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Guide to good practices

Use Cases

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Before you begin

Artificial intelligence has become a transformative element in the activity of companies, institutions and public administrations. Its ability to process large volumes of information, generate prediction patterns and automate processes opens up unprecedented opportunities to increase efficiency, improve decision-making and address highly complex challenges. However, the enthusiasm it arouses should not lead to confusing the potential of the technology with a universal solution applicable in any context.

Before going into the details of the phases and good practices that make up this guide, it is worth framing the starting point in a series of general considerations that help to place the reader in the right perspective:

AI as a means, not an end

AI should be understood as a tool that, in certain circumstances, provides differential value compared to other approaches. Its application is meaningless if it does not respond to a specific, clearly defined need, and if it is not previously evaluated whether other less complex, more economical solutions with a lower environmental impact could solve the same problem.

The central role of data

The performance of any AI system is highly dependent on the availability and quality of the data. Models based on insufficient, incomplete or biased information generate unreliable results with a high risk of error. Therefore, before starting any initiative, it is essential to have a data strategy that ensures its governance, integrity and representativeness.

Sustainability as a guiding principle

The development and operation of AI systems involve energy consumption, the need for technological infrastructures and, consequently, a tangible environmental impact. From the initial phase, there must be an explicit commitment to efficiency in the use of resources and the mitigation of the environmental footprint. This criterion not only responds to ethical or regulatory considerations but also contributes to strengthening the legitimacy of the projects in society.

The importance of governance and trust

The adoption of AI requires a robust governance framework that ensures the transparency of models, the protection of privacy and the cybersecurity of systems. The absence of these elements increases the risk of incidents, loss of trust and regulatory sanctions. Before starting a project, it should be verified that adequate policies and monitoring mechanisms are in place to ensure responsible development.

Value must be tangible and measurable

It is not enough to demonstrate technical feasibility. AI projects must be justified by their ability to generate a clear return, whether in terms of economics, operational efficiency, or social and environmental impact. This premise is essential to ensure the sustainability of investments and to prioritize those use cases with the greatest transformative potential.

1. When does it make sense to apply AI?

Artificial intelligence (AI) should not be seen as a technological panacea, but as a strategic tool that deserves to be applied only when it generates tangible and sustainable differential value and does so in an efficient way in the use of resources.

1.1. Generating significant social and environmental impact

AI should be deployed when it makes a concrete contribution to social well-being or the preservation of the environment. Its application is especially valid if it is aligned with recognized global challenges (such as the Sustainable Development Goals) and if there are real use cases that were already underway or piloted, demonstrating its capacity to transform critical sectors such as crisis response, inclusion or educational development.

At the same time, it is key to consider not only the positive impact that AI can generate in other sectors (green by AI), but also the sustainability of the technology itself (green in AI). This implies that the models, infrastructures and processes associated with the development and deployment of AI are designed with energy efficiency, minimization of the environmental footprint and responsible use of resources, thus guaranteeing that the innovation does not compromise the sustainability objectives it pursues.

1.2. Potential to curb climate change

AI makes sense when it can support climate action in a scalable way. When it identifies and optimizes interventions that can measurably reduce greenhouse gas emissions – synergizing with mitigation and resilience plans – its use ceases to be just a technological investment and becomes an engine to achieve sustainable goals at the global level.

1.3. Limited, scalable, and results-oriented approach

It is not a matter of multiplying projects without focus, but of focusing on a limited number of use cases with high potential for impact and clear return. Organizations that achieve this integrate AI into core processes, transform workflows, scale proven solutions, and rigorously measure both benefits and costs.

1.4. Conscious assessment of the environmental footprint

Even high-impact AI solutions can have significant environmental costs. Training large-scale models consumes a significant amount of energy and water and can generate more emissions than the average car over its lifetime. Applying AI with meaning also involves measuring and mitigating these externalities, considering their total footprint.

1.5. Responsible decision-making framework based on ESG criteria

The actual sustainability of an AI project is not only evaluated by its functional impact, but also by its alignment with environmental, social, and governance principles. Having structured frameworks in place to assess the materiality of an application – its environmental or social impact – the responsible governance that accompanies it, and the associated ethical risks, is essential to make judicious decisions about when to apply AI.

2. Risks of applying it incorrectly

The development of artificial intelligence solutions entails a series of risks that must be identified and managed from the initial phases of each project. Inadequate planning or deployment without control mechanisms can lead to effects contrary to the objectives pursued, generating negative impacts both in the organizational sphere and in the environmental and social spheres.

2.1. Intensive consumption of resources with no proportional return

The training and operation of large-scale models require computing infrastructures with high energy consumption and water for cooling. When these efforts do not translate into measurable or scalable benefits, the result is an inefficient use of economic and material resources. The absence of a prior cost-benefit analysis can lead to significant investments in technical capabilities that do not generate added value or sufficient return for the organization.

2.2. Increased environmental footprint

The carbon footprint and environmental impact associated with the life cycle of AI models constitute a significant risk if they are not managed properly. Factors such as the energy demand of data centers, the need for cooling infrastructure, and the generation of e-waste increase the pressure on the environment. Incorrect development, without energy efficiency measures or mitigation plans, can contradict institutional sustainability commitments.

2.3. Biases in results and lack of equity

The quality of AI results is highly dependent on the representativeness and reliability of the training data. When these contain biases, algorithms tend to reproduce or amplify them, generating results that may be discriminatory or unfair to certain groups. The absence of audit and validation mechanisms generates legal, reputational and ethical risks, especially in sectors where equity in decision-making is essential.

2.4. Data privacy and security vulnerabilities

AI models are often based on large volumes of data, sometimes including sensitive data. Failure to put in place proper governance and cybersecurity controls increases exposure to incidents such as breaches, unauthorized access, or tampering with information. These failures not only compromise the security of systems but also expose organizations to regulatory sanctions derived from non-compliance with data protection regulations.

2.5. Poor scalability and risk of obsolescence

The lack of a medium and long-term vision in the design of AI models can lead to isolated developments, with a low level of reuse and limited capacity to adapt to new contexts. This forces additional investments in parallel projects and reduces the overall efficiency of the digital strategy. In addition, rapid technological evolution increases the risk of early obsolescence of solutions that are not designed with criteria of flexibility and continuous updating.

2.6. Deficit of social legitimacy and public acceptance

The use of artificial intelligence is increasingly under scrutiny from the public, regulators and interest groups. The lack of transparency in objectives, environmental impacts or control mechanisms can generate mistrust and questions about the legitimacy of projects. This loss of trust affects both institutional reputation and the ability of organizations to maintain their social license to operate, regardless of the technical results obtained.

Use Case Definition Process

3. Identify opportunities

3.1. Analysis of internal processes

It is essential to carry out a rigorous analysis of the internal processes of the organization. This step not only ensures that future initiatives are built on solid, traceable foundations aligned with current regulatory and sustainability requirements, but also allows for **the detection of inefficiencies, bottlenecks and areas for improvement where AI can provide differential value**.

The analysis must be carried out at two complementary levels:

- **Operational**: identification of data flows, resource consumption and critical points in the execution of processes.
- **Strategic**: connecting these inefficiencies with business objectives (cost reduction, sustainability, service improvement, competitive differentiation).

From this crossover, **potential use cases emerge**, prioritized according to their impact and feasibility.

