Schneider Electric™
Sustainability Research Institute

AI for Impact

A Method for Guiding AI-Energy Applications at Scale

The Digitalization of Energy Series

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Introducing the Schneider Electric™ Sustainability Research Institute

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Global awareness of the need for a more inclusive and climate-positive world is at an all-time high. This includes reducing carbon emissions and preventing environmental damage and biodiversity loss.

Bridging the Gap Between Climate Pledges and Action.

Despite growing climate pledges and sustainability initiatives, global progress is lagging.

To bridge this gap, we need a multi-pronged approach:

- Alignment with UN SDGs: Ensure actions directly contribute to the UN Sustainable Development Goals (SDGs), providing a clear roadmap for progress.
- Science & Technology: Leverage scientific research and technological advancements to drive innovative solutions.
- Shift Foresight: Gain a deeper understanding of evolving energy landscapes, industries, and social, environmental, technological, and geopolitical trends.
- Policy & Finance: Strengthen legislative and financial mechanisms that incentivize and empower climate action.
- Public - Private Collaboration: Clearly define the roles and responsibilities of the public and private sectors in achieving these goals.

The Schneider Electric™ Sustainability Research Institute addresses these challenges by providing:

- Global & Local Scenarios Examining climate issues and opportunities at both global and local levels, informing solutions for businesses, societies, and governments.
- Forecasting & Actionable Insights: Analyzing current and future trends across energy, business, and behavior to anticipate challenges and identify actionable solutions.

Founded in 2020, our team is part of Schneider Electric, a leader in energy management and automation. We collaborate with experts across institutions and academia, and our research findings are published online.

The present research investigates the potential of Artificial Intelligence (AI) to address climate change and facilitate a successful transition towards sustainable energy systems.

We discuss the challenges hindering progress: The lack of *quantifiable data on AI's real-world impact* on emissions reduction limits the assessment of its effectiveness, the *fuzzy use of terminology* surrounding AI subfields creates ambiguity, and, the discussions often prioritize consumer-facing AI, neglecting its *crucial role in decarbonization and the energy transition*.

Introducing the 'AI for Impact Compass': a unique, data-driven tool designed to improve how we assess AI's contribution to climate action. The Compass offers a unique approach by integrating three critical dimensions not typically combined:
1. Quantified Impact: Measuring the tangible effects of AI solutions on decarbonization.
2. Scalability: Evaluating the potential for deploying AI applications, maximizing their impact across different contexts.
3. Risk: Assessing risks associated with AI deployment, and ensuring safe and trustworthy implementation.

Finally, we examine practical use cases to illustrate our findings and lay the groundwork for further research. Our aim is to provide large-scale, quantified evidences that offer more evidence of AI's impact on climate, and highlight actionable insights for policymakers, academics, and industries.

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Foreword by Hugo Quest, PhD, EPFL Researcher & Data Scientist

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Evolving AI and Energy landscape

The use of Artificial Intelligence (AI) applications in the energy sector is gaining momentum, driven by an intensive search for reliable, high-quality solutions that have shown promising research results. This growing interest is fueled by decisionmakers in both industry and policy, who are looking for ways to boost company profitability, enhance efficiency, and **support the energy transition.**

Digitalization is crucial for implementing reliable, cost-effective electrification within the modern context of the energy transition, shifting from centralized to more distributed systems. With the rapid integration of renewable energy into the grid — global annual renewable capacity additions surged by nearly 50% in 2023, reaching 510 gigawatts (GW), marking the fastest growth rate in the past two decades (1) — **AI emerges as a pivotal digitalization tool.**

AI will play a key role in redesigning future energy systems and supply chains, enabling accurate forecasting and planning of variable renewable energy sources, optimizing grid operations, managing demand, and providing automated intelligent fault detection. **Recent AI advancements impact all levels of energy systems**, from retail and distribution to transmission grid planning, operation, and generation.

Emerging AI regulation

The rapid evolution of AI applications in the energy sector promises significant benefits. However, addressing potential misuse risks through effective knowledge transfer between research, industry, and policy stakeholders presents a formidable challenge.

The European Council recently approved the **AI Act**, establishing the first global regulation for Artificial Intelligence. This legislation uses a ‘risk-based’ approach, imposing stricter rules on higher-risk AI applications. It aims to promote safe and trustworthy AI systems across the EU while protecting fundamental rights. High-risk AI systems will face stringent requirements, and certain practices, like cognitive behavioral manipulation and predictive policing, are banned.

The law also promotes transparency and mandates impact assessments for high-risk AI systems in public services. It supports innovation through AI regulatory sandboxes for real-world testing.

The new emerging policy landscapes and shifting industry goals create the **need for clear communication and comparison mechanisms for AI applications.**

Towards a unified framework to guide AI deployment

In this context, the **Schneider Electric™ Sustainability Research Institute** aims to provide new insights and tools with this research, to address the obstacles impeding progress towards safe, transparent and effective AI implementation in the energy sector.

To tackle these challenges, the concept of the **AI for Impact Compass** is introduced. Expanding on the previous three-dimensional indicator proposed in 2022 (2), this framework adopts a data-centric approach to assess AI’s contribution to climate action and the energy transition, focusing on three major criterias : 1) Impact, 2) Scalability, 3) Risk.

This study bridges the gap between researchers, industries and policymakers by providing a framework to maximise AI’s transformative potential for the energy transition through actionable insights.

From demystifying the fuzzy definitions of AI and digitalization, to applying the new AI Compass to case studies in energy systems and buildings, this work provides a clear pathway towards **Impact-Driven AI** for the energy transition.

I wish you an excellent reading.

Hugo Quest, PhD, EPFL
Researcher & Data Scientist

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(1) IEA, ‘Renewables 2023 - Analysis and Forecast to 2028’.

(2) Quest et al., ‘A 3D Indicator for Guiding AI Applications in the Energy Sector’.

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Executive summary

The looming climate crisis requires *mitigation strategies*

The scientific consensus on anthropogenic climate change is irrefutable. The Intergovernmental Panel on Climate Change (IPCC) paints a dire picture, with current trajectories exceeding the Paris Agreement's target of limiting warming to below 2°C. This scenario could have catastrophic consequences, including rising sea levels, extreme weather events, and mass ecosystem disruptions. To limit global warming to 1.5°C, a drastic reduction in greenhouse gas emissions is crucial. This requires emissions to peak before 2025 and decrease by 43% by 2030. **This requires a global paradigm shift towards sustainable practices across all sectors.**

Using AI as a *transformative power*

Given the urgency of addressing climate change, Artificial Intelligence (AI) is a potential *transformative power for accelerating mitigation efforts.* AI encompasses a range of sophisticated computational techniques, including machine learning, reasoning, computer vision, communication and more. These techniques excel at analyzing vast and complex datasets, extracting hidden patterns, making data-driven predictions, and enabling design and operations optimized decisions.

This analytical power positions **AI to play a potentially pivotal role in mitigating climate change when combined with the right decarbonization technologies**, such as electricity.

AI *with* Purpose, AI *for* Impact

However, a crucial gap exists in the current debates surrounding AI and climate change: **the lack of robust, quantifiable evidence regarding its impact on climate change mitigation**.

This deficiency stems from two main factors.

- *First*, AI terminology lacks **of standardization.** Sub-domains of AI such as machine learning and deep learning are often used interchangeably, hindering clear communication and impeding rigorous impact assessments.

- *Second*, discussions often prioritize consumer applications of AI, **neglecting critical debates surrounding its efficacy in the energy transition**, particularly large-scale decarbonization efforts.

Thus, a refined categorization of AI, along with an exploration of its innovative applications and impacts on energy demand management, is essential for harnessing AI's full potential in climate change mitigation. Such a categorization will achieve its maximal utility only if it informs or aligns seamlessly with international standards.

The power of *AI for the energy transition*

The *transformative power of AI for the energy transition* lies in its novelty and ability to **leverage mature and demonstrated decarbonization technologies,** such as **electrification** of the end-sectors. Decades of AI development have laid a strong foundation, and focusing solely on pushing entirely new concepts may prove counterproductive. When addressing climate change effectively, AI's **true potential also resides in its capacity to optimize and improve the performance of existing applications.**

The *AI for Impact Compass* as a guiding tool

Despite the energy sector's enthusiasm for AI, there remains a persistent search for methods enabling the proper identification and evaluation of dependable, impactful solutions that demonstrably address climate change while offering widespread deployability with minimal regulatory risk. To bridge this gap, we propose a fact-based, categorized approach to guide effective decisions towards AI and Energy.

The **AI for Impact Compass** offers a classification scheme for industry leaders, researchers, and policymakers.

This tool aims to establish a common baseline for effectively evaluating AI applications in the energy sector, through three main criteria:

1. Quantified Impact: This criterion aims to integrate a **science-based quantification** method to determine the AI solution potential. For this, we rely on the "Net Digital Impact" framework [(a)], which provides a framework for grounding impact calculations by considering the direct, indirect, and systemic effects of digitalization.
2. Scability Potential: This criterion assesses the potential of AI applications to be implemented widely and across multiple contexts. To achieve this, we utilize a referenced Machine Learning **maturity** index and incorporate standardized **adoption** criteria to quantify replicability.
3. Risk: This criterion aims to inherently incorporate the importance of understanding and managing the risks associated with AI usage, encompassing aspects such as market, ethics, and governance. We leverage the cutting-edge guidelines established by the **European AI Act** to assess these risks effectively.

The path forward: *Practice on large scale use cases*

While the AI for Impact Compass aims to guide and facilitate evidence-based discussions on AI for climate change mitigation, it represents **an initial step in a broader quantification process**. Our Research Institute is committed to conduct and to provide further research to precisely quantify the impact of these meta-case studies and **provide robust evidence** supporting AI's role in mitigating climate change.

(a) The full framework is defined in the 'Digital with Impact' Concept Paper, May 2024, Schneider Electric™ Sustainability Research Institute

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Why guiding AI for Impact?

Problem Statement

Decarbonizing energy systems, as mandated by global climate policies, necessitates optimizing energy usage and integrating cutting-edge digital technologies with proven climate change mitigation benefits.

While the proliferation of Artificial Intelligence (AI) applications presents promising potential in facilitating the transition towards a modern energy infrastructure, there is a conspicuous absence of a **unified and rigorous reference point** through which stakeholders can evaluate their real impact on climate change mitigation.

Research Problem

The central challenge involves creating a decision-making tool that balances practicality with robust scientific methodology Furthermore, integrating novel factors is essential to ensure the framework's applicability and efficacy in addressing urgent climate change mitigation challenges. Hence, our research takes the following factors into account:

I. Comprehensive Impact Quantification: Establishing a **rigorous method for evaluating the climate impact** of AI applications, based on a calculation methodology that encompasses direct, indirect, and systemic effects.

II. Scalability at the Core: Incorporating **scalability as an essential factor**, given the urgent requirement for efficient and effective solutions capable of being extensively implemented across diverse contexts to combat climate change.

III. Risk Assessment: Evaluating the **risk** associated with AI solutions to prevent enabling social scoring, the use of manipulative techniques, or jeopardizing the safety of critical infrastructures.

IV. Demand-side Focus: Emphasizing **demand-side climate change mitigation and decarbonization opportunity**, as an essential amount of global greenhouse gas (GHG) emissions can be attributed to energy usage

V. Separating the Grain from the Chaff: Developing a methodology to differentiate promising AI applications from those that are less so, without imposing a singular truth, to **offer preliminary guidance to stakeholders** in distinguishing between potential solutions.

Research Objectives

This study aims to address the aforementioned gap by offering a systematic approach to supporting policymakers and decision-makers in directing AI-driven impact initiatives within the energy transition.

The research encompasses two primary goals:

1. Suggest an initial **set of fundamental AI-Energy use cases** that warrant further examination in quantifying of their impact.

2. Present the **AI for Impact Compass**, which aims to deliver a reliable quantification technique and a visual aid to support decision-making processes for policymakers, investors, businesses, and public research institutions.

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Why AI and Energy is the new power couple

Energy Transition:

What is the trigger for a new season of AI?

The looming shadow and a glimmer of hope

Climate change casts a long shadow, demanding immediate action. A sustainable energy future is no longer a luxury, it is the only viable path.

Much like electricity sparked the Second Industrial Revolution and Information and Communication Technology (ICT) propelled the Third, Artificial Intelligence (AI) is poised to become a driving force behind the next transformative industrial era.

As AI technology advances to deliver widespread impact and energy transition rises on government agendas worldwide, the convergence of AI and energy presents a *critical opportunity* and challenge for governments and societies.

Can AI become the key to unlocking a *truly sustainable Fourth Industrial Revolution,* one that tackles the environmental challenges head-on?

AI-Powered Energy transition

The potential synergy between AI and energy demands our immediate attention. We need to pinpoint the areas within the energy transition where AI's impact will be most significant.

Which AI domains – *reasoning, planning, learning, and especially machine learning* – will offer the most valuable tools to mitigate climate change through energy transition?

Developing quantification methods to assess the AI-Energy coupling's success is a vital step toward harnessing its potential and guiding the energy sector toward a sustainable future.

In this chapter, we will explore the past of AI and energy and see how they have developed a symbiotic relationship, meaning they benefit and depend on each other.

Photography : Dartmouth College for the Dartmouth Summer Research Project on Artificial Intelligence August 1956. From left to right: Oliver Selfridge, Nathaniel Rochester, Ray Solomonoff, Marvin Minsky, Trenchard More, John McCarthy, Claude Shannon.

The first cycle of AI

The birth of AI: A spark at Dartmouth (1956)

AI Spring

In June 1955, ***John McCarthy***, a young Assistant Professor of Mathematics, and ***Claude Shannon***, the father of information theory then at Bell Labs, organized a 2-month, 10-man workshop on Artificial Intelligence (DSRPAI) during the summer of 1956 at Dartmouth College (1). This event fueled significant funding and research efforts towards what researchers called the "AI Spring", which marked the initial surge of enthusiasm and prepared the ground for the "AI Summer".

The workshop's inspiration stemmed from ***Alan Turing's*** groundbreaking paper "Computing Machinery and Intelligence" (2), which introduced the Turing test as a measure of machine intelligence. Inspired by this concept, the enthusiasm for AI research flourished in the following decade. It paved the way for significant advancements, including ELIZA (3), a Natural Language Processing (NLP) program developed by ***Joseph Weizenbaum*** at MIT (1964 - 1967), considered an early ancestor of today's Large Language Models (LLMs) like ChatGPT, Mistral, Gemini and many more.

AI Winter (1970s-80s)

While the initial enthusiasm for AI flourished in the 1950s and 60s, the technology's limitations and unrealistic expectations about its capabilities led to a period of reduced funding, interest, and progress known as the "AI Winter" (1970s - 80s).

Interestingly, even during the AI Winter, two foundational technologies paved the way for AI's future:

- First, ***Electricity***, was a catalyst for the Second Industrial Revolution, which provided the energy foundation for significant advancements in computing power for AI research and development (4).
- Second, *Information and Communication Technologies* (ICT), a vital driver of the 3rd Industrial Revolution, underwent significant advancements in miniaturization - exemplified by the invention of the Integrated Circuit (IC) in the 1950s - enabled the creation of smaller, cheaper transistors, leading to a dramatic increase in processing power, and interconnectedness with advancements in communication technologies like fiber optics, satellite communication, and early stages of the internet (5), both crucial to AI's progress.

AI blossoms in the 90s (and beyond)

Post 90s : the beginning of a new spring?

Ironically, in the absence of government funding and public hype, AI thrived. During the 1990s and 2000s, many of the landmark goals of Artificial Intelligence had been achieved.

Increased computing power enabling more complex algorithms, advancements in mathematical techniques like probability and statistics, prepared the ground for effective *Machine Learning (ML)* – showing early signs in Game Playing (6) : Deep Blue's victory in chess showcased AI's potential in strategic thinking; *Natural Language Processing (NLP)*: Speech recognition software like 'Dragon Dictate' marked progress in understanding human language; and ***Robotics***: Robots with basic capabilities like 'Kismet' emerged (7).

The past decade (2015 onwards) has witnessed an exponential leap in AI capabilities. No longer confined to specific tasks, AI has blossomed into a ***versatile technology***, transforming countless industries. This advancement is powered by a progressively interconnected relationship with energy, particularly electricity, which has evolved from a basic link into a mutually dependent system.

The emergence of a symbiotic AI-Energy relationship

As climate change becomes increasingly visible, the energy transition has shifted from a 'niche' concern to a universal human endeavor. Simultaneously, AI has entered a renaissance, leveraging modern technology to increase its computing power and unlock large-scale applications exponentially. Recent developments show that both energy transition and AI encompass not only energy itself, but also access to energy, social justice, and sustainable economic development. A ***symbiotic relationship*** between AI and energy emerged in this context.

