy)	3 (Moderate)	7

Section no.	Best practice	Effort implementation	Potential environmental impact reduction	Total
3.3.	**Anticipate the potential impacts of AI**			
3.3.1	Qualitatively assess AI's environmental impacts across its entire life cycle, from the design phase onward.	3 (Medium)	5 (High)	8
3.3.2	Analyze the impact of AI solutions on IT equipment.	4 (Fairly easy)	5 (High)	9
3.3.3	Determine decision points and thresholds tied to the impact assessment.	3 (Medium)	5 (High)	8
3.3.4	Check that deploying the technology does not compromise the organization's climate and sustainable-development commitments.	2 (Fairly difficult)	5 (High)	7
3.4.	**Prepare the statement of requirements**			
3.4.1	Consider agile and innovative public-procurement methods. Define outcome-focused criteria.	3 (Medium)	n/a	n/a
3.4.2	Identify and plan for strategies that mitigate the main risks identified throughout the life cycle.	4 (Fairly easy)	5 (High)	9
3.4.3	THEME: ENVIRONMENTAL TRANSPARENCY Favour a supplier that has carried out a multi-criteria LCA of the AI solution.	1 (Difficult)	5 (High)	6
3.4.4	THEME: ENVIRONMENTAL TRANSPARENCY Require the data needed to measure environmental performance.	5 (Easy)	5 (High)	10
3.4.5	THEME: HOSTING Favour data centres located in a region with a low-carbon electricity mix or a high Renewable Energy Factor (REF).	5 (Easy)	5 (High)	10
3.4.6	THEME: HOSTING Favour data centres with strong environmental performance.	3 (Medium)	4 (Moderate-high)	7
3.4.7	THEME: HOSTING Favour a host committed to reducing environmental impact.	3 (Medium)	4 (Moderate-high)	7

Section no.	Best practice	Effort implementation	Potential environmental impact reduction	Total
3.4.	**Prepare the statement of requirements**			
3.4.8	THEME: DATA COLLECTION AND MANAGEMENT Limit data to only the information necessary across AI's life cycle.	1 (Difficult)	3 (Moderate)	4
3.4.9	THEME: DATA COLLECTION AND MANAGEMENT Favour data quality over quantity.	3 (Medium)	5 (High)	8
3.4.10	THEME: DATA COLLECTION AND MANAGEMENT Optimize data cleaning, annotation, and preparation.	1 (Difficult)	5 (High)	6
3.4.11	THEME: DATA COLLECTION AND MANAGEMENT Adapt storage strategies based on how the data is used.	3 (Medium)	3 (Moderate)	6
3.4.12	THEME: DATA COLLECTION AND MANAGEMENT Limit the retention of data collected across the AI system's life cycle, particularly while the model is in use.	5 (Easy)	5 (High)	10
3.4.13	THEME: MODEL CHARACTERISTICS Favour existing, fine-tuned models rather than building one from scratch.	3 (Medium)	5 (High)	8
3.4.14	THEME: MODEL CHARACTERISTICS Choose the lightest possible model (i.e., with fewer parameters).	3 (Medium)	5 (High)	8
3.4.15	THEME: MODEL CHARACTERISTICS Favour energy-efficient models.	5 (Easy)	5 (High)	10
3.4.16	THEME: MODEL CHARACTERISTICS Optimize model performance through compression techniques.	3 (Medium)	3 (Moderate)	6
3.4.17	THEME: MODEL CHARACTERISTICS Reduce energy consumption for inference by favouring batch processing.	3 (Medium)	3 (Moderate)	6
3.4.18	THEME: MODEL CHARACTERISTICS Cache repeated query fragments to avoid unnecessary computation.	3 (Medium)	3 (Moderate)	6

Section no.	Best practice	Effort implementation	Potential environmental impact reduction	Total
3.4.	**Prepare the statement of requirements**			
3.4.19	THEME: (RE)TRAINING During (re)training, find the balance between the resources devoted to training, to improve the AI model's efficiency, and the performance gains achieved.	1 (Difficult)	3 (Moderate)	4
3.4.20	THEME: (RE)TRAINING Favour training during periods of infrastructure under-use, or during periods when the electricity grid's carbon intensity is low.	1 (Difficult)	3 (Moderate)	4
3.4.21	THEME: (RE)TRAINING Minimize the number of model retrainings.	3 (Medium)	5 (High)	8
3.4.22	THEME: INFERENCE (QUERIES) Favour models that can run locally on user devices.	3 (Medium)	4 (Moderate-high)	7
3.4.23	THEME: INFERENCE (QUERIES) Provide the option to turn the AI call on or off.	5 (Easy)	5 (High)	10
3.4.24	THEME: INFERENCE (QUERIES) Configure the model to limit the size of AI-generated responses (output tokens).	5 (Easy)	3 (Moderate)	8
3.4.25	THEME: OTHER ECO-DESIGN PRACTICES Adopt or require other eco-design practices.	3 (Medium)	5 (High)	8
3.5.	**Train teams on the framework for AI use**			
3.5.1	Include, in user training, concepts related to sustainable development and AI's environmental, social and ethical risks.	5 (Easy)	5 (High)	10
3.5.2	Specify the profiles and use cases that are authorized, to avoid non-essential uses.	3 (Medium)	4 (Moderate-high)	7
3.5.3	Encourage users to minimize the number of queries submitted to AI.	5 (Easy)	5 (High)	10