3.1.1. Process and data flow diagnostics

Map key business processes through interviews, workshops, and process modeling tools. Identify the points where the greatest consumption of resources, emissions, times or errors are concentrated. These indicators become **candidates for AI use cases**, by evidencing measurable areas for improvement.

3.1.2. Governance and risk management

Analyze what control and oversight structures already exist (compliance, quality, audit) and how they can be integrated with AI initiatives. Their absence or weakness points to **opportunities to strengthen governance with AI tools**, for example, for automated monitoring or early warning systems.

3.1.3. Reporting and transparency processes

Assess whether current internal processes generate traceable and auditable data. A lack of data quality can translate into **a use case focused on improving the consolidation and reliability of corporate information**, then enabling projects with greater impact.

3.1.4. Infrastructure and energy efficiency

Inventory data centers, hardware and software, measuring consumption and environmental footprint. This exercise reveals **opportunities to introduce AI into energy optimization, predictive maintenance, or dynamic load management**.

3.1.5. Reliability and ethics in processes

Analyze where there are risks of bias, privacy issues, or security breaches. These areas represent both risks and **spaces where ethical and responsible AI can strengthen trust and enable new services**.

3.2. Analysis of customer needs

Defining AI use cases in the sustainability space requires starting with a deep understanding of real customer needs. This analysis ensures that projects focus on solving specific problems and generating value that combines efficiency, strategic differentiation and sustainable commitment.

3.2.1. Understanding customer expectations

The starting point is to understand how customers perceive the products, services, and experiences that the organization offers. Identifying their pains**, expectations,** and opportunities for improvement allows AI to be directed towards areas where it can bring tangible change. Customer *journey* mapping and behavioral data analysis tools are critical to identifying friction points and designing more seamless, personalized, and sustainable experiences.

3.2.2. Business opportunities and competitive advantages

The needs analysis must go beyond immediate efficiency and be placed at a strategic level. Each AI use case should be evaluated based on its potential to create sustainable competitive advantage**.** This involves identifying how AI can open new market niches, improve the value proposition against the competition or strengthen the relationship with customers through responsible products and services. A strategic vision allows you to select use cases that, in addition to providing efficiency, strengthen the organization's positioning in the market**.**

3.2.3. Prioritization of needs with sustainability criteria

Not all identified needs need to be addressed immediately. The organization must prioritize those that generate the greatest positive impact in environmental, social, and economic terms. Applying dual materiality criteria – how the organization affects the environment and how the risks of the environment affect the organization – allows us to distinguish the use cases with the most strategic relevance. At the same time, transparency and ethics in the design of solutions reinforce customer trust, which becomes a competitive asset.

3.2.4. Customer-centric culture and change management

Finally, this analysis requires a cultural shift towards a truly customer-centric approach**.** This means adopting a mindset where data, sustainability and innovation are structural elements of the strategy. Leaders must foster a culture of co-creation with customers**,** foster multidisciplinary collaboration, and ensure that technology decisions reflect both business interests and societal expectations.

3.3. Stakeholders and stakeholders

Success in defining sustainability-oriented AI use cases depends not only on internal processes and customer needs, but also on the proper identification of **stakeholders**. This analysis allows us to understand who is directly involved in the design, validation, and deployment of use cases, as well as who influences or is affected by them.

3.3.1. Internal stakeholders

In the organizational field, it is useful to distinguish between three levels of involvement:

- **Operational layer**: made up of the teams that work on the day-to-day of the use case. It includes data scientists and engineers, MLOps teams, operational sustainability managers, and business analysts. They are the ones who run and maintain AI systems, ensuring data availability and technical efficiency.
- **Tactical layer**: integrates middle managers who turn strategy into viable projects. These include those responsible for business, ESG and compliance areas, as well as **AI validators** – model audit teams, ethics committees or responsible governance officers – who ensure the quality, robustness and regulatory compliance of the solutions.
- **Strategic layer**: made up of the management committee, senior management and, where appropriate, specific figures such as the Chief AI Officer. They ensure that the use case aligns with the organization's corporate strategy, risk management, and sustainability vision.

Internal forums. In addition to formal roles and bodies, many organizations reinforce participation and coordination through **internal forums**, conceived as spaces for exchange and deliberation. These forums allow for the integration of diverse perspectives and accelerate organizational maturity in AI and sustainability. Some examples are:

- **Technical innovation and data forums**: where teams share progress, good practices and learnings on the development and deployment of use cases.
- **AI ethics and responsibility forums**: spaces where employees from different areas (not only compliance) discuss ethical dilemmas, biases and the social impact of algorithms.
- **AI sustainability forums**: aimed at collectively assessing how AI projects contribute to ESG goals and identifying opportunities for improvement.
- **Internal user forums**: communities of practice that act as a bridge between business, technology and impact areas.

These forums do not replace formal committees, but they function as agile mechanisms that foster organizational culture in AI, ensure a more pluralistic voice in decision-making, and reinforce the legitimacy of the governance model.

3.3.2. External stakeholders: customers and regulators

In addition to internal actors, it is essential to identify external stakeholders, distinguishing between two types of relationship:

- **Customers and end users**: they are the main source of needs and expectations. Their feedback allows validating the relevance of a use case, assessing social acceptance, and reinforcing trust in the organization.
- **Regulators:** they set the regulatory frameworks and the limits of action. They include the European Commission, national authorities and sectoral supervisors who, through regulations such as the AI Act, the CSRD or the GDPR, establish binding obligations that condition the design and implementation of use cases.

3.3.3. Comprehensive governance framework

The integration of internal and external actors creates a governance ecosystem that ensures that AI use cases in sustainability are developed responsibly, transparently, and efficiently. While customers set expectations and regulators set the rules of the game, internal teams—from day-to-day operation to strategic direction—must coordinate to ensure that each use case is deployed with technical rigor, ethical legitimacy, and long-term viability.

3.4. Idea generation

The idea generation phase is a turning point in the process of defining sustainability-oriented AI use cases. After having analyzed the internal processes (1.1), identified the needs of the customers (1.2) and mapped the actors involved (1.3), the challenge is to transform these inputs into concrete and measurable proposals. It is not a question of promoting indiscriminate brainstorming, but of articulating a structured, inclusive and evidence-based process, capable of channelling creativity towards solutions with a real impact on the organization **(process improvement, efficiency, internal sustainability**), on society and on the environment.

According to recognized frameworks such as the **OECD's Oslo Handbook**, innovation can only be consolidated when the exploration of new opportunities is combined with the internal capacity to develop and scale them. Added to this is the need to align ideas with the European regulatory framework, especially the **AI Act** and regulations related to sustainability (CSRD, Green Taxonomy), which generate both obligations and opportunities for organizations.

3.4.1. Idea Generation Levers

Quality ideas do not arise in isolation, but are activated from a series of **levers** that serve as triggers and initial filters of relevance:

Sustainability as a driver of innovation

The ecological and social transition is not only a regulatory challenge, but a catalyst for ideas. As highlighted by organizations such as the **European Environment Agency** and global forums such as the **World Economic Forum**, AI can become a key enabler to reduce the environmental footprint, improve process efficiency and promote an inclusive economy. Examples of levers in this regard include real-time emissions measurement, energy optimisation using advanced algorithms or the creation of predictive models to manage climate risks.