- On one hand *(the direct effects)*, **AI's infrastructure requires substantial energy** : Reliable and efficient energy becomes even more critical for AI's operation and development, posing a challenge regarding resource consumption and potential environmental impact.
- On the other hand, **AI offers the potential** *(potentially through positive indirect and systemic effects)* **for a more impactful transition to modern energy systems**.

A recent IEA perspective (8) highlights the increasing complexity of the electrical system, driven by rising demand, decarbonization, and the proliferation of distributed energy resources, which necessitates advanced grid management tools.

Concurrently, the rapid advancement of AI presents a viable solution through its capacity to analyze vast datasets generated by smart grids and connected devices. In many cases, AI is gaining traction in the industry, with diverse applications and significant market potential; however **the question of the impact at scale** still needs to be better documented.

The second cycle of AI
Towards a 4th Industrial Revolution?

What sparked the Industrial Revolution?

Recognizing the signs

Projections suggest that electricity will dominate energy consumption by 2050 (IEA NZE Net Zero scenario - World Energy Outlook (WEO)). We believe this dominance necessitates a crucial next step: understanding how these new, digitalized, and electricity-driven energy systems can serve as the foundation for a fourth Industrial Revolution. *Unlike its predecessors*, this revolution must inherently address the limitations of our planet (Earth Boundaries) and pressing issues like climate change, biodiversity loss, and resource depletion.

Thinking Industrial Revolutions

Drawing on the work of Professor of Economic History ***Nicholas Crafts*** (9), we can define an industrial revolution as a confluence of two factors:

- *A General-Purpose Technology (GPT):* A technology with far-reaching applications across many sectors, such as steam, electricity, and information and communication technologies (ICT).
- *The Invention of a Method of Invention (IMI)*: A process that accelerates the creation of new knowledge and technologies.

IMIs drive productivity gains in knowledge production, while GPTs boost productivity in goods and services.

The First, Second, and Third Industrial Revolutions each brought advancements in specific areas of innovation. Reflecting on these historical experiences can provide insight into the potential impact of AI as a ***General-Purpose Technology*** and its role in driving a Fourth Industrial Revolution.

To achieve this, AI needs to be not just a GPT but also the ***Invention of a Method of Invention*** (IMI), as some writers think it may be (Cockburn et al., 2019) (10). IMIs and GPTs are generally distinct, but their synergies can lead to significant advancements. Figure 1 illustrates this.

		General Purpose Technology (GPT)	
		No	Yes
Invention of a Method of Invention (IMI)	No	Bessemer Converter Industrial Robots	Steam Power Autonomous Vehicles
	Yes	Research Laboratory Algorithms	**ICT - AI** **Electricity**

Figure 1. GPTs and IMIs. AI-Energy nexus.
Schneider Electric™ Sustainability Research, based on Nicholas Crafts.

The genesis of AI-Energy nexus

First Industrial Revolution (1760s-1830s)

Classically, the term 'First Industrial Revolution' describes economic development in Britain between the 1760s and the 1830s. It is well-known that real wages increased very slowly during this acceleration period in technological progress (11). According to ***Crafts***, the First Industrial Revolution *does not* provide a model for arguing that a General-Purpose Technology necessarily negatively impacts workers living standards. However, ***Crafts*** also points out that this First Industrial Revolution was *not coupled* with the Invention of a Method of Invention (IMI). Its capacity to transform the entire economy was limited.

Second Industrial Revolution (1870-1914)

The Second Industrial Revolution is the emergence of Electricity as a *Method of Invention*, grounded in applied science and the innovation of the industrial research and development (R&D) laboratory. This stands in stark contrast to the First Industrial Revolution, *which lacked a robust scientific foundation*. The establishment of ***Thomas Edison's*** first laboratory in Menlo Park in 1876 marked a turning point, as **the rise of electricity as a General-Purpose Technology (GPT) and the Invention of a Method of Invention (IMI)** became a defining feature of the technological advancements brought about by the Second Industrial Revolution (12).

Third Industrial Revolution (1960s-2020s)

The Third Industrial Revolution is a term often used to refer to the 1960s to the 2000s, when computer science came of age. It encompassed rapid computer hardware and software development from the mainframe, through the PC, to the Internet (Schwab, 2017) (13). A key characteristic of ICT is that it is - like Electricity - **both a knowledge technology (IMI) and a GPT** (Mokyr, 2002) (4). As an IMI, ICT not only significantly reduced the access costs of knowledge, but also provided a new technology for innovation reflected in a **significant increase in the share of patent citations**, together with significantly **more patents per R&D dollar** (Branstetter et al., 2019) (14).

What might make the AI-Energy couple unique?

According to ***Crafts***, the historical context of past Industrial Revolutions offers insights into the potential role of AI in the 4th Industrial Revolution. Hence, AI *might* present a unique possibility – being *both a GPT and an IMI*. However, *unlike past revolutions*, the **4th Industrial Revolution needs to prioritize sustainability** (15).

This raises critical questions: Can the forthcoming convergence of advancements in AI act as a **sustainable GPT** for this new era? Can this combination simultaneously drive innovation, economic growth, and environmental sustainability by supporting the shift **toward decarbonized energy systems**?

Demystifying AI:
Towards shared definitions

This section clarifies key concepts related to digitalization and its influence on the energy transition.

Digitization, Digitalization and Digital Transformation

Currently, there lacks a standardized set of definitions for digitization, digitalization, and digital transformation within the energy sector. Building upon F. Heymann et al.'s work (24) as well as other research on defining "Digital" (25) (26) (27), we propose the following foundational definitions:

Digitization (related to *Direct effects*).
Converting analog data to digital format happens relatively quickly, often at the individual company level within the energy sector. Consider a distribution network company converting its network plan to a digital version.

Digitalization (related to *Indirect effects*).
Utilizing digital technologies (ICT) across all players in the energy sector to exploit new data sources. This level aims to improve safety, efficiency, and productivity. It involves broader structural changes across the sector, taking several years to achieve. Imagine all distribution network companies digitizing their network plans and assets.

Digital Transformation (related to *Systemic effects*).
A large-scale, cross-sectoral shift in which all economic and social actors connect into an interlinked digital system fosters enhanced data exchange, analysis, and decision-making capabilities. This shift takes years to decades to achieve and fundamentally alters interactions between all market players. For example: all network companies in the gas, electricity, and heating sectors digitize their network plans and assets, sharing data on a central platform, and enabling new business models with multiple users.

Understanding the Digital toolbox

Following Heymann et al.'s recommendation, which draws upon a consensus across multiple sources (26) (28) (29), and aligns with recognized definitions (20), we will utilize the following definitions for the digital technologies that form the backbone of most uses for the energy transition.

Primary Digital Technologies.

Four technologies might offer the *broadest potential* for contributing to the energy transition.

- *Artificial Intelligence (AI)*: Methods that mimic human intelligence for learning, problem-solving, and decision-making.
- *Big Data (BD):* Reflecting the real world through massive amounts of machine-readable, often real-time data.
- *Internet of Things (IoT/IIoT):* Fusing digital and physical infrastructure through internet-connected devices.
- *Distributed Ledger (DL):* A secure, transparent way to store transactions chronologically.

Secondary Digital Technologies.

Today, these applications have *less quantified use cases* or less widespread agreement on their applications.

- *Digital Twins (DT)*: Enabled by IoT, these are simulated models of assets or even entire electricity systems, that can be used to optimize operations.
- *Robotics (RB)*: Using robots for design, construction, and operational processes in the energy sector.
- *3D Printing (3D)*: Manufacturing objects based on 3D computer models.
- *Augmented & Virtual Realities (VR)*: Enhancing the real world for human interaction.

Understanding the AI toolbox

While there is not a single, universally accepted taxonomy for AI at this point, the European Commission, through its *Joint Research Centre* (JRC), is actively involved in developing a comprehensive framework for classifying AI technologies (31). This framework aims to establish a common language for discussing AI across various sectors and applications.

The JRC is collaborating with international partners, particularly the United States, to establish a shared understanding of AI terminology and taxonomies. They propose the following classification of AI domains:

1. Reasoning (RE)
2. Planning (PL)
3. Learning (LE)
4. Communication (CO)
5. Perception (PE)
6. Integration & Interaction (II)

Note: For detailed definitions of the six domains, please refer to the Annex.

A well-defined terminology could foster a more unified approach to AI by establishing a common language for researchers, developers, policymakers, and stakeholders across sectors.

This classification could enable standardized evaluation of AI capabilities, allowing for a clearer understanding of risks and benefits. Furthermore, the terminology can inform discussions on the ethical implications of AI development and deployment, ensuring responsible use of these technologies.

Contextualizing AI:
A pivotal point in the AI-Energy history

AI is moving from theory to real-world applications

Heymann et al. (21) have identified five current scientific breakthroughs which are driving a surge in AI applications across various industries, including the power sector.

- **Powerful, affordable hardware:** The availability of Graphics Processing Units (GPUs) has significantly reduced the training time for complex AI models, as demonstrated in Figure 2 (32, 33).
- **Deep learning breakthroughs:** Significant progress in computer vision, reinforcement learning, and understanding goal-oriented behavior has unlocked new possibilities for AI applications (34).
- **Neuroscience-inspired AI:** Insights gleaned from the study of the brain have informed AI research in areas such as memory, attention, and continuous learning (35).
- **Transfer learning:** Leveraging knowledge from pre-trained models and applying it to new tasks has reduced the need for extensive data collection (34).
- **Automated machine learning (AutoML):** Automating the selection of AI models and their hyperparameter tuning has streamlined the development process, making it more accessible (36).

As a result, the expanding capabilities of AI are driving its increasing adoption by businesses across various sectors, including power (38) (39).

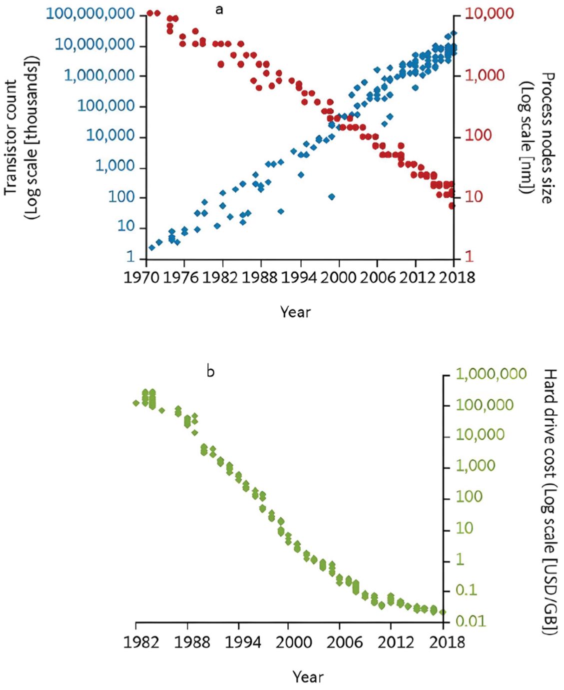


Figure 2 - Evolution of computing power, cost and data storage. The figures shows the number of transistors per CPU and technology node size (a), memory costs per gigabyte (b). Source: Heymann et al.

Research on AI's role in the power sector is not new, but interest in it is exploding

In the same study (21), Heymann et al. provide a comprehensive analysis of research on AI applications within the power sector, spanning 40 years. The findings challenge the perception of AI's involvement in energy as a novel development.

- The research reveals a well-established foundation, with the publication of the first major review on "expert systems" (an early form of AI) in the energy domain dating back to 1989 (40). Similarly, by 1997, a significant body of research on diverse AI systems tailored for the power sector had already emerged (41). These findings demonstrate that **rudimentary forms of AI,** such as expert systems and neural networks, **have contributed consistently to the power sector for over three decades.**
- Heymann further quantifies the field's growth, estimating an annual publication rate exceeding 25,000 at the intersection of power systems and AI (as of 2022). Despite this substantial volume of research, the study's authors posit that **our understanding of AI utilization within the electricity industry, along with its future potential, remains incomplete.**

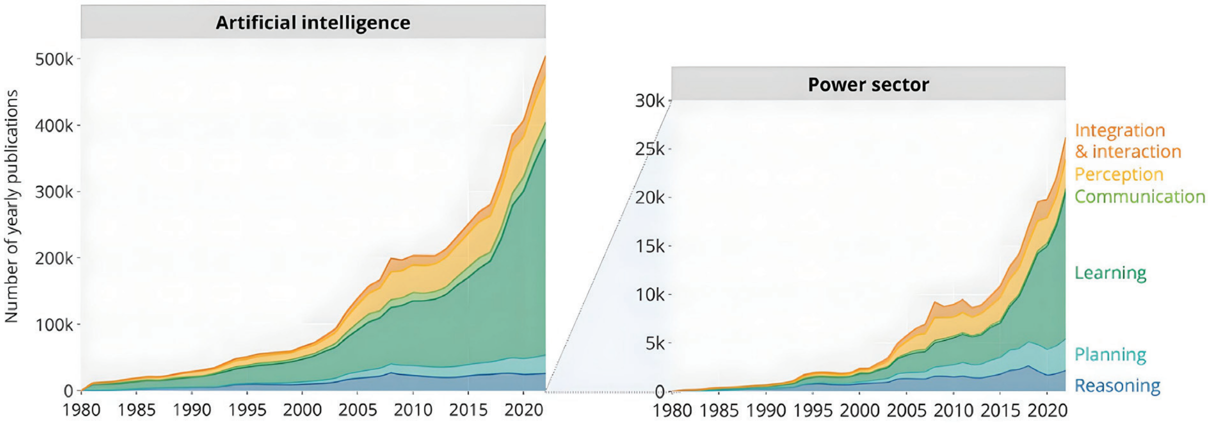


Figure 3 - 40 years of AI in the energy sector. . Source: Quest et al.

Understanding AI:
As a Transformative Power

AI permeates the three layers of digital transformations

As discussed earlier, referencing ***Crafts***' work, AI, as a "*General Purpose Technology"* and an "*Invention of a Method of Invention*", could potentially trigger the 4th Industrial Revolution. However, the sheer scale and scope of AI applications are so vast that, **it's crucial to pair AI with technologies that can deliver immediate and scalable action,** in the context of an impactful energy transition. While other digital technologies lay the groundwork for optimization and efficiency gains, AI appears to stand at the apex of the digital transformation, serving as the ubiquitous driving force behind it.

A revolution for better or worse?

AI's growing adoption in various sectors raises concerns about its environmental impact.

- While **its direct impact on emissions is currently small**, its rapid expansion and increasing computational demands could significantly increase energy consumption. However, advancements in energy efficiency and the use of renewable energy sources could help mitigate these effects.
- The **indirect impacts of AI on emissions are less clear**. While AI has the potential to accelerate the development of climate solutions, such as more efficient batteries and renewable energy integration, it could also have negative consequences, including increased electricity use in various sectors and potentially boosting fossil fuel production (through *the Jevons Paradox)*.

Furthermore, widespread AI adoption could indirectly impact emissions through its **societal and economic effects,** such as changes in poverty, food security, and social inequalities.

AI: Climate savior or culprit?

AI is rapidly transforming the global economy, with companies investing significant capital in these technologies. AI is being leveraged across various sectors to enhance operational efficiency, manage complexity, deliver personalized services, and accelerate innovation. However, as AI's societal influence grows, concerns arise regarding its environmental impact (37), particularly its effect on greenhouse gas emissions. Hence, a ***systemic approach*** is needed.

Indeed, the answer hinges on ***how*** AI models are ***developed***, and ***operated***, and the ***societal shifts they induce***. At the time of this study (June 2024), our understanding of AI's full environmental impact remains a developing area of research, which raises concerns due to the significant potential implications involved.

While important, the focus on AI's direct environmental impacts, such as energy use and emissions, has perhaps overshadowed a broader consideration of its wider ecological consequences. The pervasive nature of AI applications extends to diverse sectors like healthcare, education, mining, transportation, agriculture, and many more. These widespread applications can generate indirect effects on emissions, potentially outweighing the direct impacts, with both positive and negative outcomes possible.

To ensure the responsible and sustainable integration of AI technologies, it is imperative to conduct comprehensive assessments encompassing both direct and indirect environmental impacts, as defined in Figure 4 (42). Such evaluations will provide crucial insights for mitigating potential risks and maximizing the AI's positive contributions in addressing the global climate crisis.

