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FROM SIGNAL TO SCALE

The Industrial AI Sustainability Opportunity

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Foreword

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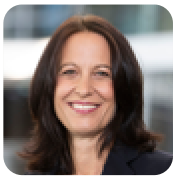
In a world increasingly shaped by resource constraints, geopolitical uncertainty, climate pressures, and growing demand for energy, infrastructure, and digital capacity, businesses are navigating two fundamental transformations: the energy transition through decarbonization and electrification, and the transition from a linear to a circular economy. Industrial AI has a pivotal role to play in helping manage the complexity that comes with both. Applied to the real world, in grids, rail networks, factories, and buildings, it has the potential to improve efficiency, resilience, and sustainability at scale.

Industrial AI has moved from a future concept to a boardroom priority. While organizations increasingly recognize AI's potential, they are only beginning to realize its full impact. Challenges around measurement, organizational readiness, and scaling successful use cases continue to limit the value that Industrial AI can deliver.

This report is helping to close that gap. It draws on real-world cases, including those generously shared by our clients in this report, to examine which sustainability use cases are delivering measurable results, and what it will take for companies to move from promising pilots to impact at scale.

One insight surprised us: almost 90% of the companies we traced are focusing on optimizing their own operations with AI. Yet the greater opportunity remains largely untapped: leveraging AI not just to optimize individual operations, but to improve how entire industrial ecosystems work together.

The future belongs to organizations that can turn complexity into opportunity. That opportunity lies not only in optimizing today's operations, but in enabling outcomes that are difficult to achieve without AI. By combining sustainability, technology, and Industrial AI, we can transform today's challenges into lasting impact for business, society, and the planet.



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From Signal to Scale sets out to answer specific questions: where is Industrial AI already delivering sustainability outcomes today, and where is the conversation still ahead of the evidence? Pressure on the planet's environmental limits is mounting, and industry contributes to that through emissions, water use, and the waste its processes generate. Another defining force of this decade is emerging: the rise of Industrial AI, whose own footprint in energy, water and hardware is still largely unmeasured. That footprint could deepen the pressure industry is already facing, or, if used deliberately, become part of the solution.

Many industry leaders are hopeful about the opportunities for sustainable impact in Industrial AI. However, proof of what it is actually delivering today, at scale, remains limited.

We built a signal database of corporate disclosures, patent filings, hiring signals, and deal activity from 100+ companies, counting only cases traceable to a named solution, customer or quantified outcome. We then tested the findings with practitioners running these deployments, and with sustainability and AI specialists across Quantis, BCG and Siemens.

This report is written for those deciding where to direct capital and attention next: industrial executives, sustainability leaders, and the teams running AI deployments. It identifies which use cases have evidence today, which remain unproven, and what separates deployments that scale from pilots that stall. The sustainability transition and the rise of Industrial AI will both continue regardless. They are, in our view, better served together than apart.

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Industrial AI's Sustainability Potential: An Emerging Opportunity

Industry is navigating two transformations at the same time: the rapid adoption of Industrial AI and the transition toward more sustainable operations and business models. Together, they create an opportunity to improve how industry uses energy, resources and assets today, while enabling more sustainable industrial systems in the future. Expectations are high, with 81% of practitioners expecting Industrial AI to drive future sustainability innovation.[1] Yet systematic evidence on where these benefits emerge, how they are measured, and what enables them to scale remains limited. This report assesses Industrial AI deployment and impact today, highlights opportunities to improve measurement and scale, and outlines Industrial AI's future sustainability potential and the actions leaders can take to realize it.

Industrial AI × Sustainability: Moving from Signal to Scale

Industrial AI is delivering mature, sustainability-relevant applications across industry, concentrated in specific capabilities and environmental outcomes. The report builds a signal database comprising 420 human-verified signals[i] across 100+ industrial companies and multiple geographies, with more than 80% of signals representing active deployments of Industrial AI solutions. Activity is strongest in Production & Asset and Energy & Materials Use, with Predictive Maintenance among the three most prevalent AI capabilities across the five sectors studied. Environmental outcomes are broadly balanced between resource efficiency and decarbonization. Circularity and value-chain decarbonization remain less prevalent today, reflecting earlier-stage applications rather than limited potential for Industrial AI, while both areas hold substantial opportunities for future impact. Overall, sustainability is rarely the primary deployment driver, with momentum strongest where environmental, operational and financial value reinforce each other.

From Scaling to Value: Measuring and Reporting What Industrial AI Delivers

Measuring operational and environmental outcomes together reveals more of Industrial AI's value and provides a stronger basis for deciding which applications to scale. Only around 40% of identified signals report a quantified sustainability-linked KPI, and measurement remains weighted toward operational outcomes, leaving environmental contributions only partially captured. Companies can build on existing operational metrics to quantify environmental outcomes more systematically and strengthen the overall value case. At the same time, a critical measurement challenge remains: understanding and accounting for AI's own environmental costs. Energy and water consumption, land use and hardware-related impacts remain considerably less visible at the application level. Greater transparency and common methodologies for bringing these costs together with measured gross environmental

i. Signals are publicly disclosed Industrial AI solutions (deployments, pilots or investment deals).

benefits will provide companies with a stronger basis for consistently assessing the net environmental impact of individual Industrial AI applications.

Scaling Industrial AI: What Separates Deployments from Stalled Pilots

Scaling Industrial AI beyond individual sites and products depends on three conditions: a sound business case, accessible data infrastructure and effective change management. Achieving this scale can extend the sustainability gains of proven applications today, while laying the foundation for future Industrial AI applications that broaden and deepen sustainability impact. Expert interviews indicate that technology itself is no longer the principal constraint. The business case must start with the right problem and account for the full deployment context; reliable data must be accessible while domain teams remain accountable for its quality; and change management requires clear ownership of AI-supported decisions, domain expertise and visible leadership support. Scaling is even more an organizational challenge than a technological one.

Vision: Unlocking Industrial AI's Full Potential for Greater Impact

Industrial AI's environmental opportunity extends far beyond today's application. Three mutually reinforcing visions show how Industrial AI can expand its environmental impact:

- **Industrial AI pushes the boundaries of industrial sustainability capabilities.** Industrial AI moves beyond optimizing today's operations to enable sustainability outcomes that are difficult to achieve without AI, from anticipating physical risks and accelerating lower-impact materials and product design to orchestrating complex energy and resource systems.
- **AI minimizes its own environmental footprint.** As AI deployment grows, **sustainability contribution will increasingly depend on reducing the resources and environmental pressures associated with delivering it.** More resource-efficient AI and lower-impact, more circular computing infrastructure increase the capability and sustainability value delivered for the resources consumed.
- **Industrial AI connects and expands optimization across industrial ecosystems.** Connected intelligence extends optimization across suppliers, manufacturers, energy systems, logistics providers, customers and recyclers creating opportunities to improve sustainability while increasing efficiency and affordability across the system. This opportunity remains largely untapped: today, almost 90% of observed activity still occurs within individual company boundaries, and cross-boundary applications such as circularity and value-chain decarbonization remain at an earlier stage of maturity.

Turning Vision into Action: What Industrial Leaders Should Do Now

Capturing this opportunity requires leaders to treat Industrial AI not only as a technology investment, but as a strategic lever for business value and industrial sustainability.

- **Board / CEO: Make Industrial AI a strategic sustainability and value lever.** Evaluate AI investments across financial, operational and environmental outcomes, and pursue opportunities across value chains and industrial ecosystems.
- **C-Suite / Function Heads: Build the conditions for Industrial AI to scale responsibly.** Invest in people, processes and data alongside technology, embed sustainability KPIs into AI business cases, and improve visibility into AI's own environmental footprint.
- **Operational Owners: Turn priorities into measurable impact.** Start where deployment evidence is strongest, define operational and environmental KPIs from the outset, and match the model, compute, sensors and hardware to the task.

1 Industrial AI's Sustainability Potential: An Emerging Opportunity

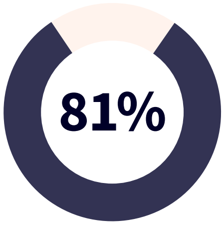
Industrial companies are navigating two profound transformations at the same time: the rapid adoption of artificial intelligence and the transition toward more sustainable operations and business models.

On the technology side, Industrial AI is gaining momentum, building on the digital and data infrastructure developed over recent decades and increasingly changing how companies design products, operate assets, and manage industrial processes. 66% of industrial companies expect AI to transform how their business operates,[2] while the Industrial AI market is projected to expand 3.5x between 2024 and 2030.[3]

In parallel, companies are transforming how they manage their environmental impact and resource dependencies. The sustainability imperative continues to grow, driven by customer demand, regulatory requirements, and the business case for strengthening resilience by reducing dependence on energy and resources. SBTi's Trend Tracker identifies industrial companies as leaders in corporate target-setting, with more than 2,500 companies having validated targets or publicly committed to setting them.[4] Two central levers for this transformation are decarbonization and resource efficiency & circularity.