Internal organizational capabilities

The most promising ideas emerge where there is a solid database of data, technological competencies and organizational culture. The **Oslo Handbook** underlines the importance of linking idea generation with internal capabilities, as medium-term viability depends on having specialized talent, digital infrastructures, and consolidated data governance processes. In this sense, the organization must be aware of its strengths and limitations before betting on certain lines of ideation.

4. Landing the use case

The landing phase is the moment when a preliminary idea is transformed into a structured and evaluative initiative. Its objective is not only to give specificity to the use case, but also to ensure that this concreteness is carried out under solid management principles, with clearly defined strategic, technological, operational and environmental criteria.

In this stage, five essential dimensions are addressed, described below.

4.1. Essentials when landing the use case

4.1.1. Definition of the scope

Landing a use case starts with the precise delineation of its scope. This delimitation must answer three fundamental questions:

- What problem or opportunity does it intend to solve?
- In which processes, areas or units will it be applied?
- What limitations and exclusions are established from the beginning?

A clear and consensual scope avoids the dispersion of efforts and facilitates the alignment of expectations. The environmental perspective must be part of this definition, ensuring that limits are established from the outset in terms of energy impact, efficiency of technological infrastructure and consistency with the organization’s sustainability commitments.

4.1.2. Design of a development roadmap

Landing does not imply the immediate deployment of a final solution, but the construction of a progressive itinerary that facilitates learning, adaptation and early validation. The roadmap must be structured in clear phases, with intermediate milestones that allow the evolution of the project to be evaluated and its continuity to be decided. In each phase, sustainability criteria must act as mandatory checkpoints that condition progress to later stages.

4.1.3. Defining tangible deliverables

To give seriousness to the process, each use case must be expressed in concrete and verifiable deliverables. These include:

- Initial use case document (objective, scope, cross-cutting criteria).
- Preliminary functional design.
- Assessment of data, technology, and organizational capability requirements.
- Preliminary impact report, with a specific section on environmental implications.

These deliverables constitute the documentary basis that guarantees traceability and accountability in decision-making.

4.1.4. Definition of decision criteria ("go/no-go")

Finally, the landing process should culminate in defining clear criteria for deciding on the continuity or scaling of the use case. These criteria must consider:

- Its strategic value and degree of alignment with the organization's objectives.
- Technical, operational and organizational feasibility.
- The preliminary cost-benefit ratio.
- Compliance with minimum criteria in terms of environmental sustainability, the overcoming of which must be considered an essential condition for progress.

4.2. Define the objective and scope of application

The clear definition of the **objective** and **scope of application** is the methodological starting point for any use case of artificial intelligence in sustainability. This phase allows the strategic vision to be translated into a concrete operational framework, avoiding subsequent deviations and ensuring alignment with corporate and regulatory commitments.

4.2.1. Objectives: strategic and measurable formulation

The objectives of a use case should be considered as **achievements** and not as ongoing activities, following the methodological logic used by institutional frameworks. Clear wording facilitates accountability and ensures that the expected impact is measurable. The objectives must comply with criteria of **specificity, measurability, achievability, relevance and**

temporality (SMART), integrating environmental, social and governance factors from the outset.

4.2.2. Scope of application: delimitation and control

The **scope** sets the boundaries of the use case, defining what is included and what is explicitly left out. This means developing a "scoping framework" containing:

- **Primary and secondary deliverables**: tangible and verifiable results, from prototypes to production models.
- **Exclusions**: Aspects out of reach to avoid unrealistic expectations.
- **Resources and constraints**: equipment, data, infrastructure, and technical or regulatory constraints.
- **Acceptance criteria**: parameters that determine when a deliverable can be considered valid.

4.2.3. Roadmap and iterative phases

The definition of the scope is reflected in a **structured roadmap**, which combines methodological clarity with adaptive flexibility. Common milestones include:

1. **Definition of the use case**: initial formulation of objective and scope.
2. **Design of the prototype or MVP (Minimum Viable Product):** construction of a first version with essential functionalities.
3. **Controlled pilot**: validation in a small environment and with defined metrics.
4. **Progressive scaling**: deployment to broader contexts, ensuring replicability and sustainability.
5. **Consolidation and monitoring**: institutionalization of the solution, with environmental and social monitoring mechanisms.

This scheme favors risk management, avoids *scope creeps*, and allows learning from early iterations to improve the final solution.

4.2.4. Integration of the environmental dimension

Sustainability should not be approached as an add-on, but as a **structural criterion of purpose and scope**. This involves:

- Incorporate environmental performance metrics into the success criteria.

- Establish application limits consistent with circular economy or climate neutrality policies.
- Assess from the outset the availability of quality environmental data for model training.
- Ensure that the objectives of the use case are aligned with regulatory commitments (e.g. European Green Deal, AI Act).

In this way, each use case is not only oriented towards technological efficiency, but also towards the **creation of sustainable value**, integrating economic, social and environmental impact.

4.3. Threats and vulnerabilities

Identifying threats and vulnerabilities in artificial intelligence (AI) systems is a critical step in the process of defining use cases. It is not just a matter of assessing technical risks, but of understanding their impact on trust, sustainability and responsible adoption of these technologies. The main risk areas can be structured around the following axes:

4.3.1. Privacy and data protection risks

AI operates on large volumes of data, much of it sensitive. Threats such as the **re-identification of individuals in anonymized datasets**, the misuse of personal information, or the lack of compliance with regulatory frameworks (such as the GDPR in Europe) constitute critical vulnerabilities. In addition, the expansion of machine learning techniques increases the surface area of data exposure, which forces measures such as differential privacy, synthetic data or homomorphic encryption to be incorporated by design.

4.3.2. Biases and fairness in models

Reliance on historical data introduces the risk of **reproducing and amplifying social, cultural, or economic biases**. These biases not only affect equity in decision-making but also deteriorate the legitimacy of the AI system in the eyes of society. Lack of data representativeness or adequate validation mechanisms can lead to discriminatory outcomes, especially in areas such as procurement, lending or management of public resources.

4.3.3. Robustness, resilience, and adversarial attacks

AI models can be targeted by attacks that manipulate their inputs to alter results (*adversarial examples*), or that extract sensitive information from training data (*data poisoning* and *model inversion*). These vulnerabilities call into question the robustness of the system and its ability to operate reliably in complex or harsh environments. The absence of adequate defense mechanisms compromises not only technical security, but also business continuity and trust in the system.

4.3.4. Explainability and traceability

The lack of transparency in complex algorithms, such as deep learning models, generates an organizational vulnerability: the **inability to explain AI decisions** to auditors, regulators, or customers. The opacity of the model makes it difficult to detect errors, analyze biases, and implement corrective measures, creating regulatory and reputational compliance risk.

4.3.5. Cybersecurity applied to AI

AI systems, when integrated into critical digital infrastructures, become targets for cyberattacks. These can target both data and models or deployment platforms. Risks include malicious model manipulation, denial of service, and exploiting vulnerabilities in federated learning environments. AI protection requires a layered approach, combining traditional cybersecurity with specific model protection measures.

4.3.6. Environmental and sustainability risks

Beyond technical threats, AI poses **vulnerabilities related to environmental impact**. Training large-scale models involves significant energy consumption and carbon emissions. This dimension, often ignored in risk assessment, must be considered as an element of organizational and social vulnerability, which requires the adoption of energy efficiency metrics and policies, as well as the selection of solutions that minimize the environmental footprint.