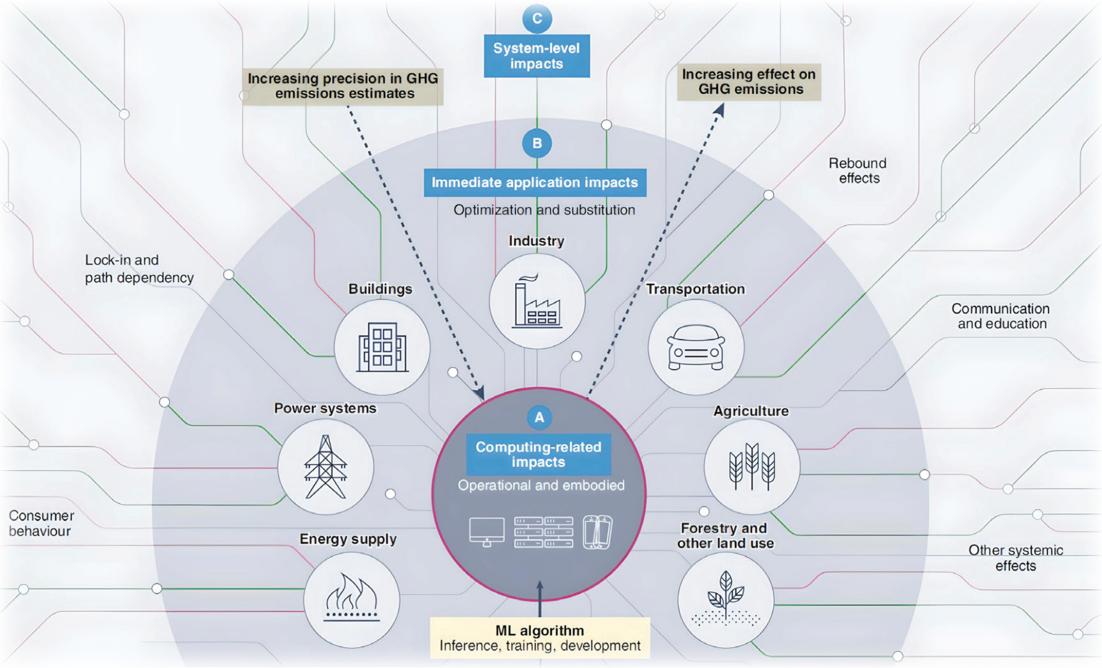
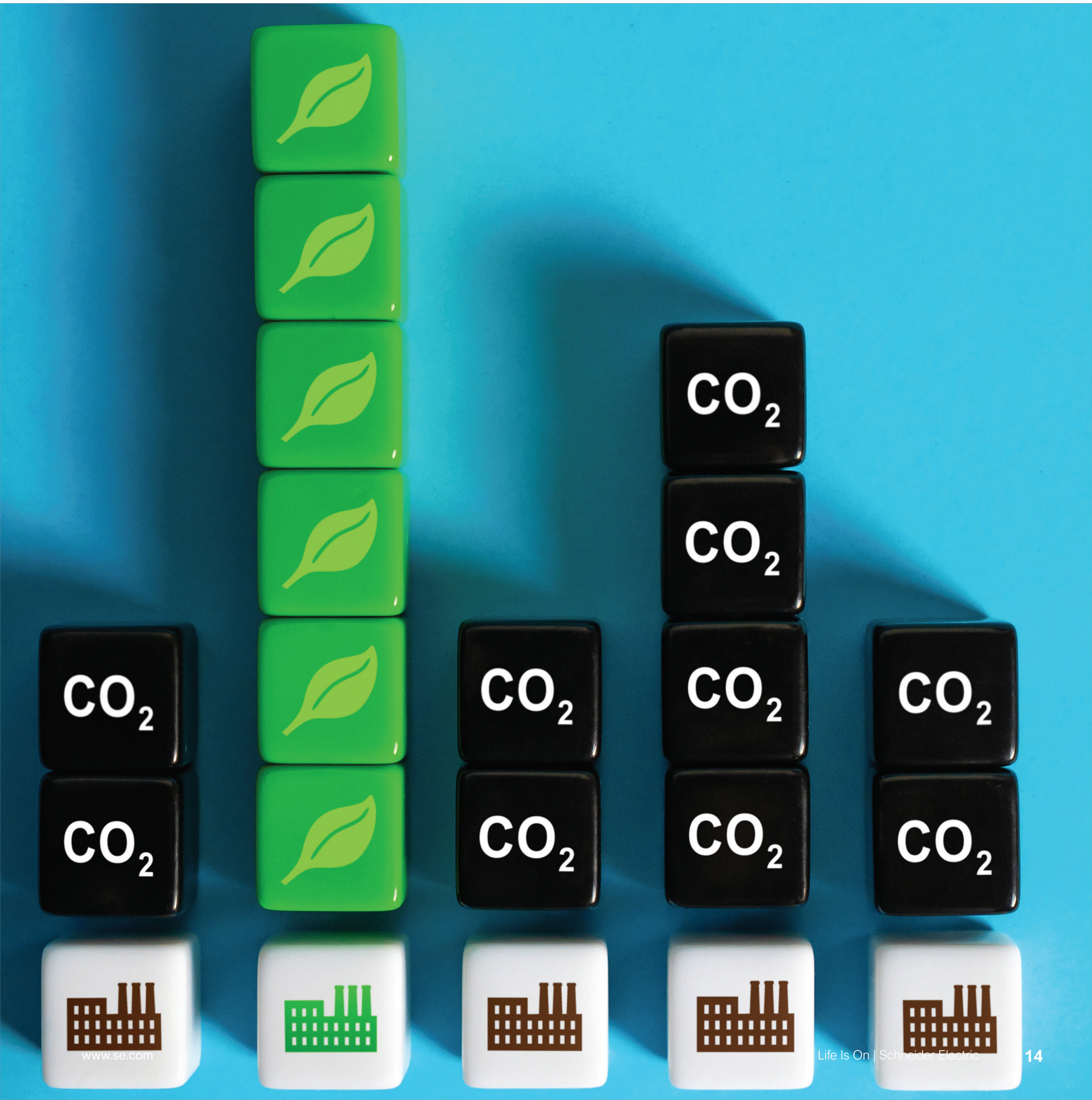


Figure 4. Direct, Indirect and Systemic effects of AI.
Source: Kaack et al.

3

AI-Energy use cases for Climate



Categorizing AI applications

The urgent need to reduce carbon emissions across all industries is driving a significant shift in how we produce and use energy.

This transition requires moving beyond individual industry goals and instead focusing on a more comprehensive approach that optimizes energy flow across the entire system.

In this chapter, we examine current and comprehensive inventories of AI use cases in the energy sector, evaluating their strengths and limitations.

We propose a first categorization of use cases to evaluate the impacts of an AI solution on an energy transition application.

Building the Blueprint
Emerging AI playbooks for the energy transition

2018: The EPRI's Playbooks

Pioneering inventories

The *Electric Power Research Institute* (EPRI), a leading American non-profit organization focused on research and development in the energy sector, identified key challenges and use cases for the future of AI-electricity systems in two publications. In 2018, EPRI released "Developing a Framework for Integrated Energy Network Planning (IEN-P)" (68) outlining a strategic framework for long-term investment planning in the electricity sector. This was followed in 2019 by a study identifying specific use cases related to these challenges (69).

Key Outcomes

EPRI's analysis reveals a list of AI-electricity synergies, categorized into three distinct areas:

1. AI for modeling the changing power system
Which focuses on adapting planning models to account for:

1.1. Operational details: New renewable resources, such as wind and solar energy, impact reliability services traditionally provided by fossil fuels. Planning needs to consider how these new resources can meet reliability needs.
1.2. Increased granularity: Like Planning models which require finer geographic and time-based detail to address new challenges.
1.3. Integrated planning: Closer collaboration across generation, transmission, and distribution planning is crucial for optimal system development.

2. AI for integrating forecasts
Key areas for improvement include:

2.1. Electric load, renewables, and distributed energy: More granular forecasting of electricity demand, Variable Renewable Energy (VRE) production, distributed energy resource (DER) adoption, and weather patterns.
2.2. Customer behavior: A deeper understanding of customer behavior, the impact of incentives on behavior, and how customer actions affect energy supply, storage, and demand.

3. AI for expanding planning boundaries
Considering a broader scope including:

3.1. New objectives and constraints: Planning must optimize for objectives beyond traditional cost-effectiveness, such as resilience, flexibility, and environmental/social goals.
3.2. Wholesale power markets: Understanding how evolving wholesale markets impact resource viability and reliability services.
3.3. Stakeholder engagement: Increased public participation requires extensive stakeholder engagement throughout the planning process.

2019: The IRENA's Brief

Innovation landscape for a renewable-powered future

The *International Renewable Energy Agency* (IRENA) rigorously assessed sixpotential use cases of AI in the power sector with a special emphasis on the integration of variable renewable energy technologies (69), which are:

1. Improving solar and wind power ***forecasting*** for better resource integration.
2. Enhancing grid stability and reliability through ***predictive maintenance*** and real-time optimization.
3 Refining demand forecasting to better match supply with consumption.
4. Enabling efficient ***demand-side management*** through personalized energy recommendations and automated controls.
5. Optimizing ***energy storage operations*** for maximum efficiency and cost reduction.
6. Facilitating ***optimized market design*** and operation for increased transparency and competitiveness.

Additionally, IRENA identifies four crucial enabling factors for the successful implementation of AI in the energy sector.

Feeding the AI for Impact Compass

The **AI for Impact Compass** (discussed in the following chapter) has integrated these factors as follows:

1. Technological maturity: Addressed through the combined assessment of AITRL (AI Technology Readiness Level) and AIARL (AI Adoption Readiness Level), determining the overall maturity of AI solutions.

2. Data availability and quality: This is directly linked to the robustness of the "Net Digital Impact" quantification framework, ensuring accurate assessment of AI's impact.

3. **Cybersecurity:** This is considered within the broader EU AI Act risk assessment levels (1 to 4), ensuring appropriate risk mitigation measures are in place.

4. Training and re-skilling: This factor is integrated into the AIARL assessment, ensuring adequate workforce preparation for AI adoption in the energy sector.

By incorporating IRENA's recommendations, the **AI for Impact Compass** aims to address key barriers to achieving large-scale impact with AI for the energy transition, while achieving responsible and ethical AI deployment.

Recent AI playbooks for the energy transition

2020: The DENA's Report

List of AI-Energy Applications identified - DENA

The DENA (Deutsche Energie-Agentur) recent, more detailed study (70) clusters nine broad application domains of AI in power systems into three fields, namely (1) maintenance and security, (2) general foundations of decision making and (3) distribution and customer services. See Figure 5 below.

Key Outcomes

The applications are further characterized by AI capabilities (audio and speech, image and face recognition, robotics, assistance systems and general data). The *nine applications* are then ranked according to their contribution to the energy transition and their maturity (closeness to commercial markets). The analysis by the authors reveals *most developed and beneficial AI use cases for the energy transition are those that are specifically related to general foundations of decision-making* (predictions, operations optimization, inventory optimization, predictive maintenance and strategic business decisions). DENA's pioneering classification of AI applications in the energy sector (see figure 5 below), based on their *(1) contribution to energy transition* and *(2) maturity level*, is a commendable step. However, *the absence of quantitative measures* limits its potential as an industry-wide benchmark.

2021: The WEF / BNEF / DENA White Paper

In a collaborative effort to accelerate the adoption of AI in the energy sector, the World Economic Forum's Global Future Council on Energy Transition, BloombergNEF, and the DENA convened a series of roundtable discussions from March to May 2021 (71). These discussions brought together leading experts from both the energy and AI fields.

The resulting white paper locates the applications in 4 areas:

1. *Renewable* power generation and *demand forecasting*
2. *Grid* operation and optimization
3. Management of *energy demand* and distributed resources
4. *Materials* discovery and innovation

The WEF identifies *15 key applications* within four areas that warrant further investigation, highlighting that the potential of AI in power grid operation and optimization will require substantial asset upgrades and replacements. Hence, the environmental impact of these evolutions needs to be considered when evaluating the corresponding AI applications.

2022: climatechange.ai Report

climatechange.ai, a collaborative research platform, enables researchers to underscore the importance of machine learning (ML) in combating climate change. Their 2022 report (72) categorizes ML applications using three key criteria:

- *High Leverage:* This indicator indicates crucial areas identified by experts where ML tools can significantly contribute to climate change mitigation or adaptation efforts.
- *Long Term:* Denotes applications whose primary impact is expected after 2040, potentially less urgent than near-term solutions.
- *Uncertain Impact:* This refers to applications whose effect on greenhouse gas emissions is uncertain or may have potential negative side effects.

However, while striving for comprehensiveness, the climatechange.ai classifications do not offer an objective quantitative ranking of the use cases.

In conclusion, none of the aforementioned recent studies distinguish between AI domains nor utilize a comprehensive, rigorous system of energy transition use cases.

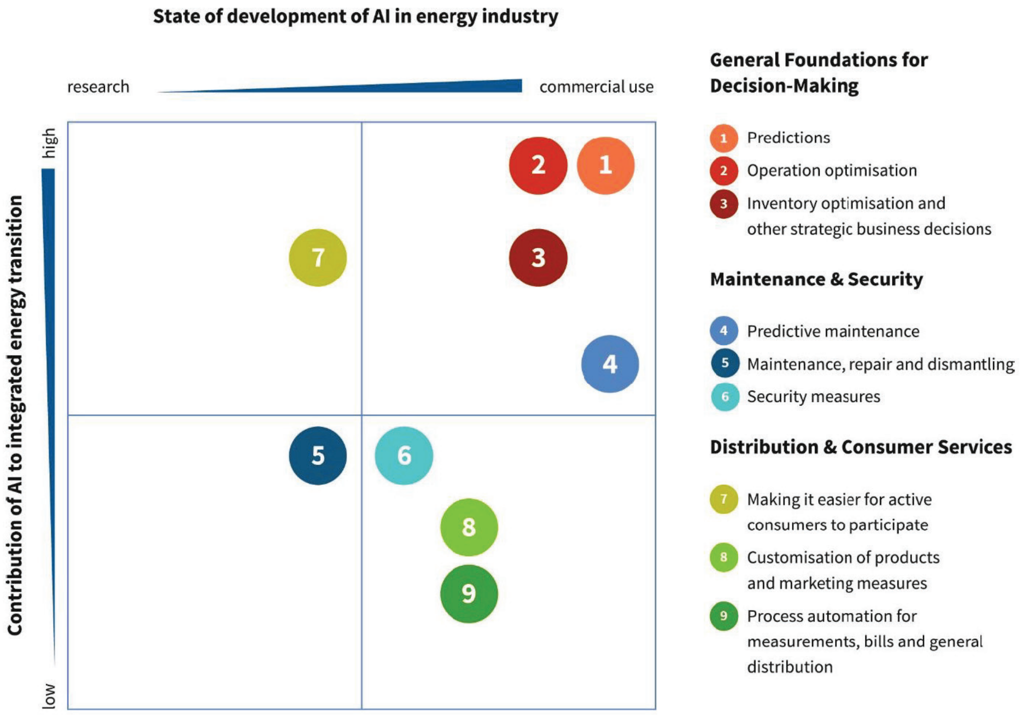


Figure 5. Relative classification of fields of application of AI in the energy industry.

Source : DENA.

Our blueprint for the future

Compiling 40 use cases for examination

In this paper, we concentrate on climate change mitigation strategies, not adaptation measures.

The following list aims to provide a *first inventory* of potential large-scale impact areas.

The categorization goal *is not to establish precise scores*, but rather to highlight areas with significant potential for large-scale GHG emissions reduction.

This will guide prioritization for in-depth, robust bottom-up assessments using recent quantification methodologies.

Based on research from EPRI, IRENA, DENA, WEF, and notably climatechange.ai, we have compiled a selection of 40 use cases spanning various energy transition domains.

The 40 use cases presented herein represent a consolidation of the selections made by each contributing organization. Variations in the phrasing of these use cases suggest that more detailed descriptions will be required in subsequent research endeavors.

Given that the primary objective of this paper is to propose a methodological framework rather than to conduct an exhaustive quantification, it is important to acknowledge that the list presented here is not intended to be comprehensive, as AI applications continue to evolve. Instead, it reflects the most widely recognized common ground among leading organizations.

The subsequent primary end-use applications are considered:

- Buildings & Cities
- Carbon dioxide removal
- Data Centers and ICT
- Farms and Forests
- Industries
- New Electricity Systems (Modern Grids)
- New Mobilities
- Transportation and Infrastructure

Despite these 40 use cases constituting a curated selection of some of the most auspicious alternatives, the subsequent chapter (Chapter IV) will propose an analytical instrument, the “AI for Impact Compass.”

This framework is designed to enable a more granular ranking of use cases through the examination of Impact, Scalability, and Risk, thereby assisting decision-makers and policymakers in prioritizing the most consequential AI applications.