While there is a strong focus on understanding the adoption, capabilities, and economic potential of Industrial AI, systemic evidence on its environmental sustainability impact remains more limited. This report examines that intersection, focusing specifically on Industrial AI's impact on environmental sustainability.[ii]

Today, **81% of practitioners expect Industrial AI to drive future sustainability innovation** (Reuters Events & Siemens, *From Pilots to Performance*, 2025). There is a clear rationale behind this expectation. Many Industrial AI applications target operational efficiencies, including improving energy efficiency, reducing waste and optimizing the use of assets and materials. Where these efficiencies reduce resource or energy requirements, they can also generate **gross environmental benefits**, defined in this report as positive environmental effects before accounting for AI's own footprint. Understanding Industrial AI's potential for **positive net environmental impact** therefore requires considering both sides: the environmental benefits it enables and the footprint associated with developing, deploying, and operating AI systems that support promising applications to scale and amplify their environmental benefits.



of practitioners expect Industrial AI to drive future sustainability innovation

Source: *Reuters Events & Siemens, From Pilots to Performance, 2025*

This report brings together market evidence, case studies and expert perspectives to examine where the evidence on Industrial AI's sustainability impact stands today, and what it takes to translate that potential into impact at scale. Chapter 2 assesses **where market momentum is strongest, which Industrial AI capabilities and use cases are gaining traction, and what is driving their deployment.** Chapter 3 examines **how consistently those benefits are measured and reported, alongside what is known about AI's own environmental footprint, to build a more complete view of net environmental impact**. Chapter 4 next explores the conditions that appear to **enable successful applications to scale**, before **looking ahead to where Industrial AI could unlock greater sustainability impact** (Chapter 5) and concluding with **actions industrial leaders can take now** (Chapter 6).

ii. Scope note. This report studies the gross environmental impacts Industrial AI demonstrates - not netted against AI's own footprint. Sustainability is addressed solely from an environmental perspective. Social impacts on jobs, labor markets, and communities are out of scope; workforce and organizational factors appear in Chapter 4 as enablers of adoption.

2 Industrial AI × Sustainability: Moving from Signal to Scale

Industrial AI is applied across industrial operations, products, and infrastructure, using technologies including machine learning, computer vision, and generative AI. Industrial leaders broadly expect AI to contribute to sustainability, with capabilities ranging from improving energy efficiency in real time, reducing GHG emissions, to simulating product designs before they are built, reducing materials used for prototyping and testing.

This chapter provides a systematic view of how Industrial AI capabilities linked to sustainability are being applied across sectors. An AI-assisted research process identified more than 420 signals across 100+ predefined industrial companies, with each signal representing a publicly documented Industrial AI deployment, announcement, or investment activity linked to a specific company and AI capability. Signals were traced to a public source and subject to source verification and human quality review.[iii] The analysis covers five industrial sectors: process industry, discrete manufacturing, energy, transportation, and infrastructure.[iv] Each signal was mapped according to 24 pre-defined AI capabilities across five clusters, the sector, and associated environmental outcome, with the resulting patterns cross-checked against expert and practitioner interviews. This provides a consistent basis for comparing Industrial AI activity across sectors and capabilities, complementing the individual deployments and case studies presented throughout the report.[v]

iii. For more information on the methodology used for the signals database, please refer to page 40.

iv. Process industry covers continuous or batch production, including chemicals, metals, cement, healthcare products and food & beverage; discrete manufacturing covers unit-based production, including automotive, electronics, industrial equipment, and aerospace; energy covers power generation, transmission, distribution, grid management, and renewables integration; transportation covers vehicles, mobile equipment, fleets, logistics, and rail; infrastructure covers buildings and other physical infrastructure where Industrial AI is applied, including building energy management and data-center operations

v. This signal database measures verified, publicly disclosed Industrial AI activity among a pre-selected set of large, disclosure-active companies. It is well suited to answering where such activity currently concentrates, by sector and capability, among companies visible enough to study this way. It is not a random sample of all industrial AI deployment, and it cannot support a claim about what share of all Industrial AI activity, globally, these patterns represent. Selected biases include: companies with more public disclosure are overrepresented, and deployments that failed or were never publicized are invisible.

The signal analysis finds evidence for wide deployment of Industrial AI capabilities with relevance for sustainability. At the same time, practical experience suggests that AI capabilities are mainly established for operational and financial reasons, with secondary benefits for their environmental impact. Tim Lüken, Head of Innovation at Gebrüder Dorfner, observes that **"Sustainability is rarely the primary driver for AI adoption, but frequently emerges as a side product of process/efficiency optimization,"** while Peter Schwendner, Professor and Director at the Institute for Wealth and Asset Management, similarly describes decarbonization as **"more of a signposted label, but not the real trigger for a business decision."**

The strength of this relationship also depends on the operating context. As **Sebastian Koecher, Managing Director and Partner at BCG**, notes, "a clear business case for AI is often not sustainability-related at all. For example, reducing gas consumption is a strong AI driver in Europe, but a weaker one in the regions with lower gas prices, which is part of why some AI-for-sustainability initiatives especially in [the materials and process industry] sector are first piloted/implemented in Europe prior to getting rolled out to further geographies."

The sustainability case for Industrial AI is therefore often strongest where environmental and operational value reinforce each other. Circularity and value-chain decarbonization represent untapped potential for Industrial AI, with applications in these areas still at an earlier stage of maturity.

> *"Sustainability is rarely the primary driver for AI adoption, but frequently emerges as a side product of process/efficiency optimization."*
>
> - **Tim Lüken**, Head of Innovation at Gebrüder Dorfner

2.1 Scaling of Industrial AI: Strong Evidence for Deployment across Sectors

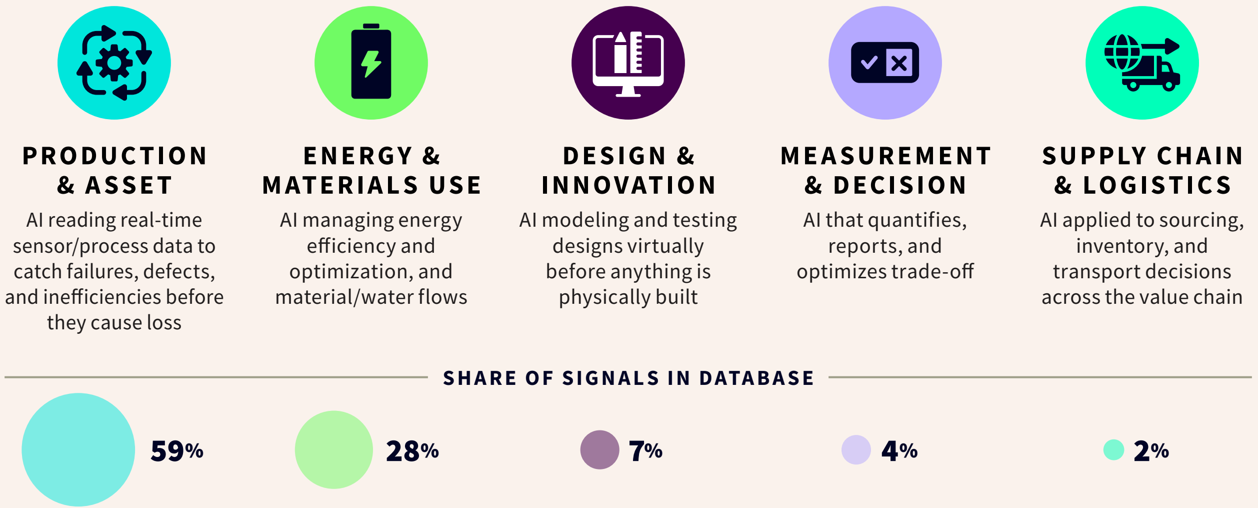
The signal analysis shows that Industrial AI capabilities linked to sustainability are already being applied across industrial sectors and have largely moved beyond experimentation. **More than 80% of the signals identified represent active deployments**, while around 10% relate to announcements of planned AI deployments, an investment or deal activity, including funding rounds, M&A, and capital commitments.

Industrial AI activity is broad, spanning sectors, geographies, and companies. The 420 signals identified by the signal analysis cover all five sectors, and no small group of companies dominates the evidence: the ten companies with the most signals account for just **18% of the total**. This indicates that observed activity extends well beyond a small group of leading adopters.

Within this broad deployment, however, activity is concentrated in a smaller set of capabilities. To understand where Industrial AI is being applied, the signal analysis groups the 24 identified capabilities into five functional clusters according to where and how AI acts in industrial operations. Figure 1 **provides this first view of the market, presenting the clusters and their relative prevalence across the signal database.** Three clusters, “Production & Asset,” “Energy & Materials Use,” and “Design & Innovation,” together account for **94% of all signals**. “Production & Asset” alone represents 59%, followed by “Energy & Materials Use” at 28% and “Design & Innovation AI” at 7%.

FIGURE 1

Industrial AI capability clusters and their share of observed activity



Source: Quantis and BCG analysis

Concentration is also visible within the five clusters themselves, across the 24 AI capabilities (see Table 1). A small number of individual capabilities account for much of the observed activity, led by predictive maintenance and process control within "Production & Asset," energy efficiency and grid management within "Energy & Materials Use," and digital twin & simulation within "Design and Innovation."