Section no.	Best practice	Effort implementation	Potential environmental impact reduction	Total
3.5.	**Train teams on the framework for AI use**			
3.5.4	Raise staff awareness of resource-intensive features.	5 (Easy)	5 (High)	10
3.5.5	Inform the user of the environmental impact of their query.	1 (Difficult)	3 (Moderate)	4
3.6.	**Measure and disclose performance**			
3.6.1	Make sure the model remains effective, accurate and lean once deployed, and that operating practices keep evolving in the right direction.	3 (Medium)	5 (High)	8
3.6.2	Put in place monitoring and reporting on sustainability indicators.	1 (Difficult)	5 (High)	6
3.6.3	Avoid becoming dependent on overly heavy models, and periodically re-examine the need to keep maintaining AI tools over time.	3 (Medium)	5 (High)	8
3.6.4	Put in place a strategy for reusing and extending the service life of the AI model internally and/or within the community.	2 (Fairly difficult)	5 (High)	7

Checklist

Section	Checklist for (eco-)responsible acquisitions of AI solutions	
3.1.	**When defining the need, have you...**	
3.1.1	...clearly stated and documented the problem or need to be addressed (the reason for the acquisition)?	☐
3.1.2	...put together a multidisciplinary team to support you throughout the process? (in defining the need and features, the issues to take into account, the acquisition criteria, and input during design and deployment, etc.)	☐
3.1.3	...identified different solutions (both without and with AI) that could address the identified problem or need?	☐
3.1.4	...carried out an assessment of the positive and negative effects (environmental, social, economic) associated with these solutions, in order to make decisions that are informed and aligned with the organization's objectives?	☐
3.1.5	...consulted the market to learn about potential options and their features and responsible practices?	☐
3.1.6	...determined whether the AI system (or its features) is a relevant solution?	☐
3.1.7	...determined the type of AI solution suited to your need?	☐
3.2.	**For sound management and governance in acquiring an AI solution, have you...**	
3.2.1	...established a multi-stakeholder governance framework with internal and external stakeholders (including the internal multidisciplinary team) to support decision-making on the solution's acquisition and deployment?	☐
3.2.2	...determined a process for consulting and informing the public about the AI system's implementation, where the solution may affect them?	☐
3.2.3	...put in place monitoring mechanisms for the AI system?	☐
3.2.4	...established a clear record of responsibilities specifying who is responsible for the various aspects of the AI solution being acquired?	☐

Section	Checklist for (eco-)responsible acquisitions of AI solutions	
3.3.	**To properly identify AI's potential impacts and be able to avoid or mitigate them, have you...**	
3.3.1	...assessed the environmental impacts of AI solutions across their entire life cycle, in order to make decisions that are informed and aligned with the organization's policies? (1st-, 2nd- and 3rd-order impacts)	☐
3.3.2	...analyzed the AI solution's impact on IT equipment, to avoid premature hardware renewal? (low-bandwidth or offline connection, effect on devices, operating systems, web browsers)	☐
3.3.3	...determined the decision points and thresholds tied to the impact assessment, to be observed if substantial changes are made to the AI system's design?	☐
3.3.4	...checked that deploying the solution does not compromise the organization's climate and sustainable-development commitments?	☐
3.4.	**To prepare the statement of requirements, have you...**	
3.4.1	...considered agile, innovative and/or outcomes-based procurement methods in the acquisition and contract-execution conditions?	☐
3.4.2	...identified and planned for strategies that mitigate the main risks identified throughout the life cycle?	☐
	...defined criteria related to the supplier's environmental transparency? Namely:	
3.4.3	Favour a supplier that has carried out a multi-criteria LCA of the AI solution.	☐
3.4.4	Require transparency on the AI solution's environmental performance throughout its life cycle.	☐
	...defined criteria to reduce the environmental impacts of hosting the AI solution? Namely:	
3.4.5	The renewable energy factor of the hosting site(s) (the region's renewable electricity mix, or REF calculated per ISO/IEC 30134-3 or equivalent).	☐
3.4.6	The environmental performance of the hosting site(s) (PUE, CUE, WUE, ERF or other indicators) (or at least bidders' ability to provide this information).	☐
3.4.7	The bidder's (or, if subcontracted, the host's) actions to reduce the environmental impact of the hosting site(s) (relating to site location and impacts on ecosystems and biodiversity, energy consumption and GHG emissions, water consumption and its quality-controlled return to the environment, responsible acquisition and management of equipment to extend its service life, etc.).	☐