4.3.7. Regulatory and compliance risks

The evolution of the regulatory framework, both at European (AI Act) and international level, introduces a risk of non-compliance for organizations that develop or deploy AI without an adequate governance framework. Failure to align with these requirements can lead to economic sanctions, operational restrictions, and loss of institutional legitimacy.

4.4. Use case challenges and issues

The deployment of an artificial intelligence use case in the field of sustainability requires recognizing, from the outset, the main technical challenges that condition its success. These challenges are not merely operational but affect the long-term viability of solutions and their ability to generate real impact.

4.4.1. Data quality and availability

Data quality is one of the main critical points. AI models depend on the completeness, representativeness, and consistency of training and operation data. Incomplete, biased, or heterogeneous datasets degrade technical performance and generate unreliable results. Therefore, data management should be seen as a strategic axis of the use case and not a secondary task.

4.4.2. Integration with existing technological infrastructures
Legacy systems often have interoperability limitations and compatibility issues with modern architectures. Incorporating AI models into production environments requires investments in interfaces, data pipelines, and deployment platforms that ensure scalability, resiliency, and operational security.

4.4.3. Degradation and model drift
Over time, models tend to lose predictive power due to evolving data or behavioral patterns. Detecting and mitigating these deviations require advanced monitoring systems and periodic recalibration protocols. The absence of these measures compromises the reliability and value of the use case.

4.4.4. Technical robustness and life-cycle sustainability
Initial implementation can yield promising results, but without a maintenance plan, models run the risk of becoming obsolete. Traceability and explainability of automated decisions are growing requirements, especially in regulated and sustainability-oriented sectors.

4.4.5. Complexity in AI project management
AI projects require consolidated methodologies, specialized professional profiles and adequate technological resources. The lack of these elements, coupled with high infrastructure and operating costs, translates into barriers that can significantly reduce the expected return of the use case.

4.5. Reliability considerations
Reliability in artificial intelligence (AI) systems is not an isolated concept. It is the condition that ensures that the technology can be adopted, monitored and used with confidence both within the organization and by customers, partners or regulators. A reliable system is one that:

1. It works consistently over time.
2. It can be verified and audited.
3. It meets the expectations of all stakeholders.
4. It generates trust in the organization as a whole.

4.5.1. Technical consistency
The first step in ensuring reliability is to demonstrate that AI produces **consistent and reproducible** results. To do this, organizations must apply a set of technical practices that reduce variability:

- **Stress tests and adverse scenarios:** check how the system responds to sudden changes in data or unforeseen situations.
- **Production monitoring:** detect deviations from the model (model drift or data drift) that can alter the quality of the results.
- **Model maintenance:** Adjusting algorithms when data patterns or operational context change.
- **Redundancy and resilience:** having alternative mechanisms that guarantee continuity if the system fails.

A consistent system conveys security: it always delivers similar results when faced with similar problems.

4.5.2. Verifiability and Auditability

It is not enough for the system to "work"; it must be **able to prove it**. Verifiability implies that the performance of the system can be verified with clear metrics and, above all, independently audited.

- **Traceability:** Each result of the system must be linked to the data sources and intermediate decisions that generated it.
- **Explainability (XAI):** Allowing users and auditors to understand why an algorithm has made a particular decision.
- **Regular audits:** both internal and external, following recognized frameworks (e.g. NIST AI RMF in the US or EU recommendations).
- **Documentary records:** training, validation and use reports that serve as a "black box" to monitor the evolution of the system.

This dimension is especially relevant in the face of regulators and authorities, since reliability cannot be just a perception, but a proven fact.

4.5.3. Stakeholder expectations

Reliability does not have the same meaning for everyone. Each stakeholder expects something different from the system:

- **Internal teams:** they want AI to reduce errors and improve operational efficiency. A model that fails in basic tasks quickly loses credibility within the organization.
- **Customers and end users:** They expect fair, transparent, and bias-free outcomes. In this sense, reliability is also linked to the perception of fairness.

- **Regulators and supervisors:** they demand legal compliance, security, data protection and respect for ethical principles. Reliability, for them, is synonymous with verifiable compliance.

A good management system translates these expectations into **measurable indicators**, such as acceptable error rates, service level agreements (SLAs), or specific privacy and security metrics.

4.5.4. Organizational Trust and Governance

Ensuring reliability also means having governance structures that ensure it on an ongoing basis. The most advanced organizations have created:

- AI committees are responsible for oversight and prioritization.
- Model validation and risk management forums.
- Internal and external audit bodies specialized in AI.

These spaces not only review the technical aspects but also align reliability with the business strategy and with the social and environmental commitments of the organization. Governance makes reliability an **institutionalized attribute**, and not a specific feature of a specific project.

4.5.5. Reliability as a competitive advantage

Beyond the technical or regulatory obligation, reliability becomes a **strategic differentiator**. An AI perceived as trustworthy builds trust with customers, attracts collaborations with other organizations, and reduces reputational risks. Indeed, in a context where AI is increasingly questioned for bias, lack of transparency or social impacts, reliability can make the difference between an accepted or rejected innovation.

4.6. KPIs to measure success

Measuring success in AI use cases requires a structured approach that combines objectivity, strategic alignment, and a balance between quantitative and qualitative metrics. To avoid arbitrariness in the process, it is essential to define a clear methodological framework that guides both the **creation** and **validation** of key performance indicators (KPIs).

4.6.1. KPI creation process

The starting point is the shared definition of what "success" means for each stakeholder. This involves articulating expectations from three levels:

- **Business**, where KPIs must reflect value creation, efficiency and differentiation in the market.
- **Technology**, where the robustness, scalability and resilience of the AI system are evaluated.

- **Society and regulator**, where the focus is on sustainability, regulatory compliance and the trust generated.

Once this framework has been defined, it is recommended to establish governance mechanisms that include the participation of technical, management and ethical validation profiles, so that KPIs are not reduced to operational metrics disconnected from the global impact.

4.6.2. KPI Categories

To make the measurement comprehensive, KPIs are grouped into four broad categories:

- **Technical KPIs**: reflect the system's ability to operate reliably and efficiently. Examples: accuracy in predictions, system availability, response times, scalability in production.
- **Business KPIs**: Quantify economic impact and organizational adoption. Examples: savings in operational costs, increase in revenue derived from AI, percentage of automated processes, adoption rate by employees or customers.
- **Sustainability KPIs**: measure the contribution to the fulfillment of environmental and social objectives. Examples: reduction of carbon footprint in automated processes, energy efficiency of models, number of projects aligned with the SDGs.
- **Trust and governance KPIs**: ensure that the system is perceived as secure, ethically and regulatorily compliant. Examples: frequency of audits performed, number of bias incidents detected and corrected, level of explainability achieved in critical models.