1	Buildings & Cities - AI for approaching low-data settings
2	Buildings & Cities - AI for data for smart cities
3	Buildings & Cities - AI for flexibility and microgrids
4	Buildings & Cities - AI for gathering infrastructure data
5	Buildings & Cities - AI for HVAC optimization
6	Buildings & Cities - AI for low-emissions infrastructure
7	Buildings & Cities - AI for modeling energy use across buildings
8	Buildings & Cities - AI for occupancy detection
9	Buildings & Cities - AI for rooftop solar integration
10	Carbon dioxide removal - AI for direct air capture
11	Carbon dioxide removal - AI for sequestering CO2
12	Data Centers & ICT - AI for energy efficiency and AI-ready DC
13	Data Centers & ICT - AI for flexibility at DC level
14	Farms & Forests - AI for managing forests
15	Farms & Forests - AI for monitoring peatlands
16	Farms & Forests - AI for precision agriculture
17	Farms & Forests - AI for remote sensing of emissions
18	Industries - AI for adaptive control
19	Industries - AI for Climate-friendly chemicals
20	Industries - AI for Climate-friendly construction
21	Industries - AI for operational efficiency through modern maintenance
22	Industries - AI for optimized energy demand
23	Industries - AI for recommender systems
24	Industries - AI for reducing food waste
25	Industries - AI for reducing overproduction
26	New Electricity Systems - AI for accelerating fusion science
27	New Electricity Systems - AI for accelerating materials science
28	New Electricity Systems - AI for forecasting supply and demand
29	New Electricity Systems - AI for improving scheduling and flexible demand
30	New Electricity Systems - AI for managing existing controllable technologies
31	New Electricity Systems - AI for modeling emissions
32	New Electricity Systems - AI for reducing life-cycle fossil fuel emissions
33	New Electricity Systems - AI for reducing system waste
34	New Electricity Systems - AI for using cleaner electricity sources
35	New Mobilities - AI for battery and storage management
36	New Mobilities - AI for electrification of fleets / Electrical Vehicles
37	Transportation and Infrastructures - AI for alternative fuels and electrification
38	Transportation and Infrastructures - AI for improving vehicle efficiency
39	Transportation and Infrastructures - AI for modal shift
40	Transportation and Infrastructures - AI for reducing transport activity

Table 1. 40 AI-Energy use cases for Climate Change Mitigation.
Schneider Electric^{TM} Sustainability Research,
Based on EPRI, IRENA, DENA and climatechange.ai

4

AI for Impact Compass

Guiding the evaluation of the environmental interest of AI applications

Despite the energy sector's enthusiasm for AI, industry leaders and policymakers are still searching for a method to evaluate the environmental interest of dependable, impactful AI solutions that can be widely deployed with minimal risk and demonstrably address climate change.

We argue for a more fact-based and contextual approach to AI discussions. In response to the evolving landscape of applications and regulations in the energy sector, the **AI for Impact Compass** proposes a scheme to classify these applications.

This tool is intended for industry, researchers, and policymakers alike. Its goal is to provide a common baseline for visually comparing AI applications based on three factors.

Leveraging existing frameworks from diverse research entities, this Compass proposes an enhanced indicator for classifying AI applications **for a sustainable energy transition.**

Two new elements are integrated:

Impact Quantification: The "Net Digital Impact" approach (Schneider Electric™ Sustainability Research Institute) grounds impact calculations by quantifying the direct, indirect, and systemic effects of AI applications.

Scalability: This dimension evaluates the potential of a solution to maximize its deployment across contexts.

We will describe this approach further in this chapter.

The need for a flexible AI evaluation tool

Current AI-Energy evaluation tools exhibit limitations

With the rise of AI applications across industries, classification and comparison frameworks have emerged to facilitate comparing existing solutions. In this context, we compared recent AI frameworks with the Sustainability Research Institute **AI for Impact Compass** to further highlight its relevance. Quest et al. (43) highlight that several existing frameworks offer valuable insights, but often lack the necessary flexibility or target audience for broad application. The literature below is taken from the study *'A 3D indicator for guiding AI applications in the energy sector'* (43) by Quest et al.

- **OECD Framework** (44)**:** This policymaker focused framework offers a comprehensive approach but requires detailed analysis across a vast number of dimensions, potentially hindering its accessibility for non-experts.
- **McKinsey Global Institute Framework** (45): This business-oriented framework prioritizes economic potential, particularly focusing on deep learning applications, limiting its broader applicability.
- **Lee et al. Frameworks** (46) (47): These frameworks offer innovative methods for assessing energy savings potential, but lack clear actionable outputs for broader application beyond energy savings.
- **Bahrammirzaee's work** (48) analyzes artificial neural networks, expert systems, and hybrid intelligence systems in the financial sector using application domain, algorithm type, and performance as evaluation categories.
- Similarly, **Nsoesie** (49) emphasizes performance, input data, algorithms, and annotation needs when assessing AI applications within the healthcare sector.
- In the energy sector, **Antonopoulos et al.** (50) compare AI applications specifically for demand response programs, focusing on algorithm selection and the targeted problems addressed in various studies.

Table 2 summarizes these existing frameworks.

In 2022, **Quest et al.** (43) presented a comprehensive framework for evaluating AI applications, encompassing the key dimensions of risk, maturity, and improvement. Notably, their work included a user-friendly graphical representation, facilitating identifying promising AI solutions.

A critical examination of this framework reveals the potential for further enrichment through the inclusion of two additional dimensions:

1. Quantified Impact Assessment:

Current evaluation methods often lack a standardized approach to measuring the impact of AI applications Incorporating of a ***quantified impact assessment***, based on a recognized methodology, would allow for a more objective evaluation of the application's real-world benefits. This could involve measuring economic gains, social good achieved, or environmental improvements, depending on the specific application domain.

2. Scalability Assessment:

While Quest et al.'s maturity dimension focuses on the level of development completeness, it does not explicitly address the application's ability to be ***effectively replicate across diverse contexts***. The inclusion of a **scalability analysis** would address this limitation.
Scalability encompasses not only technical replicability but also adaptability to varying operational environments and data sets. This expanded notion emphasizes the importance of repeatability and context-specific functionality. More specifically, we propose the combined use of an **Artificial Intelligence** ***'Technology Readiness Level'***, and an ***'Adoption Readiness Level'*** to further provide solid references for quantification.

AI-Energy framework	Source	Publication	Target audience			Framework goal	Input data requirements	Applicability to AI-Energy use cases	Actionable and visual ouput	Regulatory Risk factor	Scalability factor	Quantified effects
			Industry	Policymakers	Research							
McKinsey Global Institute AI frontiers insights.	Chui et al.	2018	x			Identify and quantify the economic benefits of advanced AI techniques across industries and business functions.	Medium	No	No	No	No	No
OECD Framework for the classification of AI systems.	OECD	2022		x		Develop a comprehensive framework for characterizing AI systems based on factors relevant to policy development.	High	Yes	No	No	No	No
Universal workflow of AI for energy savings + AI implementation framework development for building energy savings.	Lee et al.	2022	x		x	Identify practical AI & build a framework for deploying them to optimize building energy use.	Medium	Yes	No	No	No	No
Implementation of AI: Roadmap for business model innovation.	Reim et al.	2022	x			Develop a phased roadmap with clear steps for implementing AI solutions across the firm's key operations.	Low	Yes	No	No	No	No
3D indicator for guiding AI applications in the energy sector.	Quest et al.	2022	x	x	x	Developing a multi-criteria decision-making framework for promising AI applications: a stakeholder-oriented typology.	Low	Yes	Yes	Yes	No	No
Schneider Electric Sustainability Research: AI for impact Compass.	SRI	2024	x	x	x	Guiding the most impact AI applications for the energy transition, with a specific focus on the scalability potential across contexts and the risks.	Low	Yes	Yes	Yes	Yes	Yes

Table 2. Comparative table of the main characteristics of six recent AI frameworks.
Schneider Electric™ Sustainability Research Institute. Based on Quest et al.

The AI for Impact Compass

Main Principles

Quantifying the Impact

The *Net Digital Impact Score quantifies this dimension*, **denoted as IS ∈ [1, 4]**, and reflects the potential leverage of an AI application. It measures the environmental impact of AI applications, ranging from negative impact (e.g, positive carbon footprint, IS = 1) to positive impact (e.g, negative carbon footprint, IS = 4). For our assessment, IS will focus on **greenhouse gas (GHG)** emissions to evaluate the decarbonization potential of AI.

Quantifying the Scalability

This dimension, denoted as the Scalability Score **SS ∈ [1, 9]**, is determined by combining the ***Artificial Intelligence Technology Readiness Level*** (AITRL) and the ***AI Adoption Readiness Level*** (AIARL).

- The **AITRL** is a specialized adaptation of the *Machine Learning Technology Readiness Level (MLTRL)* model proposed by ***Lavin et al.*** (50), a general maturity model to address ML specifically, assesses the technological maturity of the ML system. Following a thorough review and analysis of the MLTRL, we have determined that its scope can be broadened to encompass the entire field of Artificial Intelligence (AI). This generalization is deemed viable without encountering major conceptual issues.
- The **AIARL** is derived from the ARL developed by the *U.S. Department of Energy (DOE)* (51)*,* and assesses the ability of an AI technology to optimize its implementation across

Quantifying the Risk

This dimension, denoted as **RS ∈ [1, 4], quantifies the Risk Level**. As a reference, we have adopted the categorization from the European Commission's AI risk framework. Hence, RS ranges from 1 (minimal risk) to 4 (unacceptable risk), where a lower score indicates a less risky application.

Defining weighting schemes

As proposed by ***Quest et al.,*** an indicator can be designed to include a sensitivity aspect, focusing on one or more specific criteria. To handle this, the AI for Impact Compass allows for different weighting options.

- It incorporates weighting factors ($\omega_\alpha \in [0, 1]$, $\alpha = 1, 2, 3$) associated with each dimension (Impact, scalability, and risk).
- These weights sum to 1 ($\Sigma^3_{\alpha=1}\ \omega_\alpha = 1$) and can be adjusted to reflect the specific priorities and risk tolerance of different stakeholders or scenarios.

Establishing what-if sensitivity decision postures

Decision posture 1: Balanced
This posture represents a ***baseline approach*** where all three dimensions (Impact, scalability, and risk) are considered equally important. The weights associated with each dimension are equal ($\omega_1 = \omega_2 = \omega_3 = 1/3$).

Decision posture 2: Climate Impact
This posture prioritizes AI applications that have a clearly demonstrated positive environmental impact. Here, a higher weight is assigned to the Impact dimension ($\omega_1 = 0.6$) and Scalability dimension ($\omega_2 = 0.3$) reflecting the importance of a mature and readily deployable solution. Conversely, lower weight is assigned to Risk ($\omega_3 = 0.1$) as the focus is on short term climate change mitigation.

Decision posture 3: Risk-Avoidance
This posture prioritizes minimizing potential risks associated with AI applications. It aligns with the interests of policymakers who aim to ensure AI development adheres to *regulatory frameworks*. Here, the Risk dimension receives the highest weight ($\omega_3 = 0.8$), reflecting the paramount importance of safety and regulatory compliance. Conversely, lower weights are assigned to Impact ($\omega_1 = 0.1$) and Scalability ($\omega_2 = 0.1$) as the primary concern is mitigating risks.

Final scoring calculation

The overall assessment uses a continuous scale for the **Total Score, denoted as TS ∈ [0, 1]**, where 0 represents the lowest potential benefit and 1 signifies the greatest potential - combining ***Impact at Scale with limited Risk*** - for climate change mitigation.

To facilitate decision-making regarding potential AI applications, the climate impact score is further categorized as follows:

- **TS < 0.3: Limited Impact** - Applications scoring below this threshold warrant careful consideration or even exclusion due to potential negative impact on climate goals.
- **0.3 ≤ TS < 0.6: Contextual Impact** - Applications within this range may offer climate benefits, but their use should be evaluated based on specific contexts to maximize positive environmental impact.
- **TS ≥ 0.6: Potential High Impact** - Applications surpassing this threshold demonstrate substantial potential for mitigating climate change and merit prioritization for further, in-depth analysis on an individual basis.

Total Score Formula

$$TS = 1 - [\omega_1 \cdot |4 - IS| / 3 + \omega_2 \cdot ((\, |9 - AITRL| / 8 + |9 - AIARL| / 8) / 2) + \omega_3 \cdot |1 - RS\,| / 3]$$

Quantifying the Impact

For many years, the absence of robust methodologies hindered fact-based discussions regarding the impact of digital technologies. However, the emergence of frameworks like ITU-T L.1480 (53), EGDC (54), and NZI4IT (55) has given access to quantitative assessment methods. This shift empowers various stakeholders, including industries, to move beyond solely qualitative assessments. In May 2024, the Schneider Electric™ Sustainability Research Institute further contributed to this advancement by developing a holistic framework – the *Net Digital Impact framework* (50), encompassing the full spectrum of impacts, ranging from direct effects on specific entities to indirect and systemic consequences across broader economic and societal systems. Based on this framework, we propose a scoring declination through the *Impact Score*. This Impact Score denoted as 'IS', reflects the potential impact of an AI application on pre-defined sustainability criteria. The score is calculated in two steps.

Step 1: Calculating the Net Digital Impact Ratio

This step quantifies the relative magnitude of positive and negative impacts on GHG emissions, which is the chosen criterion for environmental impact in this publication.

- The left part of the framework designates ***negative environmental effects***, which potentially contribute to environmental degradation.
- Conversely, ***positive impacts*** that promote environmental sustainability are assigned to the right.

The ratio calculation involves determining the quotient between the sum of positive impacts (Σ Positive Impacts) and the absolute values of the sum of negative impacts (Σ | Negative Impacts |). Mathematically, this is expressed as:

Ratio = Σ Positive Impacts / Σ | Negative Impacts |

Methodological note: The Ratio should integrate both the timeframe for impact assessment and the necessary underlying assumptions (such as the evolution of service usage, the efficiency of data centers, and decarbonization of the electricity used...). In assessing environmental impact, we have expressed results as a ratio of positive to negative outcomes, rather than a simple difference. This approach offers several advantages. Firstly, it normalizes impacts across projects of varying scales, allowing for meaningful comparisons. Second, it aligns with the concept of an "environmental return on investment," where negative impacts are akin to investments and positive impacts are the resulting benefits. This framing emphasizes the need to maximize positive outcomes relative to the environmental costs incurred.

Step 2 : Calculating the 'IS' Score

Based on the calculated ratio, the IS score is assigned using a pre-defined scoring rubric. This rubric establishes specific ranges for the ratio that correspond to varying levels of environmental benefit:

- Ratio < 0.5: This outcome indicates that the negative environmental impacts outweigh the positive impacts. In this scenario, the IS score is assigned a value of 1, signifying a minimal or potentially detrimental environmental effect.
- Ratio between 0.5 and 1.5: This range represents an uncertainty zone where the positive and negative impacts are relatively balanced. The IS score is assigned a value of 2, reflecting the inconclusive nature of the environmental impact.
- Ratio between 1.5 and 5: This outcome suggests that the positive environmental impacts are greater magnitude than the negative impacts. The IS score is assigned a value of 3, signifying a positive environmental contribution.
- Ratio > 5: This outcome signifies a highly beneficial environmental impact. The IS score is assigned a value of 4, highlighting the significant positive contribution of the AI application to environmental sustainability.

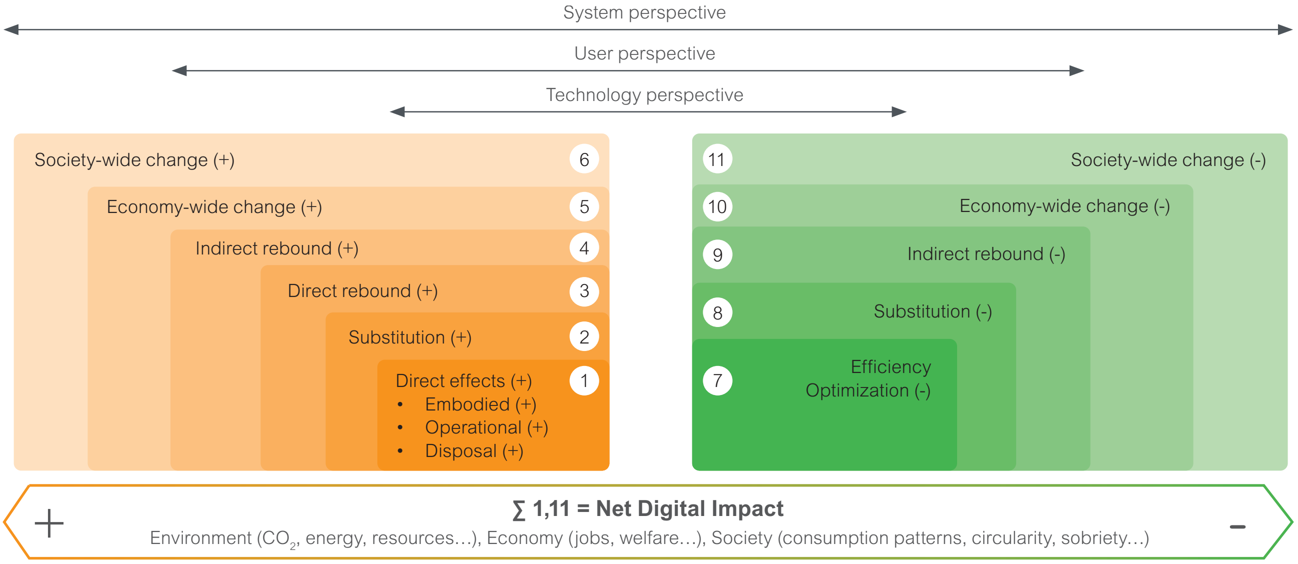


Figure 6. The Net Digital Impact Framework.
Schneider Electric™ Sustainability Research Institute, 2024.