TABLE 1

Overview of AI capabilities split into five clusters share of signals *(n=420)*

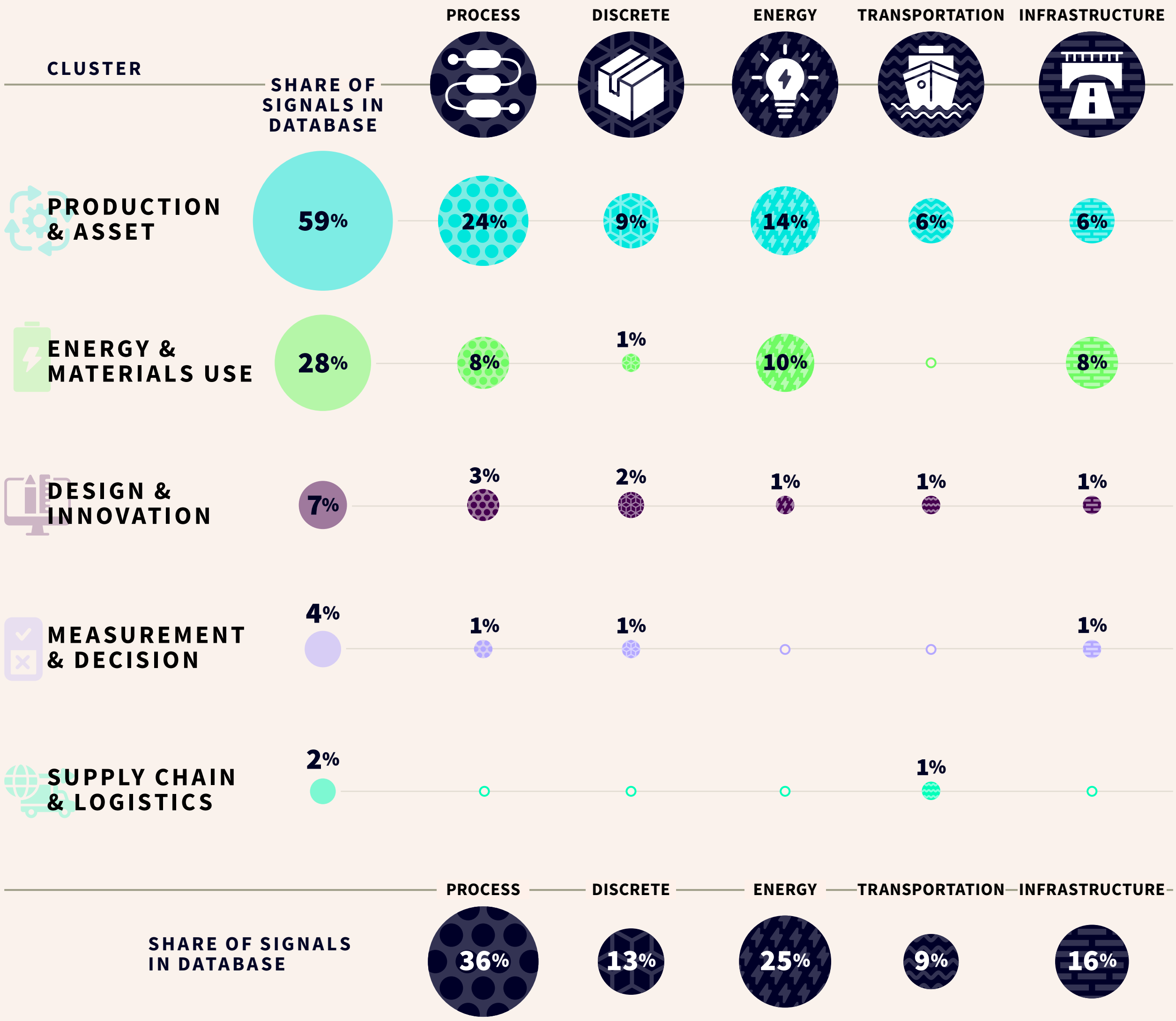
Cluster	AI CAPABILITY	SHARE OF SIGNALS
PRODUCTION & ASSET	Predictive maintenance	14%
	Process control + APC	12%
	Asset performance management	10%
	Quality control + machine vision	8%
	Autonomous systems + robotics	7%
	Cooling optimization	4%
	Industrial copilots	2%
	Production planning + scheduling	1%
ENERGY & MATERIALS USE	Energy efficiency + optimization	10%
	Grid management + flexibility	8%
	Building energy management (BEMS)	5%
	Waste sorting + recycling	2%
	Water management	2%
	Emissions monitoring / CEMS	1%
DESIGN & INNOVATION	Digital twin + simulation	5%
	Generative design	1%
	Materials discovery	1%
	AI-enhanced PLM	<1%
	AI-assisted R+D for sustainability	<1%
MEASUREMENT & DECISION	Decision intelligence / scenario optimization	2%
	Carbon footprint calculation (PCF/LCA)	2%
SUPPLY CHAIN & LOGISTICS	Supply chain optimization	1%
	Fleet + logistics optimization	1%

Source: *Quantis and BCG analysis*

The analysis shows sustainability-relevant Industrial AI signals across all five industrial sectors, with differences in the capabilities deployed. Process industry accounts for 36% of signals, followed by energy at 25%, infrastructure at 16%, discrete manufacturing at 13%, and transportation at 9%. This uneven distribution largely reflects the composition of the database, in which process industry also represents around a third of the companies analyzed, and should therefore not be interpreted as differences in overall Industrial AI adoption across sectors. Looking within sectors, **Production & Asset** is the largest capability cluster in most sectors, with particularly high representation in process industry and energy. Infrastructure is the main exception, where **Energy & Materials Use** is more prevalent, driven by capabilities such as building energy efficiency and cooling optimization; as illustrated in Case study #1 through Aspern Smart City's application of an AI Energy Load Optimization solution.

FIGURE 2

Distribution of Industrial AI signals by capability cluster and sector *(across all 420 signals)*



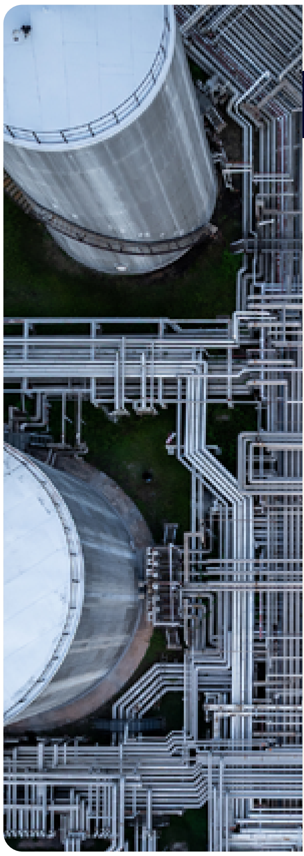
Source: *Quantis and BCG analysis*

CASE STUDY #1

Predictive by Design: AI supports forecasting of energy load, PV generation and electricity prices

[BUILDING ENERGY MANAGEMENT, INFRASTRUCTURE, AUSTRIA]

- **Challenge:** Building/campus energy management, at **Aspern Smart City** in Vienna (Austria). Balancing energy costs and carbon usually means running batteries, heat pumps and PV against fixed, rule-based schedules, while grid fees are rising and load grows more volatile with electrification.
- **AI solution:** Energy Load Optimization (ELO), powered by the b.eos engine, forecasts loads, on-site generation and electricity prices, then predictively dispatches the site's flexible assets, layering AI on top of the existing rule-based Peak Demand Limiting control rather than replacing it.
- **Gross operational and environmental gains expected**: Optimized self consumption, reduced Grid Charge, and improved efficiency, leading to reduced energy costs and CO2 emissions.



CASE STUDY #2

AI predicts machine failure in the steel industry

[PREDICTIVE MAINTENANCE, PROCESS INDUSTRY, AUSTRALIA]

- **Challenge:** At **BlueScope's** Port Kembla plant, fixed-schedule and reactive maintenance across a large and dispersed set of assets meant failures were often caught only after they happened, causing unplanned downtime and costly emergency repairs.
- **AI solution:** The plant deployed Senseye Predictive Maintenance, a machine learning technology that builds a digital fingerprint of each asset's normal behavior from condition data (vibration, current, torque, pressure), and flags early signals of wear so that maintenance can be prioritized before failure occurs. Catching degradation early cuts emergency repairs and extends equipment lifespan.
- **Gross operational and environmental gains expected:** Reduced unplanned energy spikes, operational process stops, emergency repairs, and associated CO2 savings.

Looking at top-ranked AI capabilities within each sector reveals which individual capabilities are currently deployed most. Figure 3 ranks the three most prevalent Industrial AI capabilities within each sector. While the leading capabilities differ, asset-focused capabilities recur across otherwise distinct operating environments. **Predictive maintenance ranks among the top three capabilities in all five sectors**, while asset performance management and autonomous systems & robotics appear among the top three in multiple sectors. This reinforces the broader finding that asset reliability, performance, and the avoidance of unplanned failures are among the most widely observed applications of Industrial AI across industry. Case Study #2 provides a practical example of predictive maintenance in the process industry.

FIGURE 3

Top three most present Industrial AI capabilities in each sector *(with share of AI capability signal count per sector)*

	#1 CAPABILITY	#2 CAPABILITY	#3 CAPABILITY
PROCESS	25% Process control + APC	13% Energy efficiency + optimization	13% Predictive maintenance
DISCRETE	30% Quality control + machine vision	19% Autonomous systems + robotics	11% Predictive maintenance
ENERGY	26% Grid management + flexibility	22% Asset performance management	18% Predictive maintenance
TRANSPORTATION	21% Predictive maintenance	21% Asset performance management	16% Autonomous systems + robotics
INFRASTRUCTURE	26% Building energy management	16% Cooling optimization	10% Predictive maintenance

Source: Quantis and BCG analysis

2.2 Where Industrial AI's Gross Positive Impacts Are Concentrated

Having established where Industrial AI is being deployed and which capabilities dominate, the next question is **what environmental outcomes these capabilities are associated with**. For this study, each signal with a sustainability link is mapped to one of two principal impact domains: **decarbonization** and **resource efficiency & circularity**.