4.6.3. Representative examples

Examples of each category can be given for example:

Category	Example KPIs	Indicator Description
Technicians	Model accuracy (%)	*Percentage of correct predictions vs. actual data*
	Average response time [ms]	*Speed with which the system returns results in production*
	System Availability [%]	*Percentage of time the system is fully operational*
	Critical Incidents Reported []	*Number of technical failures in production with a relevant impact.*

	Energy consumption by inference [kWh]	*Energy efficiency of models in production.*
Business	Use case ROI [%]	*Relationship between benefits obtained and costs associated with implementation.*
	Increase in revenue attributable to AI [%]	*Improvement in sales or other revenue generated by AI.*
	Reduction of operating costs [%]	*Percentage of savings compared to the previous process.*
	Internal adoption rate [%]	*Proportion of employees actively using the solution.*
	Production Time [months]	*The speed with which an MVP or full case is deployed.*
Sustainability	Reduction of CO_2 emissions [t/year]	*Reduction of greenhouse gases is attributable to the use of AI.*
	SDG-aligned cases [%]	*Level of contribution of the projects to the Sustainable Development Goals.*
	Energy consumption per workout [kWh]	*Environmental impact of model training.*
	Reduction of physical resources [%]	*Efficiency in the use of materials thanks to AI digitalization.*
Trust and governance	AI audits completed []	*Internal or external security, ethics, and compliance checks.*
	Biases detected and corrected []	*Identified cases of discrimination and corrective measures applied.*
	Model explainability [scale 1–5]	*The degree to which outputs can be interpreted by humans.*
	User satisfaction index [NPS, etc.]	*Perception of trust and value provided by the AI solution.*
	Degree of regulatory compliance [%]	*Degree of compliance with standards or regulations (e.g. GDPR, AI Act).*

4.6.4. Evaluation and acceptance criteria

Defining KPIs is only the first step: their usefulness depends on establishing clear acceptance criteria. This means:

- Set **performance thresholds** (e.g. "minimum accuracy of 90%" or "reduction of at least 15% in costs").
- Ensure **regular review** to adjust KPIs as the use case, market, or regulatory requirements evolve.
- Incorporate **qualitative criteria** such as customer perception of trust or organizational reputation, which provide a dimension that hard data does not capture.

4.6.5. Balance between quantitative and qualitative

A common risk in AI projects is overweighting quantitative indicators (accuracy, ROI, savings), leaving qualitative indicators (trust, satisfaction, reputation) in the background. The balance between the two allows capturing not only operational efficiency, but also social and organizational acceptance, critical elements for the sustainability of the use case in the long term.

5. Selection of applicable technologies

The selection of technologies is a critical factor in ensuring the viability and impact of an AI use case. It is not enough to know the options available; it is necessary to evaluate its maturity, efficiency, sustainability and compatibility with the organization's strategy. This section organizes the main applicable technologies into six blocks: foundational models, reuse techniques, specialized architectures, sustainable deployment, optimization through AI and reference cases.

5.1. Pre-trained and foundational models

Pre-trained and foundational models constitute the most widespread technological base today. These models, trained on large volumes of data in multiple domains, offer generalist capabilities that can be adapted to a wide range of specific tasks.

Their main value lies in the **reduction of costs and development times**, as they allow organizations to take advantage of previously trained architectures instead of developing solutions from scratch. In addition, they open the door to advanced functionalities, such as multimodal processing (text, image, audio), natural language analysis at scale or content generation.

Among the most outstanding models are:

- **GPT and open variants (GPT-Neo, GPT-J),** as examples of foundational language models.
- **CLIP**, oriented to the link between text and image.

- **Whisper**, specialized in multilingual voice recognition.
- **EfficientNet**, optimized vision model with a resource-efficient approach.
- **DistilBERT and TinyML,** which represent lines of work aimed at lighter and more sustainable models.

The evolution towards more sustainable foundational models has led to the development of architectures with a smaller energy footprint, maintaining a balance between performance and efficiency.

5.2. Methods of reusing and adapting models

One of the most effective strategies to apply AI efficiently is the **reuse of existing models** through different adaptation techniques:

- **Transfer Learning** allows you to reuse representations learned in one domain to apply them to another, with a much lower computational cost than training from scratch.
- **Knowledge distillation:** A technique that compresses a complex model into a smaller one, with reduced energy consumption and faster inference times.
- **Parameter-Efficient Fine-Tuning (PEFT):** methods such as *adapters* or *LoRA* allow you to adjust only a part of the model, significantly reducing the resources needed for its training.
- **Modular models:** architecture that facilitate the combination of reusable components, increasing flexibility.
- **Graph Neural Networks (GNNs):** Applicable to problems with relational structures, such as financial fraud or logistics networks, with an especially valuable focus on complex environments.

These techniques are critical to reducing training costs, speeding up deployment cycles, and minimizing the environmental impact associated with compute-intensive.

5.3. Sustainable deployment strategies

Once a model has been developed or adapted, its operation requires strategies that ensure an efficient and responsible use of resources:

- **Optimized inference: techniques** such as quantization, parameter pruning, or the use of specialized hardware can reduce latency and power consumption during execution.
- **Sustainable scalability:** Apply large-scale inference policies that balance output quality and power consumption.

- **Dynamic resource provisioning:** Flexibly allocated compute based on demand, avoiding infrastructure underutilization.
- **Cloud deployment with sustainability criteria:** taking advantage of *green cloud* environments and suppliers with emission reduction policies and the use of renewable energies.
- **Energy impact monitoring:** establish metrics and KPIs (e.g. *Power Usage Effectiveness*, carbon intensity of the software) that allow the evaluation of the operational footprint of the system and ensure its continuous improvement.

5.4. AI to optimize AI

Artificial intelligence itself is used as a tool to improve the efficiency of your internal processes:

- **Automated Machine Learning (AutoML): Automated** selection of architectures and parameters to reduce training times.
- **Neural Architecture Search (NAS):** Automated exploration of architectures that optimize accuracy and power consumption.
- **Compilers and hardware-aware optimization (e.g. TVM):** translation of models to run optimally on specific hardware.

This category reflects the maturity of the technological ecosystem, where AI becomes a self-optimizing mechanism, increasing scalability and reducing the environmental footprint.

6. Impact analysis

The concept of *impact* on artificial intelligence is heterogeneous and multifaceted. There is no single universal definition, since the meaning depends on the prism from which it is evaluated: environmental, social, economic or regulatory. In this way, what represents a tangible benefit for one area of the organization, for another, may imply a latent risk or an ethical challenge. This diversity requires a structured approach that allows for an integrated understanding of the consequences of each case of use.

The main difficulty is that impacts are rarely reducible to a single indicator. Environmental effects, such as carbon emissions or the energy consumption of technological infrastructure, are relatively quantifiable. However, social impacts – such as trust, inclusion or citizen perception – are more intangible in nature. Even economically, traditional cost-benefit metrics tend to fall short if considerations of risk, sustainability, and long-term legitimacy are not integrated.

In recent years, frameworks and standards have been developed to guide this task. In the environmental field, emission measurement protocols and life cycle management standards provide a well-established benchmark. For social and governance analysis, international reporting frameworks and European sustainability regulations set out clear guidelines for incorporating intangible factors. In the economic sphere, complementary methodologies to traditional financial approaches are emerging, which integrate social and environmental returns together with strictly monetary returns.

Impact analysis should not be conceived as an accessory exercise, but as a fundamental pillar to ensure the legitimacy and sustainability of artificial intelligence in organizations. Only through a consistent, transparent evaluation framework aligned with strategic objectives is it possible to assess the benefits, risks and commitments involved in each use case in a balanced way. In addition, this analysis must be reviewable and comparable over time, allowing cumulative learning to be generated and strengthening the position vis-à-vis regulators, customers and society in general.

6.1. Environmental impact

Analyzing the environmental impact of artificial intelligence (AI) requires a broad view, as its effects manifest themselves at different levels and with varying intensities. These impacts are not homogeneous: they depend on factors such as the scale of the model, the infrastructure used, the geographical location or the origin of the energy. The specialized literature usually distinguishes between **direct impacts**, derived from consumption and operation, and **indirect impacts**, linked to the life cycle of equipment and the supply chain.