Quantifying the Scalability (Maturity Part)

Assessing the true impact of digital solutions, particularly AI, is difficult due to the challenge of measuring their scalability. Many studies are theoretical and fail to account for real-world complexities, leading to ***inaccurate extrapolations***. Even studies with quantified evidence (GeSI, GSMA) often lack reliable methods for scaling their findings. To address this, the **Scalability Score (SS)** is introduced. Combining the ***maturity*** of AI technology (AITRL) and the ***ease of deployment*** (AIARL), it aims to provide a more accurate assessment of the potential impact of AI solutions by considering scalability from the outset.

AITRL assessment

Lavin et al., in a publication in Nature (56) , leveraging their expertise in both spacecraft engineering and machine learning, have created the 'Machine Learning Technology Readiness Levels' (MLTRL) framework, which employs Technology Readiness Levels (TRLs) to assess and convey the advancement of ML/AI systems during their development and deployment. Here are the fundamental levels as scales-criteria for scoring.

- *Level 0 (First principles):* Focuses on literature review, mathematical foundations, and understanding data. Code is not required, but data readiness is assessed.
- *Level 1 (Goal-oriented research):* Low-level experiments are conducted to analyze model properties using sample data. Code is research-caliber, and semantic versioning practices are initiated.
- *Level 2 (Proof of Principle development):* Active R&D is initiated in testbeds, with a formal research requirements document. This is a key decision point for moving towards prototyping or further research.
- *Level 3 (System development):* Code development focuses on interoperability, reliability, maintainability, and scalability. Code becomes prototype-caliber and product engineering is involved to define SLAs and SLOs.
- *Level 4 (Proof of Concept Development):* The technology is demonstrated in actual scenarios using real data. This involves scaling up data collection and processing, evolving experiment metrics, and considering AI ethics.
- *Level 5 (Machine learning capability):* The technology transitions from an isolated solution to a module in a larger application. Knowledge and expertise are shared, and the focus is on scaling data pipelines and addressing data governance challenges.
- *Level 6 (Application development):* Significant software engineering is undertaken to achieve product-caliber code. ML modules are robustified, model explanations are validated, and deployment settings are thoroughly addressed.
- *Level 7 (Integrations):* The technology is integrated into existing production systems. Tests for specific scenarios, a "golden dataset," metamorphic testing, and data intervention tests are implemented. Data governance is prioritized, and ethical considerations are revisited.
- *Level 8 (Mission-ready):* The technology is demonstrated to work in its final form under expected conditions. Additional tests cover deployment aspects, and a go/no-go decision for deployment is made.
- *Level 9 (Deployment):* The focus is on maintenance engineering, monitoring data quality, concept drift, and data drift. Automated evaluation and reporting are implemented, and mechanisms for retraining and improving models are established.

Calculation

The associated Maturity Level corresponds directly with the AITRL scoring number (from 1 to 9).
Note : TRL = 0 is not part of the evaluation.

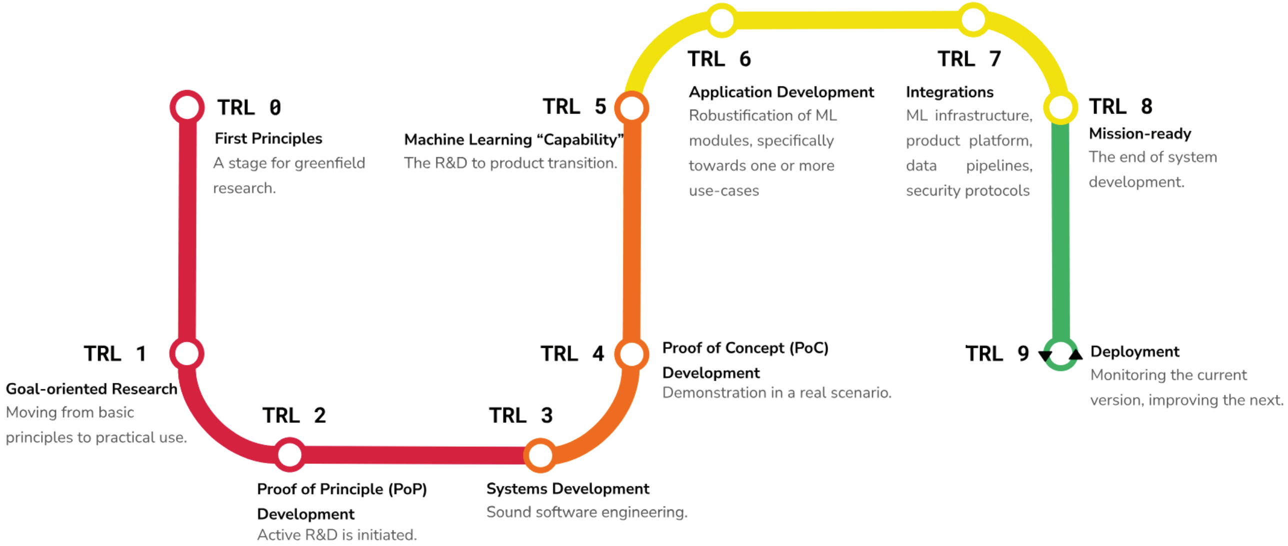


Figure 7. Artificial Intelligence Technology Readiness Levels.
AITRL spans research (red) through prototyping (orange), productization (yellow), and deployment (green).
Source: Lavin et al.

Quantifying the Scalability (Adoption Part)

AIARL assessment

To successfully deploy a technology, it's not enough to focus on its technical readiness. The economic viability and acceptance within the broader ecosystem are equally crucial. This realization led the Office of Technology Transitions (OTT) (51) to develop the AI Adoption Readiness Level (AIARL) framework as a complement to the traditional Technology Readiness Levels (TRL).

The AIARL framework goes beyond technical aspects and **assesses the broader adoption criteria across 17 dimensions**, encompassing four key areas: the technology's ***value proposition***, ***market acceptance***, ***resource availability***, and ***societal license to operate***. By evaluating these factors, the AIARL framework provides a comprehensive view of a technology's readiness for adoption, helping to identify and mitigate potential barriers to successful deployment at scale.

Each factor can be defined as 'Low', 'Medium', or 'High'.

Category #1: Value Proposition

Assesses the ability of a new technology to meet the functionality required by the market at a price point that customers are willing to pay, to meet market demand.

The criteria considered are:
1. Delivered Cost
2. Functional Performance
3. Ease of Use / Complexity

Category #2: Market Acceptance

Captures the target market(s) demand characteristics and barriers posed by existing players - including competitors, customers, and other value chain players.

The criteria considered are:
4. Demand Maturity / Market Openness
5. Market Size
6. Downstream Value Chain

Category #3: Resource Maturity

Determines barriers standing in the way of inputs needed to produce the technology solution.

The criteria considered are:
7. Capital Flow
8. Project Development, Integration, and Management
9. Infrastructure
10. Manufacturing and Supply Chain
11. Materials Sourcing
12. Workforce

Category #4: License to operate

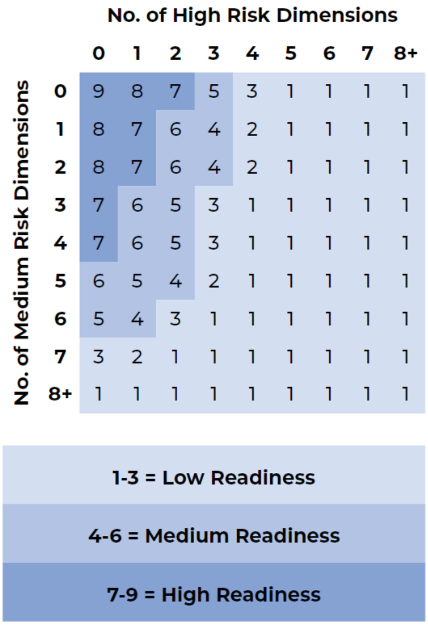
Identifies the societal (national, state, and local), non-economic barriers that can hinder the deployment of a technology.

The criteria considered are:
13. Regulatory Environment
14. Policy Environment
15. Permitting and Siting
16. Environmental and Safety
17. Community Perception

Calculation

Instructions for determining AIARL Score:
- Count the total number of barriers evaluated as "High".
- Count the total number of barriers evaluated as "Medium"
- Refer to the look-up table to identify the corresponding ARL Score based on the number of "High" and "Medium" dimensions.

The given number corresponds to the determined Adoption Level.



No. of High Risk Dimensions

No. of Medium Risk Dimensions

	0	1	2	3	4	5	6	7	8+
0	9	8	7	5	3	1	1	1	1
1	8	7	6	4	2	1	1	1	1
2	8	7	6	4	2	1	1	1	1
3	7	6	5	3	1	1	1	1	1
4	7	6	5	3	1	1	1	1	1
5	6	5	4	2	1	1	1	1	1
6	5	4	3	1	1	1	1	1	1
7	3	2	1	1	1	1	1	1	1
8+	1	1	1	1	1	1	1	1	1

1-3 = Low Readiness

4-6 = Medium Readiness

7-9 = High Readiness

Figure 8. Combining the risk dimensions into an AIARL score. Office of Technology Transitions, U.S. Department of Energy.

Quantifying the Risk (Regulatory)

This section defines the rationale behind the risk assessment criteria and the way to determine it.

Why integrate Risk as a primary criterion?

The digitalization of the energy sector is driven by the increasing availability of data from smart meters and grid operations, necessitating efficient analysis solutions. Quest et al. indicates that AI presents itself as a potential cornerstone for utilities, offering projections of up to 25% reduction in operating expenses and 20-40% performance gains in areas like safety, reliability, and customer satisfaction (57). To achieve these benefits, AI integration necessitates a strategic shift, fostering data-driven decision-making and optimizing systemic and process efficiency.

The meteoric rise of AI has positioned it at the forefront of research, industry, and policy discussions. This rapid evolution encompasses not only models and algorithms but also a paradigm shift towards **autonomous AI applications**, potentially operating with independent decision-making capabilities (58), (59). However, alongside this progress, concerns regarding ***explainability***, ***transparency***, and ***algorithmic bias*** are gaining prominence in the regulatory landscape.

Broader issues of ***cybersecurity*** and ***regulatory compliance***. compound these concerns.The inherent risk associated with AI solutions stems from the underlying models, particularly the ***opaqueness of neural networks*** and their tendency to create “black box” outcomes. While these networks excel at approximating complex, non-linear functions for problem-solving, their outputs are often difficult to interpret and control, hindering operational oversight. This lack of explainability will likely become more pertinent as neural network adoption expands, potentially exacerbating the overall risk profile of AI applications.

In order to anticipate this governance challenge, the European Union introduced a risk assessment for both AI development strategies and legal framework (60). This aligns with their broader vision of harnessing digital advancements to create a human-centric, sustainable, and resource-efficient future (61 - 64).

Risk assessment

The recently proposed EU AI Act (65), published on **July 12th, 2024**, represents a new approach to AI regulation. It aims to promote the creation of high-quality and trustworthy AI applications while mitigating potential risks associated with AI deployment through regulations and sanctions.

The AI Act classifies AI according to its risk:
- ***Unacceptable risk*** is prohibited (e.g. social scoring systems and manipulative AI).
- Most of the text addresses ***high-risk AI systems***, which are regulated.
- A smaller section handles ***limited risk AI systems***, subject to lighter transparency obligations, which are regulated to ensure the risk is properly mitigated. Developers and deployers must inform end-users that they are interacting with AI, such as in the case of chatbots and deepfakes.
- ***Minimal risk is unregulated*** (including the majority of AI applications currently available on the EU single market, such as AI enabled video games and spam filters – at least in 2021; this is changing with generative AI).

Most obligations fall on providers (developers) of high-risk AI systems.
- Those who intend to place on the market or put into service high-risk AI systems in the EU, regardless of whether they are based in the EU or a third country.
- And also third country providers where the high risk AI system’s output is used in the EU.

Users are natural or legal persons that deploy an AI system in a professional capacity, not affected end-users.

Calculation

For risk assessment, we leverage the EU AI risk framework (66). This robust framework categorizes AI applications based on their *a priori* potential for harm. It assigns a **Risk Level (RS)** ranging from 1 to 4, with 1 signifying minimal risk and 4 indicating unacceptable risk. By employing this framework, we ensure a clear understanding of the potential hazards associated with an AI application. Lower RL scores indicate applications with less risk, allowing for a more streamlined development and deployment process.

Risk assessment levels

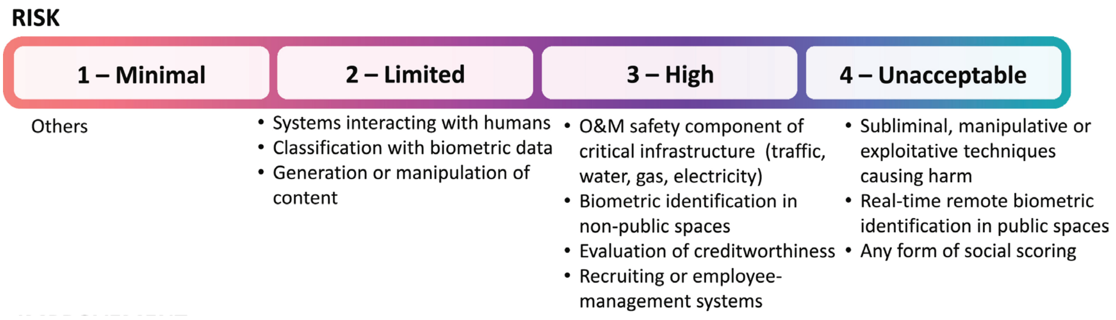


Figure 9. Risk Level Assessment.
Source: EU AI risk framework.

Total Score Assessment: A Summary

Criteria	Notation		Referential for assessement	Approach	Criterias
Impact	IS		Net Digital Impact Framework (based on ITU-T L.1480, EGDC, NZI4IT)	Scoring related to the Impact Ratio = Σ Positive Effects / Σ | Negative Effects |	If Ratio < 0.5: The negative impacts outweigh the positive impacts.
					If Ratio between 0.5 and 1.5: Uncertainty zone where the positive and negative impacts are balanced.
					If Ratio between 1.5 and 5: The positive impacts have a greater magnitude than the negative impacts.
					If Ratio > 5: Highly beneficial environmental impact.
Scalability	SS	AITRL	Lavin et al.	9 Maturity levels	Goal-oriented research: From principles to practical use
					Proof of Principle development: Active R&D initiated
					System development: Sound software engineering
					Proof of Concept development: Demonstration in real scenario
					Machine learning capability: R&D to product transition
					Application development: Robustification of ML modules towards use-cases
					Integrations: ML infrastructure, product platform, data pipelines, security protocols
					Mission-ready: End of system development
					Deployment: Monitoring the current and improving the next
		AIARL	OTT DOE	4 Assessment categories	Value Proposition Assessment
					Market Acceptance Assessment
					Resource Maturity Assessment
					License to Operate Assessment
Risk	RS		EU AI Act	4 Risk levels	Minimal risk
					Limited risk
					High risk
					Unacceptable risk

Total Score	TS	General Formula	TS < 0.3: Limited Impact - Applications scoring below this threshold warrant careful consideration or even exclusion due to potential negative impact on climate goals.
			0.3 ≤ TS < 0.6: Contextual Impact - Applications within this range may offer climate benefits, but their use should be evaluated based on specific contexts to maximize positive environmental impact.
			TS ≥ 0.6: Potential High Impact - Applications surpassing this threshold demonstrate substantial potential for mitigating climate change and merit prioritization for further, in-depth analysis on an individual basis.

What-if sensitivity scenarios	Scenario #1 : Balanced ; Impact weight = ω1 = Scalability weight ω2 = Risk weight ω3 = 1/3
	Scenario #2 : Climate Impact ; Impact weight = ω1 0,6 ; Scalability weight ω2 = 0,3 ; Risk weight ω3 = 0,1
	Scenario #3 : Risk Avoidance ; Impact weight = ω1 = 0,1 ; Scalability weight ω2 = 0,1 ; Risk weight ω3 = 0,8

Table 3. AI for Impact Compass - Assessment and Scoring tool.
Source: Schneider Electric™ Sustainability Research Institute.

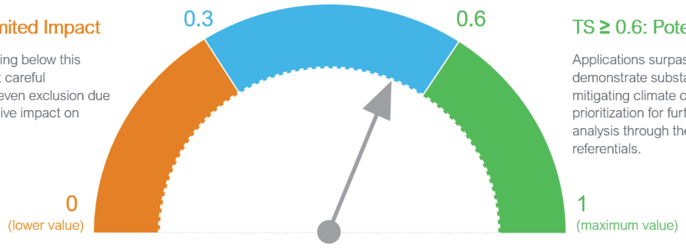
Graphic representation of Total Scoring

0.3 ≤ TS < 0.6: Contextual Impact

Applications within this range may offer climate benefits, but their use should be evaluated based on specific contexts to maximize positive environmental impact.