Decarbonization captures reductions in greenhouse gas emissions, either from a company's own operations and energy use **(Scope 1 and 2)** or across its value chain **(Scope 3)**. **Resource efficiency and circularity** capture different ways of reducing usage of materials, water and other resources. Resource efficiency focuses on using fewer resources in production and operation, for example through yield optimization, scrap and defect reduction, or extending asset life to avoid replacement. Circularity focuses on keeping products, components and materials in use or returning them to use through reuse, repair, refurbishment, remanufacturing, recycling and material recovery. **For a more granular view, the analysis therefore distinguishes four impact domains: operational decarbonization, value-chain decarbonization, resource efficiency and circularity.**

Figure 4 brings these environmental outcomes together with the five capability clusters introduced in Section 2.1, showing both where environmental momentum is concentrated (measured through distribution of the 420 signals) and which types of Industrial AI capabilities are most strongly represented within each impact domain.

FIGURE 4

Distribution of Industrial AI signals by environmental impact domain and capability cluster *(across all 420 signals)*

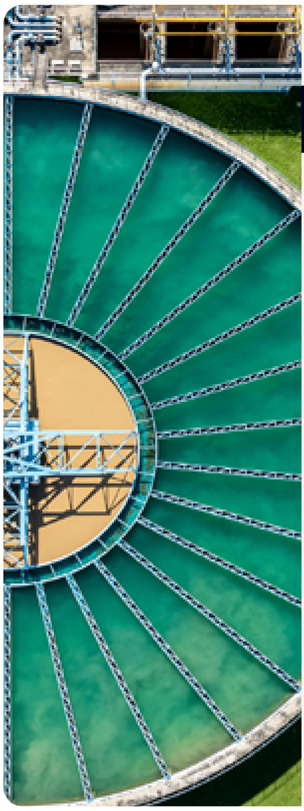
	PRODUCTION & ASSET	ENERGY & MATERIALS USE	DESIGN & INNOVATION	MEASUREMENT & DECISION	SUPPLY CHAIN & LOGISTICS	TOTAL
DECARB: OPERATIONAL	17%	21%	2%	1%	0%	40%
DECARB: VALUE CHAIN	2%	1%	1%	1%	1%	7%
RESOURCE EFFICIENCY	40%	4%	4%	1%	1%	50%
CIRCULARITY	1%	2%	0%	0%	0%	3%

Source: *Quantis and BCG analysis*

Two patterns stand out. First, observed activity is broadly balanced between resource-related and decarbonization impact domains. Resource efficiency & circularity account for **53% of signals**, compared with 47% for decarbonization. Figure 4 also shows that these outcomes are driven by different capability clusters: resource efficiency is strongly concentrated in "Production & Asset," while operational decarbonization has a larger contribution from "Energy & Materials Use."

This pattern is consistent with the expert interviews: approximately two-thirds of the Quantis and BCG experts interviewed identified resource efficiency as a primary gross environmental impact domain associated with Industrial AI. As **Cornelius Pieper, Managing Director and Senior Partner at BCG**, observes, "[Resource] efficiency is the strongest link between AI and industrial sustainability," while also providing a direct economic rationale through lower resource and energy costs. Two practical examples of how AI increases resource efficiency, are provided in Case study #3, where a smart dosing system reduces the chemical inputs needed in a water treatment plant, and Case study #4, where Rolls-Royce shows how generative design and digital twins reduce material input.

Second, capabilities that more often require action across organizational boundaries or the reuse of already-consumed materials remain much less prevalent. Circularity accounts for only 3% of observed signals, reflecting the earlier maturity of circular-economy practices rather than a lack of applicability or potential for Industrial AI. Nearly two-thirds of these signals relate to waste sorting and recycling, where Industrial AI helps recover materials that have already been consumed and return them to productive use. The evidence therefore suggests that Industrial AI is currently more prevalent in reducing resource inputs and losses than in keeping products, components and materials in circulation through reuse, repair, refurbishment, remanufacturing, recycling or recovery.



CASE STUDY #3

Dosing by Design: AI trims chemical use in water utilities

[WATER MANAGEMENT, PROCESS INDUSTRY, CHINA]

- **Challenge: Faried Electromechanical Engineering**'s water treatment plant in northwest China, serving 60,000 residents, required heavy manual tuning and constant inspection to dose flocculant correctly, adjusting by hand for seasonal flow and raw-water turbidity.
- **AI solution:** Machine vision, process-data analytics and edge control set the polyaluminium chloride (PAC) dose automatically. The value lies in the integration: water-treatment know-how, machine vision, sensors, PLC control and edge computing fused into one closed loop, giving resource-constrained plants a feasible path to automation.
- **Gross operational and environmental gains expected**: Reduced chemical/flocculant consumption, and associated CO2 savings.

This tracks the broader picture: only 6.9% of materials used globally are cycled back into the economy rather than virgin-extracted,[5] and even in the EU, the circular material use rate reached just 12.2% in 2024.[6,7] Experts interviewed in this study attribute circularity's limited AI use more to the maturity of circular economy practice than to AI capabilities. **Pierre Collet, Global Footprint Lead at Quantis,** frames the constraint as informational: “AI isn't applied much to circularity, but that's not much about AI capability. It's more that circular economy advancements just aren't mature enough yet.”

A similar gap appears within decarbonization. Operational decarbonization accounts for **40% of all signals**, while value-chain decarbonization represents only **7%**. Scope 3 capabilities typically act indirectly through supplier engagement, product design, logistics, or emissions information rather than controlling an emitting process directly. Much of the observed activity therefore focuses on improving transparency, including supplier-data ingestion, emission-factor matching, and product-footprint calculation. These capabilities can inform lower-emission decisions, but do not necessarily reduce emissions on their own.

CASE STUDY #4

AI-driven design improves part manufacturing performance delivering emissions reductions in aerospace

[GENERATIVE DESIGN, DIGITAL TWIN & SIMULATION, DISCRETE MANUFACTURING, UNITED KINGDOM]

- **Challenge: Rolls-Royce** faced complex requirements for a critical jet-engine component: a hydraulic lubrication and scavenge pump, where disconnected workflows led to long lead times, redundant iterations, and difficulty meeting strict aerospace standards.
- **AI solution:** The company used NX CAM Co-Pilot, which recommended the machining operations (the cutting steps a CNC machine follows to produce the part), cutting programming time. Automated Coordinate Measuring Machine (CMM) probing then verified the finished part against design tolerances, closing the loop on inspection.
- **Gross operational and environmental gains expected:** It proved to design pieces that are 25% lighter and 200% stiffer, leading to expected fuel savings and extended service life. Digital-twin iteration also cut material used for less physical prototyping.

3 From Scaling to Value: Measuring and Reporting What Industrial AI Delivers

As Industrial AI moves from pilots toward broader deployment, financial resources for AI are becoming increasingly finite; companies are asked to prioritize AI capabilities that create sufficient value. This **shifts the focus from scalability alone to the full value an application creates** across financial, operational, and environmental dimensions. **Capturing that full value requires companies to systematically measure the outcomes an application delivers.** This chapter examines how far companies have progressed in reporting KPIs for identified AI signals and highlights the need to assess AI's own environmental costs to build a more complete view of its net impact.

3.1 Industrial AI Deployment is Ahead of Systematic Impact Measurement

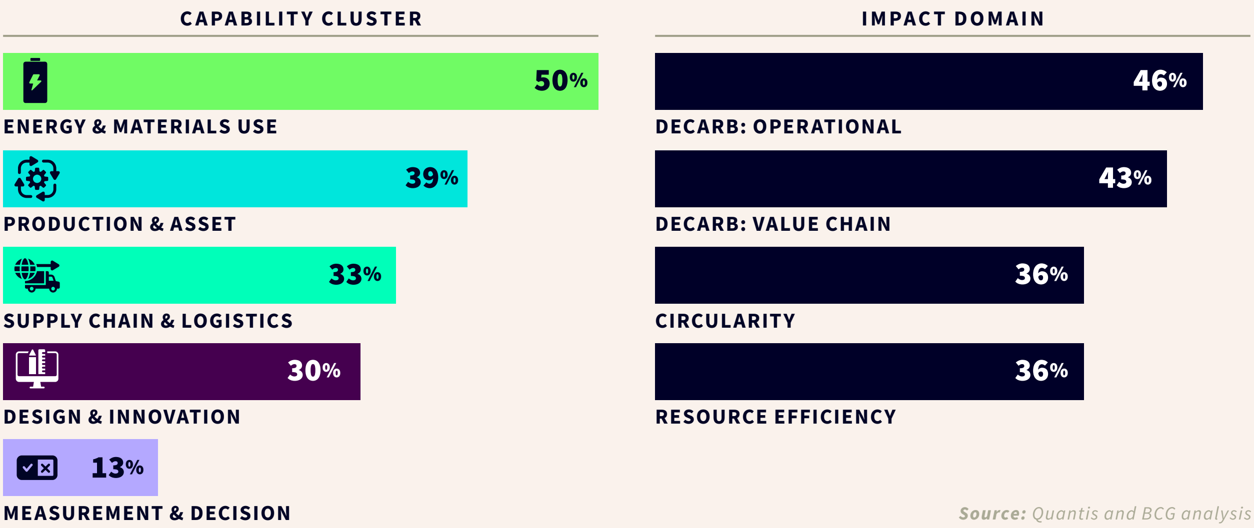
While Industrial AI deployment is widespread, systematic measurement of its impact domain remains less mature. Only around **40% of the signals identified by this signal analysis report at least one quantified KPI linking to sustainability**, and **among those that do, 95% report just one or two KPIs.** This is relatively low, as a single Industrial AI application can affect several dimensions at once (e.g. CO2 emissions and a resource efficiency metric). **Relying on only a few KPIs can therefore leave part of the value created by an application unmeasured.**