Section	Checklist for (eco-)responsible acquisitions of AI solutions	
3.4.	**To prepare the statement of requirements, have you...**	
	...defined criteria to reduce the environmental impacts related to data collection and management? Namely:	
3.4.8	Limiting data to the information necessary to achieve the solution's expected performance (type of data, use during (re)training, testing and inference, selection criteria).	☐
3.4.9	Selecting data to prioritize quality over quantity (data provenance across the life cycle, justification).	☐
3.4.10	Data cleaning, annotation and preparation actions to optimize training and avoid excessively long training runs (data-preparation procedure, justification).	☐
3.4.11	Storage strategies differentiated by how frequently data is used (strategies, technology choices, adjusting the volume of hot and cold data, etc.).	☐
3.4.12	Actions to check the relevance of data generated while the model is in use (metadata, registers, etc.) and to limit its collection and retention.	☐
	...defined criteria related to the model's characteristics to reduce its environmental impacts? Namely:	
3.4.13	Fine-tuning existing models rather than developing a solution from scratch.	☐
3.4.14	Using lightweight models (i.e., with fewer parameters) (a Small Language Model [SLM] rather than a Large Language Model [LLM]).	☐
3.4.15	Selecting models with better energy efficiency compared with others (justification of the model choice supported by existing comparative-ranking tools).	☐
3.4.16	Model optimization actions (explanation of the techniques used, justification, collaboration with users).	☐
3.4.17 & 3.4.18.	Actions to reduce inference energy consumption, such as batch processing, caching repeated query fragments, or others (explanation of the techniques used, justification).	☐
	...defined criteria to reduce environmental impacts during model (re)training? Namely:	
3.4.19	The actions (techniques or approaches) in place to stop training the model once it has reached its established optimal performance level.	☐
3.4.20	Measures to favour training during periods of infrastructure under-use or low electricity-grid carbon intensity.	☐

Section	Checklist for (eco-)responsible acquisitions of AI solutions	
3.4.	**To prepare the statement of requirements, have you...**	
	...defined criteria to reduce environmental impacts during model (re)training? Namely:	
3.4.21	The model's retraining needs and the strategies to limit them (frequency, reasons justifying each retraining, mechanisms for tracking and assessing retraining effectiveness, qualitative and quantitative assessment of improvements, associated environmental impacts).	☐
	...defined criteria to reduce the environmental impacts of inference? Namely:	
3.4.22	Verification that the models can run locally on user devices, without those devices needing to be upgraded?	☐
3.4.23	The option to turn the AI call on or off depending on the different usage profiles established by the organization.	☐
3.4.24	The option to limit the size of AI-generated responses (output tokens).	☐
	...explored the possibility of incorporating other eco-design practices for a digital solution?	
3.4.25	Adopting or incorporating eco-design criteria based on existing frameworks.	☐
3.5.	**To ensure responsible use of the AI solution (or its features), have you...**	
3.5.1	...included, in user training, concepts related to sustainable development and AI's environmental (social and ethical) risks?	☐
3.5.2	...specified the profiles and use cases that are authorized, to avoid non-essential uses?	☐
3.5.3	...encouraged users to minimize the number of queries submitted to AI?	☐
3.5.4	...raised staff awareness of resource-intensive features?	☐
3.5.5	...ensured the user is informed of their query's environmental impact?	☐

Section	Checklist for (eco-)responsible acquisitions of AI solutions	
3.6.	**To ensure the AI solution's performance and usefulness are measured and disclosed, have you...**	
3.6.1	...defined requirements to ensure the model remains effective, accurate and lean once deployed, and that operating practices keep evolving in the right direction?	☐
3.6.2	...put in place monitoring and reporting on sustainability indicators?	☐
3.6.3	...planned a process for reviewing and periodically re-examining the need, to avoid becoming dependent on overly heavy models or on AI tools?	☐
3.6.4	...put in place a strategy for reusing and extending the AI model's service life internally or within the community?	☐

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