6.1.1. Direct impacts

- **Energy consumption**: Training advanced AI models involves considerable electrical expenditure. The magnitude of the impact depends largely on whether the electricity comes from renewable sources or fossil fuels.
- **Water use**: Data centers that support AI operation need cooling systems that use large volumes of water. In water-stressed regions, this dependence can become a critical factor.
- **Emissions from use**: Although training concentrates most of the energy consumption, the inference phase also generates relevant emissions when the systems are applied intensively and on a large scale.

6.1.2. Indirect impacts

- **Electronic waste (e-waste):** The constant renewal of specialized hardware (GPUs, TPUs and other components) produces an increasing flow of electronic waste whose proper management is not always guaranteed.

- **Technological infrastructure**: The construction and expansion of data centers, as well as the necessary investments in electricity and telecommunications networks, have their own environmental footprint.

- **Critical Mineral Extraction**: The production of devices and components requires lithium, cobalt, nickel, or rare earths. The extraction of these resources involves deforestation, intensive use of water and the generation of emissions, in addition to being associated with social and geopolitical tensions.

6.1.3. Measurement methodologies

Environmental impact can be measured using different comparative methodologies that allow for the evaluation of use cases in a standardized way:

- **Life Cycle Assessment (LCA):** Considers all phases of the system, from the extraction of raw materials to the end of their useful life.

- **Carbon footprint accounting**: Calculates CO_2 equivalent emissions, differentiating between direct, indirect emissions from energy consumption and emissions along the value chain.

- **Operational indicators**: Tools such as *Power Usage Effectiveness* (PUE) allow measuring the energy efficiency of a data center, while water consumption indicators provide visibility into the water footprint.

6.1.4. Management considerations

Incorporating these variables into the AI use case definition process is key to making informed decisions. Some common practices include:

- Compare the impact of different technological alternatives to select the most efficient option.

- Introduce environmental criteria in the processes of prioritization and selection of use cases.

- Ensure that the communication of these impacts is integrated into the organization's sustainability reporting and ESG commitments.

6.2. Social impact

6.2.1. The need to measure social impact

The social impact of an artificial intelligence initiative applied to sustainability cannot remain in the realm of the intangible or merely declarative. For stakeholders – both internal and external – it is essential to have mechanisms in place to translate AI's contribution into observable and verifiable metrics. Measurement not only validates the effectiveness of interventions, but also facilitates strategic decision-making, accountability, and comparison between projects.

At the same time, it is worth underlining the complexity inherent in the process: many of the social results are qualitative in nature, materialize over different time horizons and affect different groups. Hence, it is essential to rely on recognized methodologies that allow the evaluation to be rigorous and comparable.

6.2.2. Main recognized methodologies

There are different frameworks and methodologies for social impact assessment that have achieved wide international acceptance. Among them are:

- **SROI (Social Return on Investment):** Considered one of the most comprehensive standards, SROI translates social, environmental and economic results into monetary terms, establishing a ratio between the investment made and the social value generated. Its value lies in the fact that it allows the social profitability of a project to be expressed, in a simple metric, something that is easily understandable by managers, investors and regulators.
- **Social Reporting Standard (SRS):** A reporting framework that standardizes the way the social impact of initiatives and organizations is described. Its main contribution is transparency and comparability, offering a clear structure for documenting objectives, activities, results and impacts, beyond exclusively financial metrics.
- **Theory of Change:** This approach starts from the identification of the desired social objectives and defines the logical chain of activities, intermediate results and final impacts that must occur to achieve them. While it doesn't always include monetization, it's a powerful tool for aligning expectations and verifying strategic consistency.
- **Logical Model:** Similar to the Theory of Change, but more focused on the relationship between inputs, outputs and outcomes. Its advantage lies in the clarity and simplicity to map how invested resources are converted into social results.
- **Hybrid methodologies:** In practice, many organizations combine quantitative metrics (e.g., number of beneficiaries, emission reduction) with qualitative metrics (e.g.,

perception of improvement in quality of life), achieving a more comprehensive and representative approach to reality.

These methods, although different, coincide in the need to:

1. **Define clear and verifiable indicators.**
2. **Link results to strategic objectives.**
3. **Incorporate both the perspective of the direct beneficiaries and that of society as a whole.**

The incorporation of these methodologies into the analysis of the social impact of AI guarantees greater legitimacy, helps to avoid arbitrariness and makes it easier for organizations to make evidence-based decisions, aligning their technological strategies with a real commitment to sustainability and equity.

6.2.3. Categories of indicators in social impact

When implementing these methodologies, the indicators are usually organized into categories that allow different dimensions of social value to be captured:

1. **Quantitative indicators:**
   - Number of beneficiaries.
   - Increase in the employability of vulnerable groups.
   - Percentage reduction in the digital divide.
2. **Qualitative indicators:**
   - Perception of improvement in subjective well-being.
   - Testimonies of benefited communities.
   - Quality of relations between organization and stakeholders.
3. **Monetized indicators:**
   - Calculation of the SROI (e.g. €1 invested = €2.5 of social value generated).
   - Estimated value of the savings in social costs (health, education, labour) attributable to the project.

6.2.4. Validation and transparency processes

It is not enough to define indicators; it is necessary to establish acceptance criteria that guarantee their reliability and avoid arbitrariness in the selection. To this end, it is recommended:

- **Stakeholder participation:** Include beneficiaries, regulators, and experts in the design of metrics to ensure relevance and legitimacy.
- **Data triangulation:** combining internal sources, external surveys, and public data.
- **Independent audits or validations:** increasingly used to strengthen the credibility of social impact reports.

Transparency becomes a critical value: communicating not only the positive results, but also the methodological limitations and the learnings obtained in the process.

6.2.5. Challenges in measuring social impact

The application of these methodologies faces several challenges:

- **Attribution:** Determine precisely how much social change can be attributed to the AI project and how much it is to other external factors.
- **Temporality:** some impacts require years to manifest, which makes it difficult to integrate them into short evaluation cycles.
- **Monetary valuation:** translating qualitative changes into monetary figures involves value judgments and assumptions that can be debatable.

Even with these limitations, the global trend points to the consolidation of standardized and auditable metrics, which reinforces the credibility of organizations that apply AI for sustainable purposes.

6.3. Economic impact

The economic impact of artificial intelligence (AI) in the framework of use cases should not only be assessed in terms of cost savings, but also in terms of its ability to transform business models, generate new revenue streams and strengthen the competitiveness of organizations. In this sense, AI acts as a **double lever**: on the one hand, it increases operational efficiency by reducing time and costs; on the other, it drives value creation through innovations in products, services and management processes. Specifically, the economic impact can be quantified through a combination of direct and indirect financial indicators, aligned with the business objectives:

1. **Operational cost savings**

Measuring reductions in man-hours, processing costs, errors, or rework, comparing the situation before and after the adoption of the use case.

2. **Revenue Increase**
   Estimation of new revenue streams or improvements to existing ones, such as increased sales, improved cross-selling/upselling, reduced churn, or accelerated time-to-market.
3. **Productivity and efficiency**
   Indicators such as output per employee, cycle time of key processes or capacity to absorb a greater volume of demand without a proportional increase in costs.
4. **Implementation and operation costs**
   Total cost of ownership (TCO) consideration: development, licensing, infrastructure, maintenance, model governance, and change management.
5. **Return on Investment (ROI) and Payback Time**
   Calculation of the expected ROI and payback period, using conservative, baseline, and optimistic scenarios to reflect the associated uncertainty.