The first question is where systematic measurement is already most established. Figure 5 compares the share of signals reporting at least one quantified KPI across both the five AI capability clusters and the four environmental impact domains. Signals are prevalent for **"Energy & Materials Use" (50%)**, followed by "Production & Asset" (39%), "Supply Chain & Logistics" (33%), "Design & Innovation" (30%), and "Measurement & Decision" (13%). Across environmental outcomes, operational and value-chain decarbonization have higher rates of KPI reporting than resource efficiency and circularity. Looking at the impact dimension, **Decarbonization is reported more often with KPIs (>43%) than resource efficiency and circularity (both 36%).**

At the individual capability level, measurement also varies considerably, with established AI capabilities such as Cooling optimization and Energy efficiency & optimization measuring and reporting KPIs more frequently than others. This reinforces that these capabilities present more established and measurable sustainability applications of Industrial AI (see Table 2).

FIGURE 5

Share of signals with at least one reported KPI, by capability cluster and environmental impact domain *(across all 420 signals)*



Source: *Quantis and BCG analysis*

TABLE 2

Overview of AI capabilities split into five clusters and KPI reporting *(across all 420 signals)*

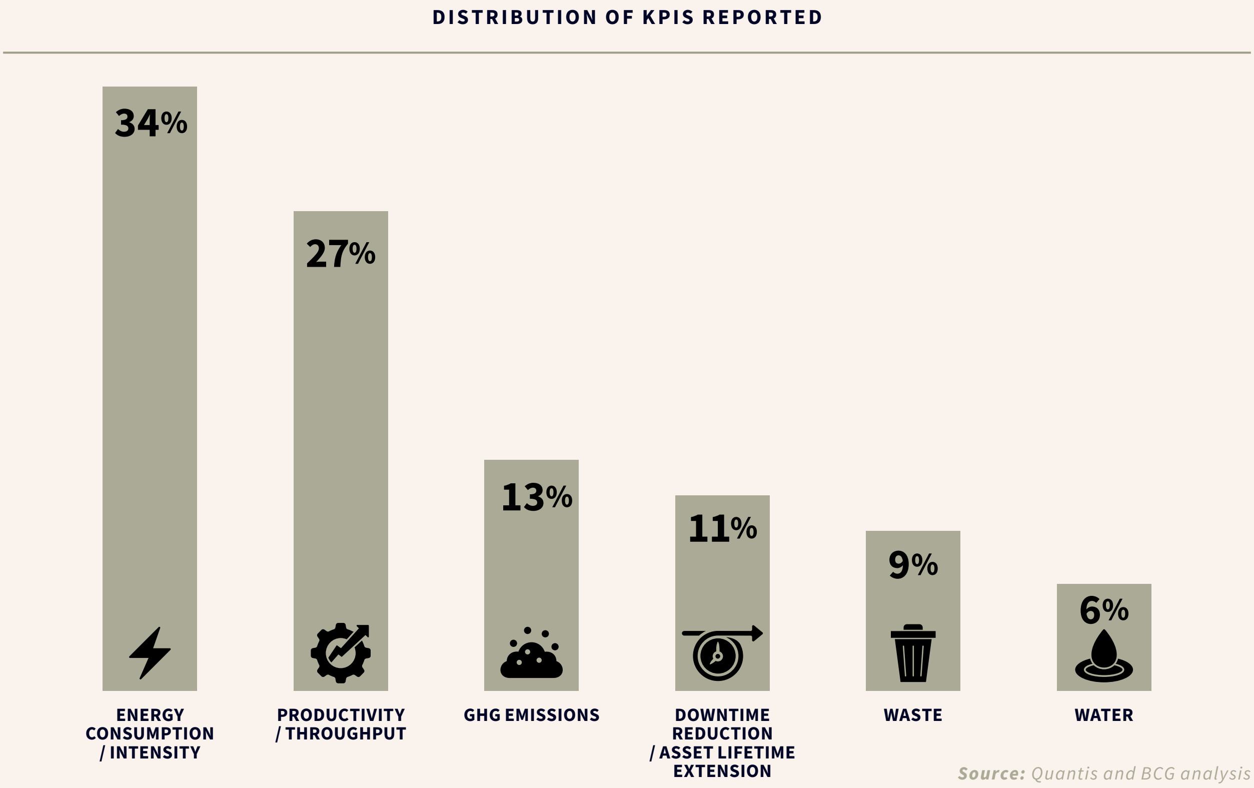
	AI CAPABILITY	CAPABILITIES CONNECTED TO AT LEAST ONE KPI
PRODUCTION & ASSET	Predictive maintenance	38%
	Process control + APC	44%
	Asset performance management	26%
	Quality control + machine vision	39%
	Autonomous systems + robotics	32%
	Cooling optimization	76%
	Industrial copilots	22%
	Production planning + scheduling	33%
ENERGY & MATERIALS USE	Energy efficiency + optimization	71%
	Grid management + flexibility	25%
	Building energy management (BEMS)	55%
	Waste sorting + recycling	30%
	Water management	71%
	Emissions monitoring / CEMS	25%
DESIGN & INNOVATION	Digital twin + simulation	16%
	Generative design	67%
	Materials discovery	50%
	AI-enhanced PLM	0%
	AI-assisted R+D for sustainability	100%
MEASUREMENT & DECISION	Decision intelligence / scenario optimization	0%
	Carbon footprint calculation (PCF/LCA)	29%
SUPPLY CHAIN & LOGISTICS	Supply chain optimization	33%
	Fleet + logistics optimization	33%

Source: *Quantis and BCG analysis*

Measurement frequency, however, does not show what companies actually measure. Figure 6 therefore looks only at the total **235 KPIs reported across the signal database** and shows what they measure. **KPIs linked to decarbonization make up the largest share,** with Energy consumption/intensity (34%) and GHG emissions (13%). This is followed by more operational KPIs of Productivity/throughput (27%) and Downtime reduction/ asset lifetime extension. Lastly, resource efficiency KPIs make up the smallest share with waste (9%) and water (6%).

FIGURE 6

Distribution of KPIs reported *(across the signals with KPIs)*



Source: *Quantis and BCG analysis*

To understand whether the environmental outcomes identified in Chapter 2 are reflected in measurement, Figure 6 compares **reported KPIs against all signals within each of the four environmental outcome domains, including signals that report no KPI**. This provides an indicative view of how consistently the environmental benefit associated with an Industrial AI application is supported by a relevant quantified measure.

The comparison suggests that some environmental outcomes remain only partially captured by the KPIs reported. Among signals associated with operational decarbonization, 36% report energy consumption or intensity and only 14% report GHG emissions, despite these being among the most direct measures of the associated environmental benefit. For resource efficiency, direct resource measures are less prevalent, with only 7% of signals reporting waste and 3% reporting water, while 18% report productivity or throughput, highlighting operational aspects. These patterns do not imply that every capability should report the same KPIs, but they indicate an opportunity to **more consistently complement measures with environmental KPIs that substantiate the sustainability outcomes associated with Industrial AI.**

FIGURE 7

Distribution of reported KPIs within each environmental outcome domain, on the basis of total signals *(across all 420 signals)*

	ENERGY CONSUMPTION / INTENSITY	PRODUCTIVITY / THROUGHPUT	DOWNTIME REDUCTION / ASSET LIFETIME EXTENSION	GHG EMISSIONS	WATER	WASTE	TOTAL SIGNALS PER OUTCOME
DECARB: OPERATIONAL	36%	11%	3%	14%	4%	2%	170
DECARB: VALUE CHAIN	18%	21%	0%	11%	4%	4%	28
RESOURCE EFFICIENCY	6%	18%	9%	1%	3%	7%	208
CIRCULARITY	7%	7%	7%	7%	0%	21%	14

☐ = Impact domain x KPI pairs expected to show highest signal density

Source: *Quantis and BCG analysis*

A cross-validation confirms the findings of the signal database: the study reviewed the most recent sustainability reports of 30 large global industrial companies,[vi] assessing whether and how they connect AI use cases or capabilities to sustainability impact domains and quantified KPIs. Around **60%** make an explicit connection between Industrial AI and a stated sustainability impact domain, while **only 17% support that connection with a quantified performance claim**. Around **one-third show no explicit Industrial AI × sustainability connection despite discussing AI elsewhere in their reports,** and the prevalence of AI mentions is **similar among companies with and without validated SBTi targets, suggesting that even companies with established sustainability commitments do not yet report the environmental impacts of Industrial AI more systematically.** Where companies report environmental impacts associated with Industrial AI, they more often focus on sustainability benefits enabled for customers than on improvements to their own environmental footprint. For example, one heavy-equipment manufacturer credits an AI-enabled predictive maintenance program with reducing fuel consumption and associated emissions at a customer's operations.