TS < 0.3: Limited Impact

Applications scoring below this threshold warrant careful consideration or even exclusion due to potential negative impact on climate goals.



TS ≥ 0.6: Potential High Impact

Applications surpassing this threshold demonstrate substantial potential for mitigating climate change and merit prioritization for further, in-depth bottom-up analysis through the international referentials.

Figure 10. Graphic representation of the Total Scoring from the AI for Impact Compass.
Source: Schneider Electric™ Sustainability Research Institute.

Use cases preliminary ranking

The 40 curated use cases were assessed using the AI for Impact calculation sheet. For each use case, we determined:

- Impact Score (IS): Through a preliminary quantification based on Literature Reviews and Schneider Electric data. Due to the complexities involved in precisely calculating the full effects of digital on a use case, we assigned a score of 2 ("uncertain") for all IS values.
- Scalability Score (SS): Combining the AI Adoption Technology Readiness Level (AITRL) and the AI Adoption Level (AIARL), based on established references.
- Risk Score (RS): Using the EU Act scale.

To visualize the potential sensitivity of the scoring, we conducted assessments under three scenarios:

- Conservative: Assumes IS = 2 and conservative estimates for AITRL, AIARL, and RS.
- Average: Assumes IS = 2 and strictly follows guidelines for AITRL, AIARL, and RS.
- Optimistic: Assumes IS = 3 and strictly follows guidelines for AITRL, AIARL, and RS.

The preliminary assessment highlights ten use cases for further exploration in our research roadmap. We emphasize that while our list is comprehensive, it does not fully capture the complexities of this evolving field. Therefore, caution is advised when interpreting these findings.

As a reminder, the scoring interpretation is as follows:

$TS < 0.3$: Limited Impact
$0.3 \leq TS < 0.6$: Contextual Impact
$TS \geq 0.6$: Potential High Impact

Ten high potential use cases for further study

Buildings and Cities.
B1. HVAC optimization. (Purpose of Chapter V)
B2. Flexibility and microgrids.

New Electricity Systems.
E1. Forecasting supply & demand.
E2. Improving scheduling and flexible demand.

Industries.
I1. Optimized energy demand.
I2. Operational efficiency through modern maintenance.

Data Centers & ICT.
D1. Energy Efficiency and AI-ready DC
D2. Flexibility at DC level

New Mobilities
M1. Electrification of Fleets / Electrical Vehicles
M2. Battery & Storage Management

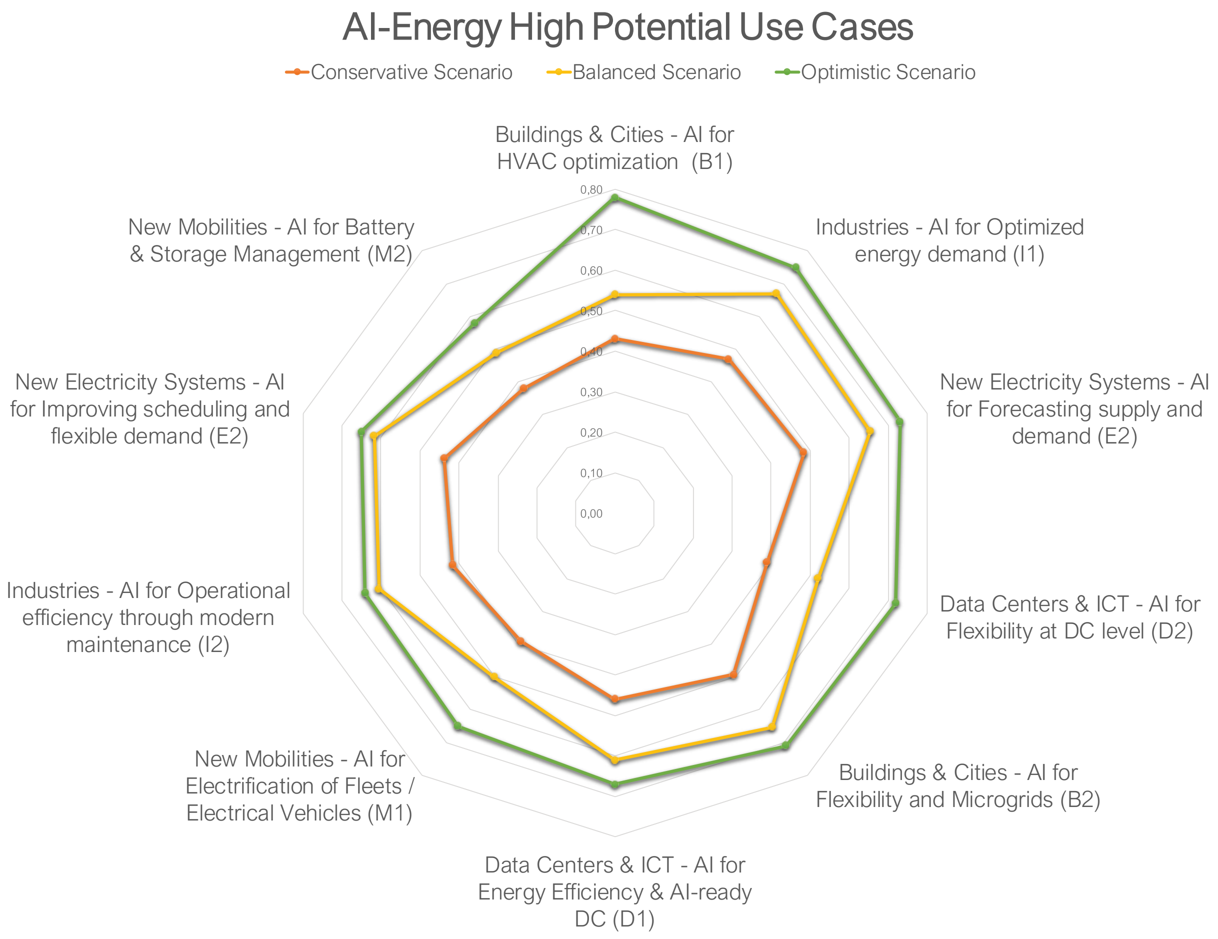


Figure 11. Preliminary ranking of AI-Energy use cases through the AI for Impact Compass.

Schneider Electric™ Sustainability Research Institute.

5

An Example: AI-Powered HVAC in Buildings

AI-Powered HVAC : What is at stake?

Buildings, including residential and commercial, consume approximately 40% of the world's primary energy and account for around 30% of global CO2 emissions (76). Therefore, reducing energy consumption in buildings is crucial for achieving sustainable development and lowering carbon emissions (77).

Heating, ventilation, and air-conditioning (HVAC) systems account for 35%-65% of the total energy consumption in buildings, making them a significant target for energy savings.

With rising energy prices and increasing HVAC usage, there is an economic and environmental motivation to improve the energy efficiency of HVAC systems.

According to the International Energy Agency (IEA) (78), the peak power load of countries with currently low HVAC penetration rates is expected to increase by around 45% by 2050.

AI has emerged as a promising solution to address these challenges. AI can optimize HVAC systems for energy savings and improved thermal comfort, which traditional methods struggle to achieve. Machine learning algorithms can learn complex patterns, make informed decisions, and optimize performance based on feedback from the environment.

Machine learning has been applied to HVAC systems since the 1990s, and research (79) has shown that it can reduce energy consumption by 5%-30% and improve indoor comfort.

In this chapter, we apply the AI for Impact Compass to the AI-powered HVAC use case, providing a practical example of how to quantify its potential impact. We will also delve into the advantages and challenges associated with this methodology.

Setting the context

Why utilize AI/ML in HVAC Building Systems?

As economies develop, a greater emphasis is placed on indoor comfort, with higher requirements for HVAC control, while modern buildings are becoming more dynamic and complex.

Older buildings, unlike modern structures with advanced materials and integrated Building Management Systems (BMS), often lack the inherent efficiency of newer designs. Implementing AI in these existing buildings provides a compelling solution for achieving significant energy savings without disruptive renovations. This is especially attractive for managers of large portfolios of aging buildings.

The growing trend of air conditioning installations in households is increasing the charge load, particularly during peak electricity demand periods. This surge in demand can potentially threaten the safety of power grids. Additionally, modern buildings now have more complex scenarios that include on-site generation, energy storage systems, and electric vehicle charging, which further complicates the building service system.

The stability and intermittency of on-site generation systems, such as solar photovoltaics, also pose challenges to the building service system. To optimize the energy efficiency of these grid-interactive energy-saving buildings, flexible control methods that can manage the increasing complexity of the building service system are necessary.

The two goals of AI-powered HVAC.

Thermal control and forecasting: Thermal comfort is a multifaceted concept that encompasses various factors, such as air temperature (76), radiation temperature (77), (78), airspeed (79), and relative humidity (80). Additionally, personal factors such as metabolic rate (81), clothing insulation (82), age (83), gender (84), and adaptation (85), (86), also play a significant role in determining thermal comfort. Accurate forecasting of temperature requirements within the HVAC system is crucial for efficient operation. ML algorithms, such as deep belief networks, present an alternative to traditional physical models. These data-driven approaches can potentially achieve higher accuracy with lower computational demands compared to traditional methods (73), (74).

Energy savings: Machine Learning can be employed to develop intelligent control systems for HVAC units. Deep Reinforcement Learning (RL) has been shown to be particularly effective in this domain. Kazmi et al. (75) demonstrated that deep RL can achieve significant energy reductions (up to 20%) while requiring only a minimal set of sensor data (air temperature, water temperature, and energy use). Similar advancements have been made in optimizing the cooling systems of data centers.

The whole approach is described in Figure 12. Machine learning is a collection of algorithms and statistical models that enable computers to learn from data and improve their performance on a specific task without being explicitly programmed. It forms the foundation of many artificial intelligence (AI) systems.Machine Learning can also learn from an environment and optimize performance from experience with a feedback loop involving rewards and penalties.

Furthermore, AI reduces the reliance on skilled HVAC engineers for system optimization. A well-trained AI system can apply its knowledge of various building types and situations to autonomously manage HVAC controls, freeing up human resources for more strategic tasks.

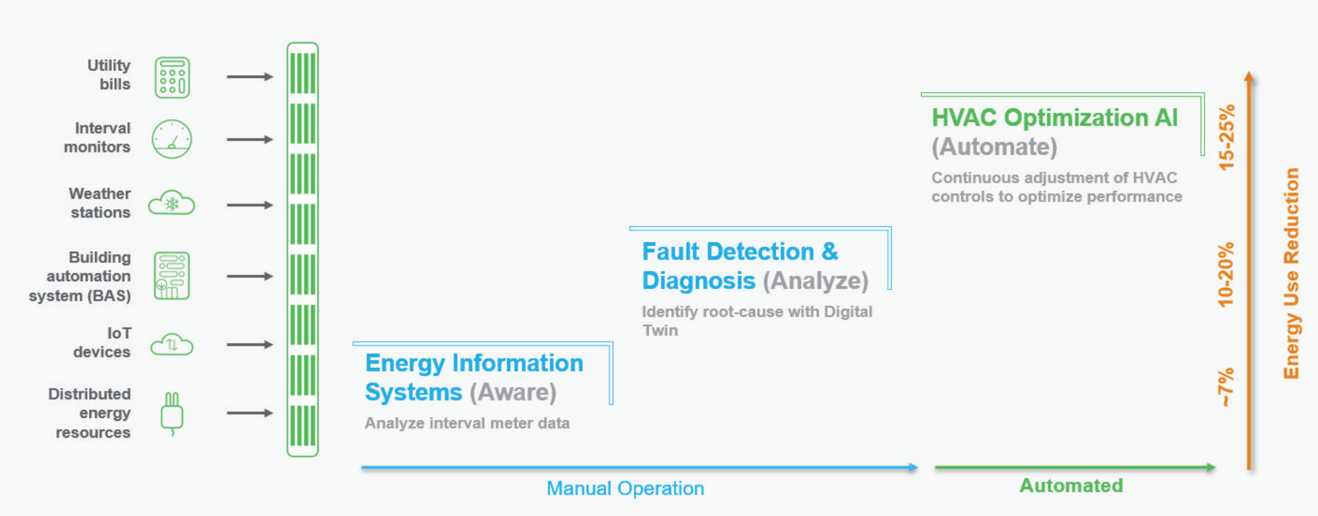


Figure 12. AI-Powered HVAC Approach.
Source: Schneider Electric

Case Description

Project's Inception in Stockholm's Educational Assets

The Stockholm Inner City School Board (SISAB) (86) is responsible for the ownership, operation, and maintenance of over **600 preschools, primary schools, and colleges** in Stockholm, Sweden.

This extensive portfolio necessitates a **significant annual energy budget of approximately €24.3 million** ($26.5 million). Thus, even minor enhancements in energy efficiency can lead to significant cost savings and a lower carbon footprint for the portfolio. These savings can be strategically utilized to either reduce their operational budget or reinvest in the implementation of innovative energy-saving technologies. The educational facilities managed by SISAB vary considerably ***in size*** (ranging from 100 to 48,000 square meters) and ***age*** (between 7 and 15 years old). Maintaining a comfortable year-round learning environment for the 200,000 students and staff necessitates the **implementation of diverse heating setpoints across these facilities**.

Prior to 2013, SISAB encountered challenges due to the utilization of multiple, vendor-specific building management interfaces. However, a centralized operations center, modeled after a network operations center used for data center management, was established in 2013. This centralized system now serves as the sole platform for implementing building control modifications, including adjustments to heating system setpoints. **Even on-site technicians require specific authorization to make adjustments within their designated school building.** Previously, due to the involvement of numerous contractors, tracing the history of control modifications proved to be a significant challenge.

To enhance the real-time control of heating and ventilation systems, SISAB has progressively deployed temperature and CO2 sensors within their school buildings, accumulating a current total of over 20,000 sensors. This sensor network generates an estimated one million data points daily. However, neither the existing heating and ventilation systems nor the current maintenance personnel possess the capability to **effectively analyze this vast dataset to identify optimal setpoints** and subsequently implement real-time adjustments.

Main objectives

In light of the aforementioned background, SISAB identified three key challenges that necessitated solutions:

- **Energy Cost Reduction:** Minimize overall heating energy consumption and the associated costs while ensuring a consistent indoor temperature of 20°C (68°F).
- **Non-intrusive Implementation:** Develop a solution that seamlessly integrates with the existing buildings and systems, eliminating the need for equipment replacements.
- **Real-Time Data Analysis and Optimization:** Establish a system capable of analyzing the extensive sensor data to determine optimal heating setpoints and implement real-time adjustments for improved energy efficiency.

Project Preliminary Assessment

We did a preliminary assessment of this project to check if it has the potential to be a referential use case in terms of depth of analysis. In the present paper and the next pages, we will only go through a first assessment through the AI for Impact Compass, but we will publish a second research with a holistic quantification of the effects by 2024.

The criteria for the case selection are the following:
- Representative sample of over 600 buildings.
- Wide variety of building profiles and technologies (legacy to modern IoT).
- Availability of real measurements for heating energy savings, electricity savings, occupant complaints, and payback.
- Use of Reinforcement Learning technology with a decade of practical use.
- Strong local ecosystem and stakeholder collaboration for a comprehensive view of the case and associated data.
- Potential for scalability and replicability in addressing major climate change topics of HVAC in buildings, aiding decision-makers (policy, investors).