6.3.1. Operational efficiency and cost optimization

The application of AI algorithms makes it possible to automate repetitive and low-value-added tasks, significantly reducing the dependence on human resources for manual processes. These systems help minimize errors, improve execution speed, and reduce recurring operating expenses.

The integration of AI solutions in areas such as document management, demand forecasting or inventory optimization can be quantified by comparing key indicators before and after their implementation. In document management, savings are usually measured in terms of reduced hours spent on manual tasks (classification, search, validation), reduced errors and less need for rework, translated into avoided labour costs. In demand forecasting, the improvement in accuracy is reflected in a reduction in stockouts and overstock, with a direct impact on storage costs, tied up capital and losses due to unrealized sales. In inventory optimization, savings can be expressed as a decrease in the average stock level while maintaining the same level of service, or as an improvement in the cost-to-service ratio.

6.3.2. New revenue models and business transformation

AI not only brings efficiency, but it also opens the door to the creation of **new revenue models**. Organizations that adopt advanced technologies can develop more personalized products, data-driven services, and new value propositions for their customers.

6.3.3. Business resilience and competitiveness

The economic impact of AI is also reflected in resilience to changes in the environment. Organizations that integrate these technologies in decision-making, in the early detection of risks or in the modeling of scenarios strengthen their ability to adapt and ensure their competitive position. In sectors such as finance, AI has established itself as a key factor for risk management, fraud detection and portfolio optimization. More broadly, its application in strategic management allows us to accelerate the ability to respond to new market opportunities.

7. Feasibility assessment

Evaluating an AI use case is an essential phase in its lifecycle. Unlike impact analysis, which describes the economic, social and environmental effects, the purpose of the assessment is to **determine the suitability, feasibility and strategic alignment** of the case with the organization. It is a process that allows discriminating between initiatives, reducing risks and prioritizing the allocation of resources towards those with greater value potential.

Evaluation should be approached as a **multidimensional** exercise, in which regulatory, strategic, technological, operational and financial considerations converge. This holistic view ensures that decisions are not limited to immediate profitability, but incorporate factors of regulatory compliance, sustainability, organizational maturity, and ability to execute.

From a management perspective, it is key to articulate objective criteria that allow each case to be linked to corporate objectives, check its compatibility with existing systems, estimate its costs and benefits, and ensure that it can be sustained and scaled up over time. The formalization of these criteria avoids arbitrariness and provides organizations with a clear framework for decision-making.

In this sense, the evaluation of use cases should be understood not only as a pre-deployment filter, but also as a **governance mechanism** that reinforces the transparency and trust of the different stakeholders. A solid evaluation methodology helps AI projects to be implemented responsibly, aligned with the organization's strategy and capable of generating sustainable benefits over time.

7.1. Legal and ethical aspects

Regulatory compliance is the first threshold in evaluating an AI use case. Its purpose is to ensure that the initiative complies with both regulatory requirements and the internal policies of the organization, avoiding legal, ethical or reputational risks that compromise its legitimacy.

This axis must be considered from a **double perspective**:

- **External**, aimed at compliance with regulatory frameworks for data protection, information security, sectoral standards and international principles of trust in AI.
- **Internal**, linked to consistency with codes of ethics, data governance policies, sustainability guidelines and corporate risk standards.

The evaluation method consists of **inventorying a series of items grouped by risk categories** – legal, ethical, reputational, security or governance – and analyzing their degree of compliance. The result of this assessment is translated into a binary scheme **(OK/KO),** complemented by the identification of residual risks and possible mitigation measures. In this way, simplicity in decision-making is guaranteed without sacrificing the depth necessary to ensure the traceability of the process.

The compliance axis, therefore, not only verifies the legal and ethical viability of a use case but also reinforces the transparency and trust of the different stakeholders. It is an essential initial filter: only those initiatives that exceed this threshold will be able to advance to the next phases of evaluation and prioritization.

7.2. Alignment with business strategy

The integration of an AI use case into an organization should not be evaluated solely in terms of its technical feasibility or immediate economic benefits. It is essential to determine if the initiative is **aligned with the strategic objectives** defined by the entity. This axis ensures that AI efforts translate into tangible results that reinforce the corporate mission while contributing to the sustainability of competitive advantage.

The evaluation process must begin by identifying the **organization's strategic drivers**, such as improving operational efficiency, driving innovation, customer orientation, environmental sustainability, or strengthening business resilience. Each use case must be analyzed in relation to these axes to determine how it contributes, directly or indirectly, to their achievement.

The analysis methodology consists of establishing an **explicit mapping between the use case and the corporate strategic lines**. This linkage allows cases to be classified according to their level of alignment (high, medium, low), generating an objective basis for decision-making. A case with a low level of alignment, although it may show an economic return in the short term, may lack legitimacy if it does not contribute to the goals that the organization has set as priorities.

It is also relevant to integrate this assessment with planning instruments such as **strategic roadmaps** and business management frameworks. This integration ensures that the use case not only responds to specific needs but is also part of a continuous process of transformation and value creation.

The business strategy axis acts as a **relevance filter**, guiding the selection of use cases towards those that are not only viable or profitable, but also consolidate the future direction of the organization. This approach allows investment in artificial intelligence to translate into a real lever for transformation and a factor in reinforcing the corporate vision in the medium and long term.

7.3. Technological criteria

The technological viability of an AI use case depends not solely on its functionality or expected performance, but on its **ability to integrate coherently and sustainably into the organization's technology ecosystem**. This axis of evaluation seeks to ensure that the proposed solution does not become an isolated initiative, difficult to maintain or incompatible with the strategic evolution of corporate systems.

A first aspect to consider is **technological compatibility**. The use case must be able to interact seamlessly with existing platforms and systems – from databases and information repositories to business management solutions and analytical tools. Inefficient integration, functional redundancies or the creation of parallel systems without connectivity generates cost overruns and operational risks that limit the added value of the initiative.

Second, the evaluation must contemplate alignment **with the systems plan**. Most organizations have a defined technology strategy, which includes infrastructure modernization goals, migration to cloud environments, adoption of unified data platforms, or standardization of analytical tools. Any use case that does not fall within this framework may require additional unforeseen investments, compromise deadlines, or hinder the evolution of the technology architecture.

Another essential element is the **carbon footprint and sustainability of AI systems**. The training and operation of large-scale models has a considerable energy impact, which must be evaluated in terms of consumption, associated emissions and available alternatives. Opting for pre-trained models, applying hardware optimization techniques or employing energy-efficient infrastructures are measures that contribute to reducing this impact. Including this analysis in the technology assessment not only responds to an ethical and compliance requirement but also strengthens the reputation of the organization in its commitment to sustainability.

Finally, **scalability and resilience** complete the technological assessment. A case must be able to be replicated in different areas or geographies, adapt to changes in the volume of data or user demand, and maintain its operability in the face of possible technical failures. The robustness of the system, the ease of maintenance and the existence of contingency plans are determining factors to ensure its viability in the medium and long term.