This external review does not indicate what companies measure internally, but it suggests that **the environmental contribution of AI is not yet consistently quantified and communicated in sustainability reporting**. Together with the signal-base analysis, this points to an opportunity for companies to increasingly measure Industrial AI impact domains more systematically and complement existing operational KPIs with environmental measures where relevant, making positive environmental contributions more visible.

vi. Companies with annual revenues above $21B. Each company's most recent publicly available sustainability or ESG report was reviewed.

3.2 Closing the Gap: Building a Holistic Set of KPIs becomes Key

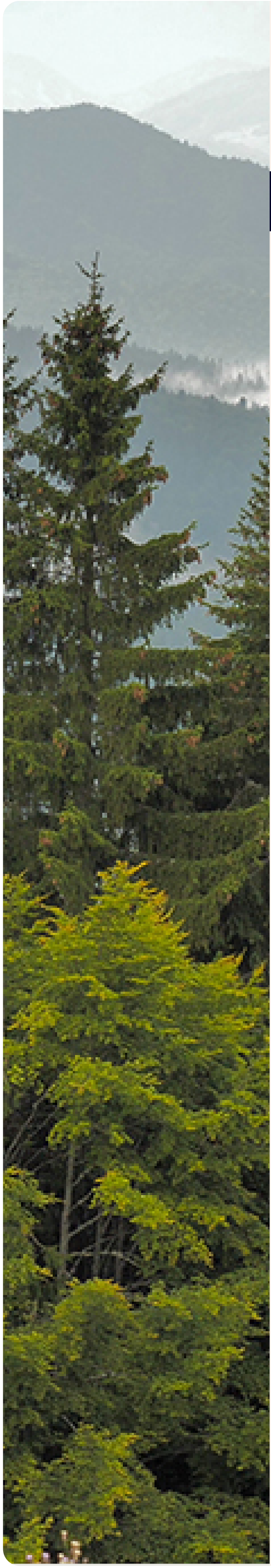
More **systematic measurement and reporting of KPIs can make the environmental value of Industrial AI more visible and strengthen the overall case for scaling**. **The opportunity is to move from undermeasurement and underreporting toward a more complete view of the value Industrial AI creates**, providing a stronger basis for deciding which capability to scale.

Closing this KPI gap does not necessarily require a new measurement system. Companies can build operational KPIs they already use, and determine whether these directly capture an environmental outcome or require translation into a sustainability KPI (see **Appendix Table 3**). For example, an energy-efficiency improvement measured through reduced energy consumption can be translated into associated GHG reductions.

Several case studies of Industrial AI deployments show what this can look like in practice. **Case Study #5** examines BMO's data center in depth, where AI-driven cooling optimization shows what it takes to translate an operational KPI into a matching environmental one.

Case Study #6 turns to Pringles, tracing how process control and energy optimization together produce both operational and environmental results that benefit the business.

Case Study #7 deep dives into BSH, where a link between higher operational control and lower material waste is made.

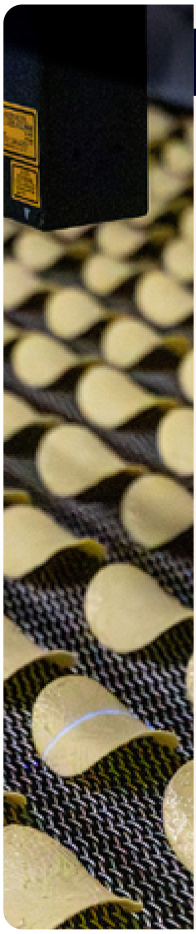


CASE STUDY #5

AI cuts energy use in data centers

[COOLING OPTIMIZATION, INFRASTRUCTURE, CANADA]

- **Challenge: BMO Financial Group**, via its Critical Environments Group at BMO's primary Data Center in Scarborough, Ontario. With heat loads rising and shifting, and infrastructure being tested, reliability is more critical than ever. As the amount of data increases exponentially, so too does the need for unfailing, dynamic, and efficient cooling operations in data centers.
- **AI solution:** White Space Cooling Optimization (WSCO) uses machine learning to dynamically monitor IT rack inlet temperatures and adjust Computer Room Air Conditioners (CRACs) to meet target temperatures with the lowest possible energy consumption. Using a network of sensors, WSCO collects temperature and air supply data in the facility. The system first learned how each CRAC influenced cooling operations, then applied the data to algorithms, adjusting CRAC airflow to maintain the correct temperature for each zone. The system went beyond alerting human operators to temperature fluctuations by autonomously adjusting. Cooling automation reduces the risk of a thermal outage and ensures consistent air temperatures among server racks and white space. Through energy optimization, air supply is matched to the demand in real time, automatically responding to temperature changes and eliminating overcooling and recirculation.
- **Current scope:** Primary data center, installed in two data rooms, operational. Since then, the solution has been rolled out to two other data centers.
- **Operational outcome:** 55% reduction in fan energy consumption in the designated area; 64% reduction in the number of operating constant-speed fan units, plus reduced speed on variable-speed units, together cutting total CRAC fan energy use.
- **Gross environmental KPIs (Quantis calculation based on assumptions):** For a small modern day enterprise data center of 1 MW, which would have ≈1.13 MW of installed cooling capacity, the ~55% operational gain in fan consumption for cooling energy is worth ~25 tCO2e/year in Ontario's low-carbon grid. This could be extended to ~250 tCO2e/year on a more carbon-intensive grid such as Germany's.



CASE STUDY #6

AI keeps dough quality consistent, in real time

[PROCESS CONTROL & APC, ENERGY EFFICIENCY & OPTIMIZATION, PROCESS INDUSTRY, POLAND]

- **Challenge:** At **Pringles'** manufacturing facility in Kutno, when production is already at peak automation, further gains mean rethinking the process itself: dough quality relies on operators' experience, with imperfect batches forcing full line stops for manual intervention; sustainability demands and supply chain volatility are driving waste reduction efforts.
- **AI solution:** Three linked AI technologies: a cloud-based AI model ingesting real-time sensor/laser/camera data to calculate the optimal dough recipe and adapt to raw-material fluctuation, feeding recommendations back to operators; an AI energy model on SIMATIC Energy Manager Pro predicting next-day consumption targets from historical and current performance; Senseye Predictive Maintenance using vibration sensors across all equipment. The technologies are connected through a Digital Thread linking manufacturing, R&D and engineering. A next step is to use Digital Twin-defined raw material specifications to support procurement decisions and enable greater flexibility in sourcing alternative ingredients.
- **Current scope:** Single-plant scale, operational. It intends to be a blueprint to extend to other Pringles sites.
- **Operational outcome:** 10% capacity increase. Projected at scale 50% less innovation time, 20% less capital per unit.
- **Gross environmental KPIs (self reported):** 13% waste reduction and 7% energy reduction, on one high-speed line at Kutno, based on one year of operations since go-live.

CASE STUDY #7

AI vision supports resource efficiency and waste reduction

[QUALITY CONTROL & MACHINE VISION, DISCRETE MANUFACTURING, GERMANY]

- **Challenge:** At **BSH Hausgeräte GmbH**, manual batch inspection catches component defects late in the assembly line; at the same time, there is the need to optimize process efficiency, reduce costs and inspection time, and minimize scrap to deliver on BSH's sustainability commitment.
- **AI solution:** Inspekto is a self-learning, self-supervised machine-vision system. It self-adjusts its optics for reflections via a proprietary anti-reflection technology and flags anomalies against the pre-trained "good" baseline in real time, with no need to manually specify image-capture or defect parameters. The inspection process is performed automatically before the assembly line, with results displayed immediately.
- **Current scope:** Single-plant scale, operational.
- **Operational and gross environmental KPIs (self reported):** Increased inspection accuracy at two stages. Early detection before parts are built into a larger assembly minimizes scrap; final-assembly inspection before shipment catches defects before they reach the customer, while also considerably increasing speed at this stage. Increased inspection accuracy drove a >90% reduction in factory scrap.

3.3 Building Awareness of AI's Environmental Costs Is the Next Measurement Challenge

While companies increasingly measure and claim gross environmental benefits from Industrial AI, the environmental costs required to deliver those benefits remain considerably less visible to individual companies: Electricity and water consumption often occur in external data centers or cloud infrastructure, while hardware-related impacts arise across manufacturing, use, and end of life.

This creates an **environmental accounting challenge**. Companies may be able to quantify the energy, waste, or emissions avoided by an Industrial AI application, but a consistent **net environmental assessment at the Industrial AI capability level is not yet feasible**. The immediate priority is to build awareness of where these costs arise and improve their visibility; over time, common methodologies will be needed to allocate AI's environmental footprint to individual capabilities and enable more comparable net-impact assessments.

Four Environmental Costs Warrant Particular Attention

The **attribution challenge** does not mean that AI's environmental costs are unknown. At system level, evidence increasingly points to four material areas: **energy demand, water consumption, land use, and hardware-related e-waste**. What remains difficult is allocating an appropriate share of these impacts to the individual Industrial AI capabilities that rely on the underlying computing infrastructure.

Energy demand

Data centers and specifically AI-focused facilities require significant energy for computation.

The IEA's central case predicts energy consumption for data centers to double by 2030, from 485 TWh in 2025 to 950 TWh, making up ~3% of global electricity demand, with AI-focused capacity tripling over the same span.[8]

Water consumption

Cooling the servers of the data centers requires significant amounts of water.