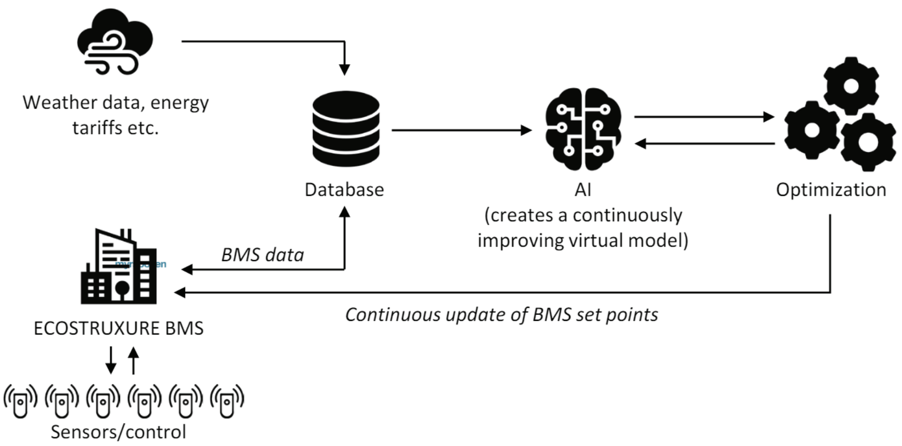


Figure 13 AI-Powered HVAC Optimization solution principles.
Source: Schneider Electric

Measurements

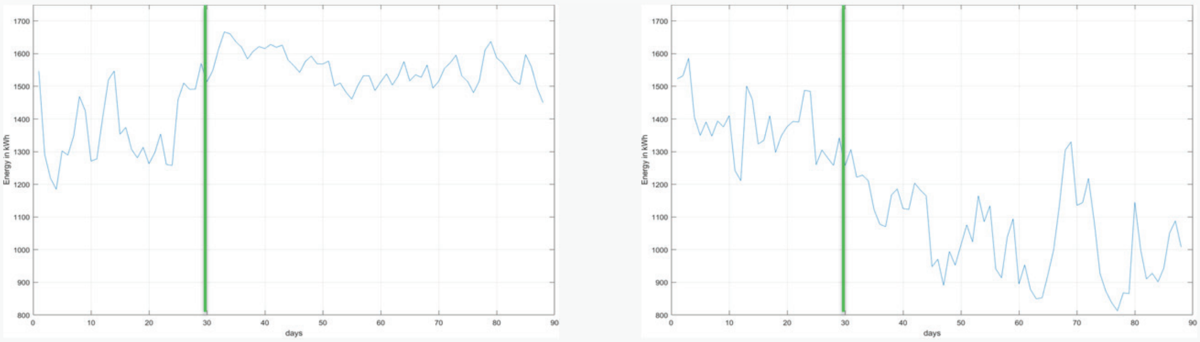
The solution deployed is an AI service on top of the existing Building Management System. The solution did not need any changes to SISAB's current components, such as building controllers. Instead, the cloud-based AI service works with their existing building management system (BMS) without replacing it. It's like having a virtual building operator using the same controls as a human would. However, unlike a human who makes changes a few times a year based on complaints, the AI solution adjusts settings every 15 minutes to continuously optimize results. It works with the conventional BMS, which handles basic management functions, while the AI service adjusts temperature and air pressure settings to achieve optimal indoor climate and energy performance.

Key measures

This study investigates the effectiveness of an AI solution implemented in 624 school buildings during the winter season (November 2020 - March 2021). Given the seasonal operation of these schools, a comparative analysis was conducted using energy bills from the preceding winter (November 2019 - March 2020) as a baseline (control group). It is important to note that the measures were taken during the COVID period. The main findings are:

- **Energy Savings:** A reduction in heating **energy consumption (4%)** and overall **electricity usage (15%)**.
- **Environmental Impact:** Greenhouse gas (GHG) emissions were reduced by **205 tons** compared to the reference scenario without the AI service, suggesting a positive indirect impact (emissions baseline : November 2019 - March 2020)
- **Occupancy Comfort:** There was a **23% decrease in complaints** from building occupants concerning comfort levels, suggesting improved temperature and air quality management.
- **Economic Viability:** The analysis suggests a favorable **payback period of 2 years**, indicating a potentially cost-effective investment in educational facilities.

Results



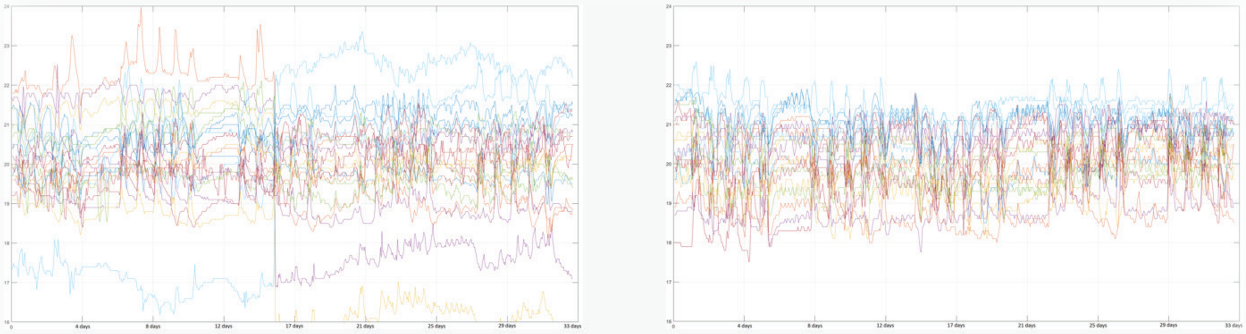
Before

The reactive nature of traditional BMS controls, coupled with increasing fluctuations and complexity of energy costs, makes it difficult to optimize energy usage and cost with the systems typically in place.

With Optimization AI

Optimization AI combines the forecasting of energy costs with the prediction of energy needs, which enables control adjustments that take both into account. This allows for the capturing of cost and energy savings by considering things like energy tariffs, flow and return penalty fees, price cuts, and daily variations.

Figure 14 - AI-Powered energy adjustments.
Source: Schneider Electric.



Before

There is no real control nor optimization of energy usage. The indoor temperature fluctuates haphazardly without any planning implemented nor an informed solution.

With Optimization AI

Our customized algorithms ensure the indoor temperature is kept within a predefined range while considering outdoor temperature, building configurations, energy tariffs, time, date, and other factors.

Figure 15 - AI-Powered temperature adjustments.
Source: Schneider Electric.

Practicing the Compass - First results

I. Impact Score (IS) : 2 on a max of 4 (2 / 4)

As a preliminary estimate, we have assigned a provisional Impact Score of 2.

This score is based on the conservative assumption that the impact ratio (the absolute value of the sum of negative impacts divided by the sum of positive impacts) must be calculated in much precisely.

For this exercise, the criteria is GHG emissions. It is important to note that GHG emissions are heavily influenced by a country's electricity sources. In Sweden, the electricity mix is largely based on renewable and low-emission sources, resulting in lower GHG emissions.

II. Scalability Score (SS) : 7.5 / 9

II.1. Technology Maturity (AITRL): 8 / 9

The technology's maturity, assessed using the Machine Learning Technology Readiness Levels (AITRL) framework, indicates a score of 8 to 9. This suggests successful integration, industrialization, and deployment with multiple version upgrades.

Following a technology assessment of the physical operations in the Stockholm areas, a review with technical experts was conducted, confirming that for this specific use case and context, an AITRL score of 8 was adopted.

The following considerations were taken into account:

Qualification of the onboarding process:
- *Connection and Categorization:* Pertinent data points are selected and classified into observable and actionable categories. Observable data includes sensor data, computed values, and external sources, while actionable data typically consists of setpoints and their respective allowed ranges.
- *Training:* The system introduces randomized offsets on control points to learn the building's behavior.
- *Application:* Building-specific models are created and applied for control decisions. Each building has its unique model, which is retrained daily using a neural net-based approach with some human-imposed heuristics. The model captures dynamic building behavior and the impact of regular activities, considering time dependencies such as the day of the week and time of day.

AI Optimization Model Predictive Control approach:
- *Model Predictive Control* (MPC) over the next 12 hours
- *Weather forecast inputs:* temperature, wind, cloud cover
- Cost function *balances energy cost and comfort*
- The previous version used a genetic algorithm, now replaced by *gradient descent-type method*
- Applied to *solve nonlinear problem*

II.1. Adoption Readiness (AIARL): 7 / 9

The Adoption Readiness Level (AIARL) has calculated using the complete CARAT tool (89), yields a score of 7, indicating a high level of readiness for adoption.

The calculation details can be provided upon request.

III. Risk Score (RS): 2 / 4

The evaluation of risk is conducted using objective criteria that consider current solutions, security of supply, and compliance with existing legislation on fundamental rights.

This assessment leads to a significant number of AI solutions being classified as high risk (88), primarily due to the energy and power sectors being deemed critical infrastructures under the EU AI Act. ***As the Act is now ratified, these technologies are facing more stringent development processes***, including impact assessments, conformity assessments, adherence to EU AI Act requirements, registration in a dedicated EU database, and obtaining CE marking. Upon evaluation using the EU AI Act classification and assessment criteria, we determine the Risk Score to be at level 2.

Total Score (TS) (from 0 to 1)

From the above, it is evident that the considered application has a moderate impact (at least in Sweden), good scalability, and low risk. Depending on the priorities and risk attitudes of the decision-maker, these factors can be aggregated in various ways.

The Total Score varies depending on the weighting scheme (decision posture). We have examined three postures with the following results:
- Decision posture #1: Balanced: TS = 0.54
- Decision posture #2: Climate Impact: TS = 0.62
- Decision posture #3: Risk Avoidance: TS = 0.4

In the "Balanced" and "Risk Avoidance" postures, the Total Score suggests a Contextual Impact (0.3 ≤ TS < 0.6), **indicating that these applications may offer climate benefits**, but their effectiveness should be evaluated on a case-by-case basis.

However, the "Climate Impact" scenario yields a TS of 0.62, suggesting a Potential High Impact (TS ≥ 0.6), **indicating a substantial potential for climate change mitigation** and warranting further detailed analysis. While the "Scalability Score" and "Risk Score" are not highly sensitive to analysis, the "Impact Score" (IS) has been set to 2, as a total quantification has not yet been conducted. In the "Climate Scenario," an IS of 3 would result in a TS of 0.71, and an IS of 4 would yield a TS of 0.91.

In conclusion, the AI for Impact Compass identifies the AI-powered HVAC use case as a potential high-priority application, or a potential "no-brainer," that warrants a comprehensive, in-depth bottom-up quantification.

Detailed Scoring

Criteria	Notation		Referential for assessement	Approach	Criterias	Scoring Range	AI-Powered HVAC
Impact	IS		Net Digital Impact Framework (based on ITU-T L.1480, EGDC, NZI4IT)	Scoring related to the Impact Ratio = Σ Positive Effects / Σ | Negative Effects |	If Ratio < 0.5: The negative impacts outweigh the positive impacts.	1	2
					If Ratio between 0.5 and 1.5: Uncertainty zone where the positive and negative impacts are balanced.	2	
					If Ratio between 1.5 and 5: The positive impacts have a greater magnitude than the negative impacts.	3	
					If Ratio > 5: Highly beneficial environmental impact.	4	
Scalability	SS	AITRL	Lavin et al.	9 Maturity levels	Goal-oriented research: From principles to practical use	1	8
					Proof of Principle development: Active R&D initiated	2	
					System development: Sound software engineering	3	
					Proof of Concept development: Demonstration in real scenario	4	
					Machine learning capability: R&D to product transition	5	
					Application development: Robustification of ML modules towards use-cases	6	
					Integrations: ML infrastructure, product platform, data pipelines, security protocols	7	
					Mission-ready: End of system development	8	
					Deployment: Monitoring the current and improving the next	9	
		AIARL	OTT DOE	4 Assessment categories	Value Proposition Assessment	From 1 to 9	7
					Market Acceptance Assessment		
					Resource Maturity Assessment		
					License to Operate Assessment		
Risk	RS		EU AI Act	4 Risk levels	Minimal risk	1	2
					Limited risk	2	
					High risk	3	
					Unacceptable risk	4	

Total Score	TS	General Formula	TS < 0.3: Limited Impact - Applications scoring below this threshold warrant careful consideration or even exclusion due to potential negative impact on climate goals.	From 0 to 1	0,54
			0.3 ≤ TS < 0.6: Contextual Impact - Applications within this range may offer climate benefits, but their use should be evaluated based on specific contexts to maximize positive environmental impact.		
			TS ≥ 0.6: Potential High Impact - Applications surpassing this threshold demonstrate substantial potential for mitigating climate change and merit prioritization for further, in-depth analysis on an individual basis.		

What-if sensitivity scenarios	Scenario #1 : Balanced ; Impact weight = ω1 = Scalability weight ω2 = Risk weight ω3 = 1/3	From 0 to 1	0,54
	Scenario #2 : Climate Impact ; Impact weight = ω1 0,6 ; Scalability weight ω2 = 0,3 ; Risk weight ω3 = 0,1	From 0 to 1	0,62
	Scenario #3 : Risk Avoidance ; Impact weight = ω1 = 0,1 ; Scalability weight ω2 = 0,1 ; Risk weight ω3 = 0,8	From 0 to 1	0,4

Table 4 -AI for Impact Score preliminary calculation. AI-powered HVAC.
Source: Schneider Electric$^{\text{TM}}$ Sustainability Research.

6

Conclusions and Perspectives

Future research, insights for policymakers

Conclusion on the research objectives

This research establishes a comprehensive method for quantifying the climate impact of AI applications, accounting for direct, indirect, and systemic effects.

Scalability is integrated as a crucial factor, ensuring that proposed solutions can be efficiently and effectively deployed across diverse contexts.

The study evaluates regulatory risk associated with AI solutions, safeguarding against social scoring, manipulative techniques, and compromising critical infrastructure safety.

By emphasizing demand-side climate change mitigation and decarbonization potential, the research acknowledges the significant contribution of energy consumption to global GHG emissions.

A methodology is developed to distinguish promising AI applications from less promising ones, providing stakeholders with initial guidance in differentiating between potential solutions.

Insights for future research

Discussions surrounding AI often focus on the latest technological advancements, which is undoubtedly exciting. However, it's crucial to recognize that **numerous AI technologies are already available** and capable of generating immediate impacts.

While the ranking of use cases may be subject to change, the ultimate goal is to **trigger a wave of meta-analyses based on the most recent quantification methods**. This will provide concrete evidence of where AI can truly make a difference.

Given the significant environmental impact of the latest models, particularly generative AI, we advocate for a focus on scalable technologies with proven impact. This approach can help avoid investments in gadgets and unsustainable solutions. The emphasis should be on **practical applications that can drive significant change**, and for which the ratio between the positive and the negative impacts is maximized.

In this regard, employing a **frugal approach** introduces a new dimension of efficiency by aligning AI efforts with anticipated positive outcomes, ultimately maximizing the return on investment.

Hence, our **current areas of research focus on deeply analyzing the impact of the most promising use cases**.

In the future, by **enhancing and expanding the AI for Impact Compass**, we strive to provide guidance that is universally accessible to diverse audiences, including academics, industry professionals, and policymakers, ensuring widespread impact and understanding.

Insights for policymakers

I. Regulate AI's Emissions Impact

- Emerging Technologies: Encourage transparent AI emissions impact Reporting for new AI-driven technologies (e.g., self-driving cars) to promote climate-friendly applications.
- Economic Incentives: Establish economic incentives (e.g., carbon taxes) that encourage greenhouse gas (GHG) emission reduction.
- Transparency & Reporting: Where applicable, encourage (and possibly require) transparent reporting of AI's lifecycle environmental impacts, including GHG emissions and energy consumption.

II. Boost AI solutions with Impact at Scale

- Research & Development: Encourage joint research in computer science, energy transition, and climate-related fields.
- Technical Readiness: Facilitate research, development, and demonstration (RD&D) programs that advance AI applications for managing climate change.
- Deployment Support: Reduce regulatory barriers to deploying AI technologies within the electricity sector that support climate goals.

III. Fostering AI & Data Sharing in the Public Sector

- Public Sector AI Capacity: Develop in-house AI implementation capabilities within relevant government agencies, particularly in strategic domains such as defense and counter-terrorism.
- Stakeholder Feedback: Establish processes to incorporate stakeholder feedback throughout the AI development and deployment cycle.
- Standardization: Develop standards and best practices to guide decisions on when and how to employ AI, including criteria for selecting AI over simpler solutions. This should encompass considerations such as which AI techniques to use, the frequency of their application, the volume of data required for training, and other relevant factors.
- Data Sharing Standards: Create standards for data collection, management, and sharing that address

Annex

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Terminology

General Terms

- Artificial Intelligence (AI): Methods that mimic human intelligence for learning, problem-solving, and decision-making.
- Artificial General Intelligence (AGI)
- Big Data (BD): Massive amounts of machine-readable, often real-time data.
- Digital Twins (DT): Simulated models of assets or systems, enabled by IoT, for optimization.
- Distributed Ledger (DL): A secure, transparent way to store transactions chronologically.
- Energy Transition: The global shift towards renewable energy sources and sustainable energy systems.
- General-Purpose Technology (GPT)
- Greenhouse Gas (GHG)
- Information and Communication Technology (ICT)
- Invention of a Method of Invention (IMI)
- Internet of Things (IoT): A network of internet-connected devices.
- Industrial Internet of Things (IIoT): IoT applied to industrial settings.
- Machine Learning (ML): A subset of AI focused on algorithms that learn from data.
- Natural Language Processing (NLP): AI focused on understanding and generating human language.
- Renewable Energy: Energy from sources that are naturally replenished.
- Smart Grid: An electricity network using digital communications technology to monitor and manage electricity flow.