In short, the technological axis evaluates not only whether the use case is technically feasible, but whether it is **coherent, aligned and sustainable**. Integration with existing systems, adjustment to the strategic technology plan, responsible management of the environmental footprint and the ability to scale with resilience are essential conditions for a use case to provide real and lasting value to the organization.

7.3.1. *Simplified assessment methodology*

- **Structured checklist**: group the assessment items into three blocks: compatibility and alignment, sustainability, and scalability/resilience.
- **Binary valuation**: classify each item as OK/KO, reserving more detailed analyses for complex or critical cases.
- **Decision and residual risks**: consider the case fit only if it obtains an OK in compatibility and alignment. In sustainability and scalability, it is possible to move forward with a documented mitigation plan.

7.4. Operational criteria

The operational dimension of an AI use case refers to the **organization's ability to efficiently deploy, maintain, and scale it**. It's not just about the system operating in a test environment but about ensuring that it can be sustained in practice with the right processes, equipment, and resources.

The main aspects to be evaluated are:

1. **Availability and quality of data in operation**
    - Verify that the necessary data streams are available with the required frequency and quality.
    - In cases based on language or generative models, analyze the **volume of tokens** and the cost associated with their processing, since it directly impacts operational feasibility.
2. **Organizational processes and capabilities**
    - Identify if the organization has basic roles, tools, and procedures to keep the system in production.
    - Assess the ability to monitor performance, resolve issues, and tune models when necessary.
3. **Scalability and operational sustainability**

- Determine if the system can scale based on demand without operating costs growing disproportionately.
- Analyze whether resource consumption (compute, storage, tokens processed) is compatible with the organization's budgets and efficiency policies.

7.4.1. Simplified assessment methodology

1. **Operational checklist**: verify that the minimum aspects of data, processes and scalability are covered.
2. **Binary valuation (OK/KO):** The use case only moves forward if the data and operational processes are secured.
3. **Volumetry analysis**: estimating at a high level, the consumption of data or tokens and their impact on OPEX, with mitigation plans if high growth is expected.

7.5. Cost-benefit ratio

Cost-benefit assessment is an essential component in prioritizing AI use cases. This analysis makes it possible to determine whether the investment required to develop and maintain an initiative is justified against the value it brings to the organization, whether in economic, strategic or reputational terms.

The first step is to identify and classify the **costs associated with the use of a lifecycle**. The initial investment, or **CAPEX**, includes the expenses related to the design, training of models, acquisition of licenses, technological infrastructure and human resources necessary for the start-up phase. In parallel, it is essential to evaluate recurring **operating costs, or OPEX**, which include elements such as data and token processing, energy consumption, continuous monitoring, storage and the intervention of specialized personnel for system maintenance.

On the other hand, the expected benefits must be analyzed. These fall into two categories:

- **Tangible benefits**, such as operational cost savings, increased revenue, productivity improvements or reduced errors.
- **Intangible benefits**, including enhancing institutional reputation, strengthening regulatory compliance, strengthening customer and partner trust, and contributing to sustainability goals.

The analysis must also incorporate the **time horizon** in which the benefits materialize. Not all use cases generate immediate returns; some require a longer payback period. In this sense, it is useful to work with differentiated scenarios (conservative, intermediate and optimistic) that allow us to estimate the evolution of the cost-benefit relationship in a more realistic way.

The valuation methodology combines recognized financial metrics, such as return on investment (ROI), total cost of ownership (TCO), and payback period. In parallel, more specific analytics frameworks, such as the Return on Artificial Intelligence (ROAI), offer tools to quantify the value derived from use cases that generate both tangible and intangible benefits. The incorporation of these instruments provides the analysis with rigour and comparability between different initiatives.

The final result of the evaluation is expressed in a classification of the use case according to its cost-benefit balance: **favorable, neutral or unfavourable**. This result serves as a decision criterion on the progress or rejection of each initiative, ensuring that resources are directed towards projects capable of generating a sustainable impact and aligned with the strategic objectives of the organization.

8. Prioritization and selection

The identification and evaluation of artificial intelligence use cases generates a broad and heterogeneous set of potential initiatives. However, not all of them have the same relevance, feasibility or strategic contribution. Hence the need to have a **systematic prioritization and selection methodology**, which allows the organization to make objective, transparent decisions aligned with its goals.

The purpose of this section is to offer a framework that facilitates the transition from the **individual evaluation of each use case** (block 4) to the **construction of a portfolio of prioritized initiatives**, which maximizes the value generated and optimizes the use of resources.

5.1 Principles of prioritization

The methodology is based on a series of basic principles:

1. **Transparency**: the evaluation and prioritization criteria must be clear, known by all relevant actors and applied in a homogeneous manner.
2. **Comparability**: cases must be analyzed with common metrics that allow establishing an objective and replicable order.
3. **Flexibility**: the methodology must be adapted to the particular strategy of the organization, adjusting weights or criteria according to the sector, digital maturity or regulatory context.
4. **Scalability**: The framework should serve both to evaluate a small number of cases and to manage a large and dynamic portfolio.

5. **Strategic balance**: it is not only about choosing the most profitable cases in the short term, but about building a balanced portfolio that combines efficiency, innovation and sustainability.

5.2 Structure of the methodology

The prioritization and selection methodology is composed of five sequential stages:

- **1. Definition of criteria and weights**

The five axes defined in the previous block constitute the basis of the model:

- **Compliance**: Mandatory threshold filter.
- **Business strategy**: contribution to the strategic objectives of the organization.
- **Technological criteria**: compatibility, alignment with the systems plan and sustainability.
- **Operational criteria**: feasibility of commissioning, maintenance and scalability.
- **Cost-benefit ratio**: financial analysis and value generated.

Each axis receives a **relative weight** depending on the importance that the organization attaches to each dimension. For example, strategy and cost-benefit may be given a higher weight, while technology and operation act as enabling criteria.

2. Individual evaluation (scoring)

Each use case is scored on the different axes following a simple and objective scale (e.g. 0–2 or 0–5).

- **Compliance** is assessed in binary format (OK/KO). Any KO implies immediate exclusion from the case.
- The other axes are assessed with a graduated score, accompanied by a brief justification documenting the decision.

- **3. Calculation of the overall score**

The score for each axis is multiplied by its weight and consolidated into a **final weighted score**. This calculation allows an objective and numerical representation of the relative value of each case to be obtained, facilitating their comparison as a whole.

4. Tierization and categorization

Based on the final score, cases are grouped into three main categories:

- **Tier 1 (High Priority):** strategic cases, with high viability and clear benefits. They are the ones that advance to immediate deployment.
- **Tier 2 (Medium Priority):** cases with potential, but requiring technical, organizational, or financial adjustments before being implemented.
- **Tier 3 (Low Priority):** Cases with low contribution, significant risks, or limited return. They are postponed or discarded.

Tierization simplifies decision-making and facilitates communication to governing bodies.

5. Qualitative review and portfolio construction

Although scoring provides a quantitative basis, it is essential to carry out a **qualitative review** with the main stakeholders (management, business areas, technology, compliance). This phase allows for the incorporation of nuances not captured in the score, such as the need to innovate in certain segments, regulatory pressure, or the opportunity to strengthen institutional reputation.

The end result is the **construction of a portfolio of use cases**, which combines:

- **Quick wins**: cases of quick return and low risk.
- **Strategic initiatives**: projects of greater scope, aligned with the long-term vision.
- **Case studies**: innovative explorations that provide learning and future positioning.

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