Global data-center water consumption for cooling is estimated at 175 million m3 in 2023, rising to 664 million m3 by 2030,[9] equivalent to 50-60 days of domestic drinking water supply in Germany.

E-waste generation

AI hardware wears out and has to be replaced after a certain timespan.

Server and storage e-waste is projected to grow from 0.2[11] to 0.8[9] Mt (2023–2030), or close to 1% of the 82 Mt of e-waste[12] projected globally in 2030.

Land use

Powering data centers takes up large amounts of land for housing servers and generating electricity.

The power supply alone occupied roughly 6,900 km^2 in 2025. By 2030 that is projected to pass 14,500[10] km^2, more than doubling, an area about the size of Montenegro.

These costs remain considerably less visible at company and application level than operational benefits. As **Teresa Ingram, Security Engineer at 1komma5°,** observes, “AI’s water, energy usage and waste are currently largely ‘off the books’.” While visibility on these dimensions is beginning to improve, many organizations applying AI do not yet systematically track these resource requirements.

The Footprint Depends on How AI Is Deployed

Until application-level accounting becomes more mature, several characteristics can indicate the intensity of AI environmental footprint. Two dimensions stand out: the model and inference requirements of the application, and the additional physical hardware required to deploy it.

- **Model and inference requirements.** Environmental resource demand depends on both the computational intensity of a model and how it is used. Discriminative models, which underpin capabilities such as predictive maintenance, asset performance management, quality control and machine vision, generally require less energy per inference than generative models. Measured across a range of tasks, the difference varies by modality, from around twenty times when comparing text classification with text generation to over a thousand times when comparing text classification with image generation.[13] The choice of model matters as well as the choice of task. Using a general-purpose generative model for work that a smaller task-specific model could carry out increases energy use per inference, even where the task itself is discriminative. However, total demand also depends on how frequently the model runs, across how many assets, whether it operates continuously, and how often the model is retrained. Relatively lightweight Industrial AI models can therefore have low resource requirements per inference, while their aggregate demand depends on the scale and frequency of deployment.
- **Physical hardware requirements.** Some capabilities, including autonomous systems and robotics or quality control and machine vision, require additional sensors, cameras, robots, edge devices, or computing equipment. This adds a manufacturing footprint alongside the resources consumed during operation. Where the larger share sits varies by type of equipment. For small, battery-powered devices, manufacturing typically accounts for most of the lifetime footprint, whereas for equipment that draws continuous power from the grid the operating energy tends to dominate.[14] The balance also shifts over time, because as the electricity supply becomes less carbon intensive, the manufacturing share of the total grows[15]. Published figures specific to industrial sensors, cameras and robots remain limited.

These dimensions provide a starting point for awareness: **the complexity, frequency of use, deployment scale, and additional hardware should be proportionate to the task the application is intended to perform.**

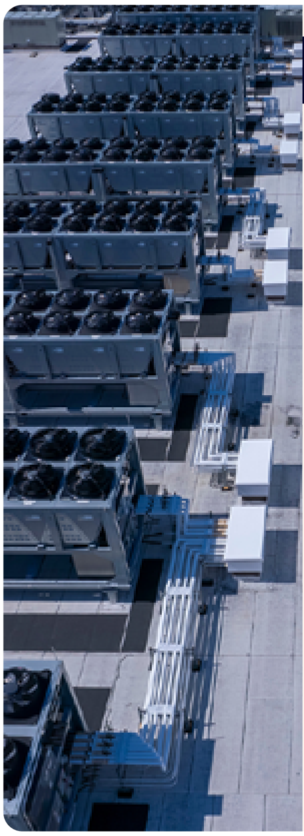
Efficiency Is Improving, but Scale Matters

AI models and their supporting infrastructure are becoming more energy efficient. IEA analysis finds that energy consumption per individual AI task has fallen substantially in recent years,[8] driven by continued advances in both software and hardware. Software-level improvements have so far delivered some of the largest and fastest reductions in energy use per AI task. Hardware improvements have also been significant, averaging roughly 30-40% per year over the past decade, though these gains are gradually slowing as transistor scaling matures.[8] The IEA notes that both channels remain important going forward; software continues to offer low-capital, near-term gains, while the more capital-heavy hardware and infrastructure improvements remain essential over the medium- to long-term.

Yet, lower resource use per task does not necessarily translate into a lower aggregate footprint. As AI becomes cheaper and easier to deploy, its use can expand **(Jevons paradox)**. A similar dynamic applies to industrial production, where efficiency gains can support higher output. As a result, aggregate environmental impacts may not decline even as resource efficiency improves. This distinction matters in a context of growing populations and societal demand, where meeting greater needs with fewer resources per unit is increasingly important.

As Industrial AI scales, both resource efficiency and aggregate environmental pressures therefore remain relevant to understanding its environmental contribution. The implication is not to constrain Industrial AI deployment indiscriminately, but to become more selective as its use expands. As **Teresa Ingram** puts it, "AI adoption needs to be selective, and applied where optimization can actually convert into real-world impact."

Case Study #8 illustrates the potential of a system-level approach, connecting infrastructure so that each benefits from the other.



CASE STUDY #8

System-Level Thinking Can Create Additional Opportunities

- **Challenge:** Data centers generate substantial waste heat that is typically dissipated rather than put to productive use. At infrastructure level, this creates an opportunity to connect growing digital infrastructure with surrounding heat demand.
- **Solution:** The Old Oak and Park Royal Energy Network in West London is expected to capture waste heat from two data centers and distribute it through a local heat network to homes and other buildings.
- **Current scope:** Infrastructure-scale development in West London, with the network expected to expand through 2040.
- **Environmental impact:** The network is expected to capture 17 MW of waste heat and, at full build-out, deliver up to 95 GWh of heat annually, enough for approximately 10,000 homes and a hospital. The example illustrates how resources associated with digital infrastructure can be considered within a wider energy system rather than at facility level alone.[16]

Toward a Common Basis for Net-Impact Assessment

Greater transparency is a necessary first step, but a consistent assessment of Industrial AI's net environmental effect will ultimately require **common rules for attributing environmental costs to individual capabilities**. Today, no common methodology identified by this study provides this full application-level assessment for Industrial AI. **Developing shared accounting principles and standards would enable a fairer comparison of capabilities by bringing enabled environmental benefits and attributable environmental costs onto a more consistent basis.**

4 Scaling Industrial AI: What Separates Deployments from Stalled Pilots

Industrial AI's momentum is no longer in question, and Chapters 1 and 2 establish that it can have gross environmental benefit, to be weighed against the resources AI itself consumes listed in Chapter 3. What remains unproven is the scale of that upside: today's evidence sits mostly at the level of a single site or product, and the largest potential gains can happen at scale if net positive AI solutions are proven. Organizations are increasingly focused on what it takes to move Industrial AI beyond a single-site or single-product win. Three topics decide it: the business case, the data infrastructure, and the change management required to operate at scale. Scaling AI is an organizational exercise before it is a technical one.

Technology is not the bottleneck

Among the experts consulted for this report, none named the technology or a specific AI capability itself as a barrier: technology is no longer the limiting factor for implementing or scaling Industrial AI.[vii]

"AI capability, technology, and processing power used to be among the biggest barriers – that's gone. Technology is no longer the blocking point."

- **Jochen Gross**, Head of Sustainability Data Strategy & Architecture at Siemens

vii. One topic linked to the technology still needs to be addressed: the organizational ownership of AI's outputs, which is discussed later in this chapter.

4.1 Business Case

For Industrial AI solutions to scale, the business case behind their application needs to be solid. The main element considered today is the financial and operational ROI. Adding the net environmental effect of Industrial AI would help further support the business case for scaling.

> *"Sustainability footprinting is a powerful lens for understanding AI's real impact. And in doing so, it often uncovers broader value, strengthening the business case for AI itself."*
>
> \- **Pierre Collet**, Global Footprint Lead, Quantis

Scaling requires **correctly defining the problem and the full context it sits within**, rather than applying Industrial AI wherever an opportunity presents itself. In ready-mix concrete, AI derived optimal pour volume from structural drawings but ignored delivery logistics and material perishability. Operators kept over-ordering as standard practice, and neither cost nor emissions savings materialized. A case built on a partial view of the process does not survive the pilot phase.

Three financial factors surrounding AI decide whether it does:

- **Physical retrofit:** Long-lived legacy assets need sensors, wiring and intervention before AI can run on them, which is far harder on brownfield than greenfield sites. Retrofit belongs in the business case as its own budget line, with separate cases for brownfield and greenfield rather than one plan for both.
- **The cost of compute:** Harder problems require more inference, and providers are shifting from flat subscriptions to metered billing. Right-sizing matters: edge, small, and deterministic approaches wherever the problem allows, frontier models only where genuinely required. "The token costs are going to eat into economics, especially for content-heavy, text-heavy, LLM-heavy use cases, less so for others like deterministic AI," says **Vuk Trifkovic, Managing Director & Partner at BCG X**.
- **Scalability (for self-deployments only):** A solution built for one plant's processes and IT systems does not transfer automatically. Designing for replication from the outset, with a common core adapted through retraining rather than rebuilt at each site, cuts the cost of each new deployment to a fraction of the first. Pilots remain essential to test adaptability.

Finally, the prior question is whether AI is the right **solution** at all.