Organizations and Initiatives

- Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI)
- Distribution System Operators (DSO)
- Global Enabling Sustainability Initiative (GeSI)
- Global System for Mobile Communications Association (GSMA)
- International Energy Agency (IEA)
- Intergovernmental Panel on Climate Change (IPCC)
- International Organization for Standardization (ISO)
- Joint Research Centre (JRC)
- Organisation for Economic Co-operation and Development (OECD)
- Transmission System Operators (TSO)
- World Resources Institute (WRI)

Technologies

- 3D Printing (3D)
- Augmented Reality/Virtual Reality (AR/VR)
- Building Management System (BMS)
- Electronic and Electrical Equipment (EEE)
- Information Technologies (IT)
- Integrated Circuit (IC)
- Local Area Network (LAN)
- Life Cycle Analysis (LCA)
- Robotics (RB): Using robots in the energy sector.

Acronyms

- GWP: Global Warming Potential
- HVAC: Heating, Ventilation, and Air Conditioning

Digitization, Digitalization, and Digital Transformation

- Digitization (related to Direct effects): Converting analog data to digital format.
- Digitalization (related to Indirect effects): Utilizing digital technologies (ICT) across all players in the energy sector to exploit new data sources.
- Digital Transformation (related to Systemic effects): A large-scale, cross-sectoral shift where all economic and social actors connect into an interlinked digital system. This fosters enhanced data exchange, analysis, and decision-making capabilities.

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Annex

EU AI Act

The AI Act aims to provide AI developers and deployers with clear requirements and obligations regarding specific uses of AI. At the same time, the regulation seeks to reduce administrative and financial burdens for business, in particular small and medium-sized enterprises (SMEs).

The AI Act is part of a wider package of policy measures to support the development of trustworthy AI, which also includes the AI Innovation Package and the Coordinated Plan on AI. Together, these measures will guarantee the safety and fundamental rights of people and businesses when it comes to AI. They will also strengthen uptake, investment and innovation in AI across the EU.

The AI Act is the first-ever comprehensive legal framework on AI worldwide. The aim of the new rules is to foster trustworthy AI in Europe and beyond, by ensuring that AI systems respect fundamental rights, safety, and ethical principles and by addressing risks of very powerful and impactful AI models.

The AI Act ensures that Europeans can trust what AI has to offer. While most AI systems pose limited to no risk and can contribute to solving many societal challenges, certain AI systems create risks that we must address to avoid undesirable outcomes.

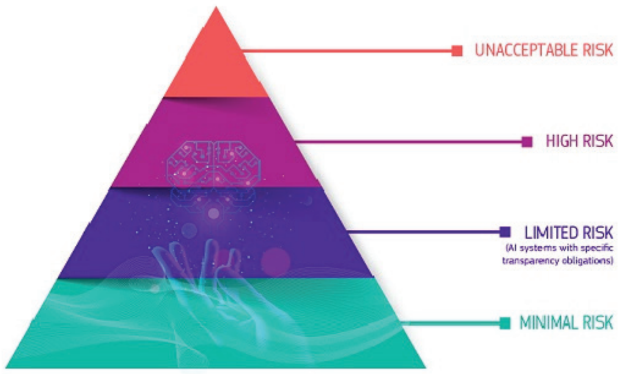
For example, it is often not possible to find out why an AI system has made a decision or prediction and taken a particular action. So, it may become difficult to assess whether someone has been unfairly disadvantaged, such as in a hiring decision or in an application for a public benefit scheme.

Although existing legislation provides some protection, it is insufficient to address the specific challenges AI systems may bring.

The proposed rules will:

- address risks specifically created by AI applications;
- prohibit AI practices that pose unacceptable risks;
- determine a list of high-risk applications;
- set clear requirements for AI systems for high-risk applications;
- define specific obligations deployers and providers of high-risk AI applications;
- require a conformity assessment before a given AI system is put into service or placed on the market;
- put enforcement in place after a given AI system is placed into the market;
- establish a governance structure at European and national level.

The Regulatory Framework defines 4 levels of risk for AI systems:



All AI systems considered a clear threat to the safety, livelihoods and rights of people will be banned, from social scoring by governments to toys using voice assistance that encourages dangerous behaviour.

High risk

AI systems identified as high-risk include AI technology used in:

- critical infrastructures (e.g. transport), that could put the life and health of citizens at risk;
- educational or vocational training, that may determine the access to education and professional course of someone's life (e.g. scoring of exams);
- safety components of products (e.g. AI application in robot-assisted surgery);
- employment, management of workers and access to self-employment (e.g. CV-sorting software for recruitment procedures);
- essential private and public services (e.g. credit scoring denying citizens opportunity to obtain a loan);
- law enforcement that may interfere with people's fundamental rights (e.g. evaluation of the reliability of evidence);
- migration, asylum and border control management (e.g. automated examination of visa applications);
- administration of justice and democratic processes (e.g. AI solutions to search for court rulings).

High-risk AI systems will be subject to strict obligations before they can be put on the market:

- adequate risk assessment and mitigation systems;
- high quality of the datasets feeding the system to minimise risks and discriminatory outcomes;
- logging of activity to ensure traceability of results;
- detailed documentation providing all information necessary on the system and its purpose for authorities to assess its compliance;
- clear and adequate information to the deployer;
- appropriate human oversight measures to minimise risk;
- high level of robustness, security and accuracy.
- All remote biometric identification systems are considered high-risk and subject to strict requirements. The use of remote biometric identification in publicly accessible spaces for law enforcement purposes is, in principle, prohibited.

Narrow exceptions are strictly defined and regulated, such as when necessary to search for a missing child, to prevent a specific and imminent terrorist threat or to detect, locate, identify or prosecute a perpetrator or suspect of a serious criminal offence.

Those usages is subject to authorisation by a judicial or other independent body and to appropriate limits in time, geographic reach and the data bases searched.

Limited risk

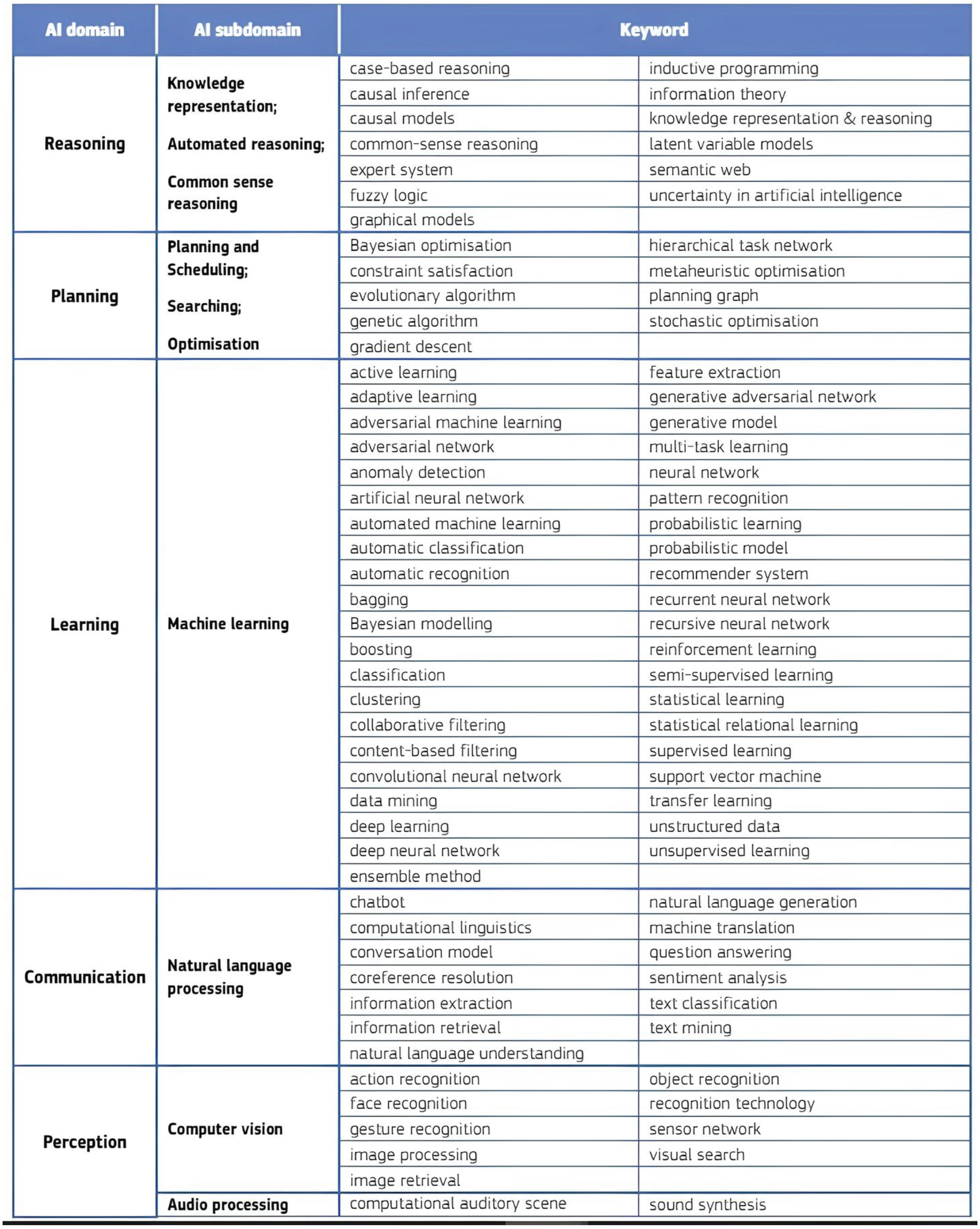
Limited risk refers to the risks associated with lack of transparency in AI usage. The AI Act introduces specific transparency obligations to ensure that humans are informed when necessary, fostering trust. For instance, when using AI systems such as chatbots, humans should be made aware that they are interacting with a machine so they can take an informed decision to continue or step back. Providers will also have to ensure that AI-generated content is identifiable. Besides, AI-generated text published with the purpose to inform the public on matters of public interest must be labelled as artificially generated. This also applies to audio and video content constituting deep fakes.

Minimal or no risk

The AI Act allows the free use of minimal-risk AI. This includes applications such as AI-enabled video games or spam filters. The vast majority of AI systems currently used in the EU fall into this category.

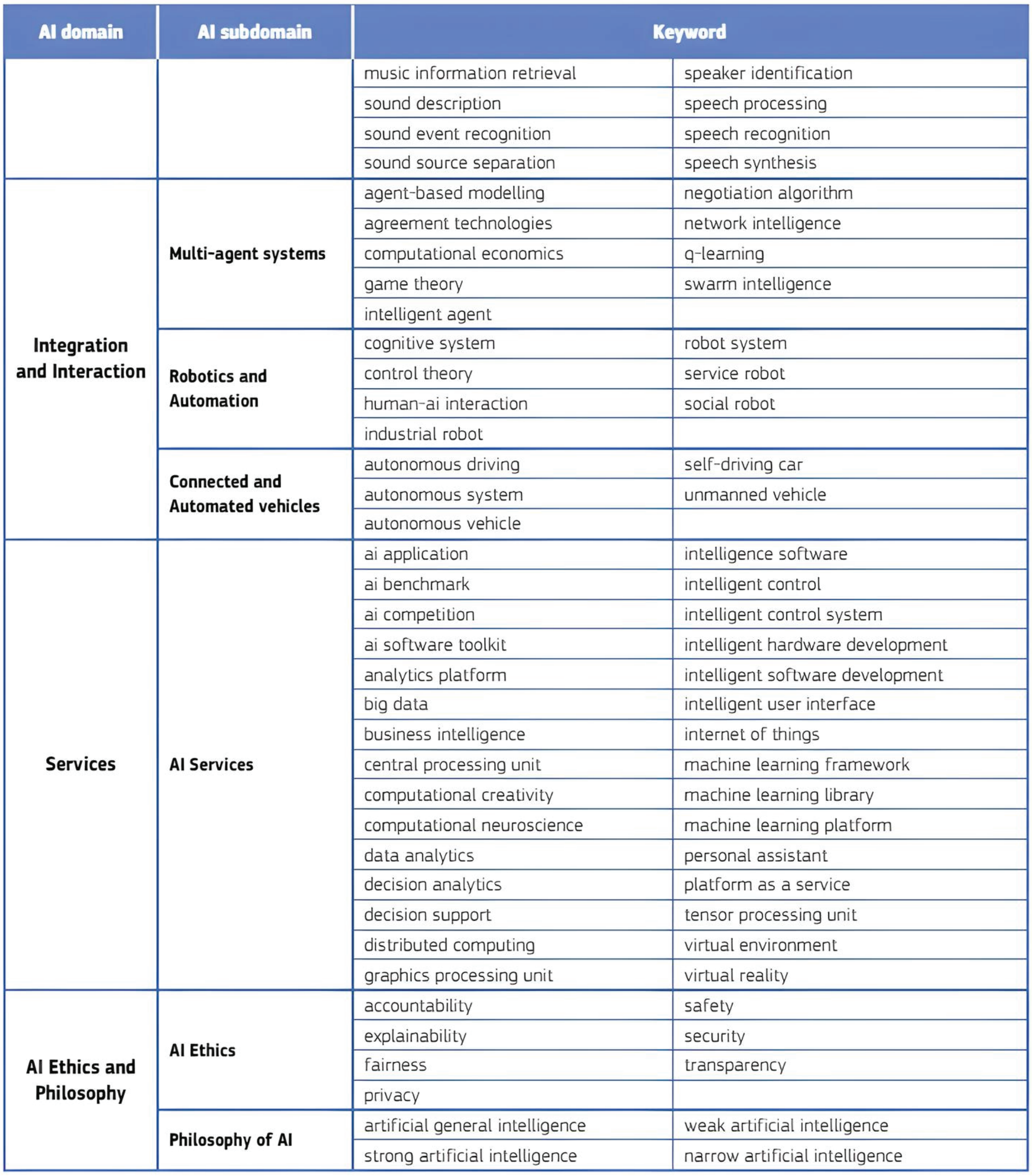
Annex

EU AI domains (1/2)
Current state-of-the-art



AI domain	AI subdomain	Keyword	
Reasoning	**Knowledge representation;** **Automated reasoning;** **Common sense reasoning**	case-based reasoning	inductive programming
		causal inference	information theory
		causal models	knowledge representation & reasoning
		common-sense reasoning	latent variable models
		expert system	semantic web
		fuzzy logic	uncertainty in artificial intelligence
		graphical models	
Planning	**Planning and Scheduling;** **Searching;** **Optimisation**	Bayesian optimisation	hierarchical task network
		constraint satisfaction	metaheuristic optimisation
		evolutionary algorithm	planning graph
		genetic algorithm	stochastic optimisation
		gradient descent	
Learning	**Machine learning**	active learning	feature extraction
		adaptive learning	generative adversarial network
		adversarial machine learning	generative model
		adversarial network	multi-task learning
		anomaly detection	neural network
		artificial neural network	pattern recognition
		automated machine learning	probabilistic learning
		automatic classification	probabilistic model
		automatic recognition	recommender system
		bagging	recurrent neural network
		Bayesian modelling	recursive neural network
		boosting	reinforcement learning
		classification	semi-supervised learning
		clustering	statistical learning
		collaborative filtering	statistical relational learning
		content-based filtering	supervised learning
		convolutional neural network	support vector machine
		data mining	transfer learning
		deep learning	unstructured data
		deep neural network	unsupervised learning
		ensemble method	
Communication	**Natural language processing**	chatbot	natural language generation
		computational linguistics	machine translation
		conversation model	question answering
		coreference resolution	sentiment analysis
		information extraction	text classification
		information retrieval	text mining
		natural language understanding	
Perception	**Computer vision**	action recognition	object recognition
		face recognition	recognition technology
		gesture recognition	sensor network
		image processing	visual search
		image retrieval	
	Audio processing	computational auditory scene	sound synthesis

EU AI domains (2/2)
Current state-of-the-art



AI domain	AI subdomain	Keyword	
		music information retrieval	speaker identification
		sound description	speech processing
		sound event recognition	speech recognition
		sound source separation	speech synthesis
Integration and Interaction	**Multi-agent systems**	agent-based modelling	negotiation algorithm
		agreement technologies	network intelligence
		computational economics	q-learning
		game theory	swarm intelligence
		intelligent agent	
	Robotics and Automation	cognitive system	robot system
		control theory	service robot
		human-ai interaction	social robot
		industrial robot	
	Connected and Automated vehicles	autonomous driving	self-driving car
		autonomous system	unmanned vehicle
		autonomous vehicle	
Services	**AI Services**	ai application	intelligence software
		ai benchmark	intelligent control
		ai competition	intelligent control system
		ai software toolkit	intelligent hardware development
		analytics platform	intelligent software development
		big data	intelligent user interface
		business intelligence	internet of things
		central processing unit	machine learning framework
		computational creativity	machine learning library
		computational neuroscience	machine learning platform
		data analytics	personal assistant
		decision analytics	platform as a service
		decision support	tensor processing unit
		distributed computing	virtual environment
		graphics processing unit	virtual reality
AI Ethics and Philosophy	**AI Ethics**	accountability	safety
		explainability	security
		fairness	transparency
		privacy	
	Philosophy of AI	artificial general intelligence	weak artificial intelligence
		strong artificial intelligence	narrow artificial intelligence

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Annex

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