> *"I always think it's best to start with the problem and find the solution independent of the technology. Sometimes AI is the solution, sometimes it's a much simpler algorithm, and there we don't really need AI, but we can still get a very good result."*
>
> \- **Julia Stadler**, co-CEO at STADLER Anlagenbau

4.2 Data Infrastructure

Industrial AI's output is only as good as the data going into it. The experts consulted for this report pointed to data infrastructure sequencing as a precondition for success. As **Vuk Trifkovic, Managing Director & Partner at BCG X**, puts it, "*the data infrastructure behind Industrial AI can be an extreme blocker... whenever Industrial AI projects have been preceded by a data infrastructure build-out, their success rate explodes*."

Ensuring the **right data is accessible** is key. The more transformative the application, the more distinct data pools it must draw on. A narrow use case might get away with one; a transformative one needs many. In most organizations, those pools sit fragmented across siloed systems, so the need compounds as scope grows.

But centralizing data isn't enough on its own. The operational teams generating that data are the ones who can maintain its quality, and a platform that pulls data away from them without keeping them accountable for its quality risks trading fragmentation for a centralized pool of degraded data. The initial infrastructure has to do both: centralize access while leaving domain teams accountable for quality and currency. *"Having data being kept in silo also is a limiting factor for scalability of AI. And today, most of the IT systems in organizations don't speak to one another,"* says **Antoine Bois Lemarquis, Industries & Services Global Lead at Quantis**

Data quality has been a second consideration for Industrial AI to scale, but a diminishing one. Generative AI now handles much of the cleaning and structuring work that historically sat as a manual bottleneck, lowering a barrier that used to gate deployment. "*For bigger companies, the barrier is the availability of data and the state of data, it costs a lot of money to maintain really good data. […] Now, it's still availability of data [that matters], you still need the data, but you have generative AI that can help you clean that to accelerate*," notes **Catherine Zwahlen, Digital Senior Director at Quantis**

Data security presents a trade-off: greater connectivity drives efficiency, but expands exposure. IT/OT convergence widens the attack surface, with each connected sensors and edge devices creating other entry points to protect. "*There is also a deliberate decision not to have [the OT assets] connected because any of these connections mean security risk*," says **Vuk Trifkovic, Managing Director & Partner at BCG X**

Industrial AI also often requires pooling data across plants, borders, or company boundaries, to train on larger datasets, or to enable the cross-boundary partnerships that system-level applications depend on. That raises legal and governance constraints. For example, in China, certain manufacturing and operational data may be classified as 'important' or 'core'. Cross-border transfers of important data generally require a government security assessment, while some sensitive data may also be subject to domestic-storage requirements, potentially constraining multinationals' ability to pool plant data across borders for centralized training.

4.3 Change Management

Accountability for machine-made decisions is a recurring theme. As **Jochen Gross, Head of Sustainability Data Strategy & Architecture at Siemens**, puts it, companies have "*learned over centuries how to deal with human error*" through built-in control structures and accountability frameworks, but lag in building an equivalent for opaque, model-based systems whose reasoning cannot be inspected.

> *"Many commercially deployed models are not open-weight, meaning external users/ researchers cannot access the model internals to investigate why it produced a particular output."*
>
> \- **Adrin Jalali**, co-Founder at Probabl

Governance frameworks exist (e.g., NIST's AI RMF, the EU AI Act) and codify accountability through designated risk ownership, mandated human oversight, and documentation requirements. Their implementation and enforcement maturity has not kept pace with deployment. Experts point to rigorous, ongoing testing as the practical alternative: it gives an accountable owner defensible grounds to accept responsibility for outputs they cannot fully explain. Again, **Adrin Jalali** highlights that "*testing is becoming a major focus area for building trust in AI-generated output. Trust has to be earned through rigorous validation, not assumed.*"

Ownership belongs with domain experts, not with a generic IT roadmap, since domain experts know the decision pathways the system is meant to follow. A tool to calculate emission factors makes the point: it failed under IT and succeeded a year later, re-led by the sustainability footprinting team. The organization attributed the turnaround not to any change in technology, but to the new team's domain expertise.

Ownership is necessary but not sufficient as domain teams still need the skills to act on it. Lower-code tooling has made it more feasible for functions outside central IT to build and deploy, but accessibility doesn't remove the skills requirement. Hiring hybrid profiles that combine data science expertise with domain knowledge is accordingly a key success factor.

> *"It is important to have people on board who are used to working in areas where they have to work with scarce data, and where a lot of overfitting happens because these people are trained to mitigate those problems from the start."*
>
> \- **Peter Schwendner**, Professor & Director at Institute for Wealth and Asset Management

Leadership must champion adoption visibly. Good practices include sharing successful cases in all-hands meetings, promoting AI training, direct conversations with skeptical employees, and "AI first" mandates across internal processes. This aligns with the broader industry view that scaling requires *"insightful, inspiring leaders who are willing to bet on emerging capabilities that may not yet be mature today, but are on the verge of transforming operations, tackling challenges previously thought unsolvable,"* says **Tomas Panek, Head of Contrail Partnerships at Google**.

5 Vision: Unlocking Industrial AI's Full Potential for Greater Impact

As Industrial AI capabilities continue to evolve and become more deeply integrated into industrial systems, their role in shaping sustainability outcomes is set to grow. What remains less clear is **the scale and balance of that impact,** including how the environmental benefits enabled by AI will compare with its own footprint as deployment expands. The visions outlined in this chapter explore **how that impact could evolve**, building on the deployment patterns identified in this study and opportunities highlighted through expert interviews.

As shown in this study, Industrial AI is already being applied across sectors to optimize production, assets, energy use, and product design, demonstrating that many Industrial AI capabilities have progressed beyond experimentation and create an impact on sustainability. To illustrate the scale of the opportunity, applying a conservative 10% reduction to projected industrial emissions in 2035 as an outcome of Industrial AI would correspond to an indicative 1.7 $GtCO_2e$ of annual emissions reductions.[viii] Yet, the potential extends beyond the gains visible today. Three visions point toward the direction of Industrial AI in the sustainability space.

First, **Industrial AI can push the boundaries of industrial sustainability**, accelerating the design of lower-impact materials and helping energy systems adapt to variable supply and circular material flows. Second, **AI can minimize its own environmental footprint**, becoming more resource-efficient and circular, reducing the impact of the infrastructure that powers it, and clarifying whether its sustainability benefits justify the resources required. Third, **connected intelligence is beginning to expand optimization beyond individual companies**, linking decisions across firms to optimize energy, material, and carbon flows across industrial ecosystems.

viii. The 10% reduction is an illustrative, deliberately conservative assumption rather than a forecast of AI-enabled emissions reductions. The 10% is set below the reductions that peer-reviewed modelling attributes to AI in the power (~12%) and mobility (~16-19%) sectors - the closest available analogues to industry (Stern et al., 2025). It also sits below what adopters report: organizations already deploying Industrial AI for sustainability measure average energy savings of 23% and CO_2 reductions of 24% (Reuters, 2025). The estimate is gross, before accounting for the environmental footprint of the AI systems delivering the reductions, and excludes potential rebound effects.

Vision 1: Industrial AI enables new sustainability capabilities

Industrial AI moves beyond optimizing today's operations to **enable more sustainability outcomes that are difficult to achieve without AI.** It can help companies anticipate physical climate risks and value chain disruptions, accelerate the discovery and engineering of lower-impact materials and processes, and coordinate increasingly complex energy systems with high shares of renewables. It can also turn product and environmental data into decisions that enable more circular products and business models.

Across these capabilities, AI changes how industry approaches sustainability in four ways: **anticipating risks** and impacts before they materialize; **designing** new materials, products and processes; **orchestrating** increasingly complex energy and resource systems; and **turning sustainability data into a real-time input** to industrial decisions, rather than a report produced after them. The vision is for sustainability considerations to become increasingly embedded in industrial intelligence itself, informing decisions alongside cost, quality, reliability and performance.

What it takes and where we are: Reliable environmental and operational data, hardware and software, digital twins and advanced AI capabilities are needed to translate intelligence into physical-world outcomes. Early capabilities show what this looks like across the industrial lifecycle: models anticipate physical risks like heat, water stress and supply disruption; design tools inform packaging that recovers more of what companies put on the market; computer vision sorts materials at industrial throughput and self-learning control systems adjust plant actuators in real time. The next evolution is the use of agentic AI: autonomous agents that are capable of orchestrating these systems to achieve specific productivity and sustainability goals. Across the value chain, AI also turns carbon reporting from a compliance exercise into a live input to procurement and operational decisions.

DESIGN & DISCOVER
AI designs new materials and solutions with sustainability in mind.

EXPERIMENT & DEVELOP
AI guides autonomous experimentation to test and define new ideas faster.

ANTICIPATE & PREPARE
AI forecasts climate risks and environmental impacts to enable earlier action.

OBSERVE & MEASURE
AI uses remote sensing and data to detect emissions and environmental changes in real time.

CIRCULATE & RESTORE
AI enables circular design, smarter resource recovery and regeneration of natural systems.

OUTCOME: New solutions, materials and insights that advance sustainability beyond today's limits.

Vision 2: AI minimizes its environmental footprint

As AI deployment grows, its **sustainability contribution will increasingly depend on reducing the resources and environmental impacts required to deliver it**. This requires progress on two distinct fronts: making **AI itself more resource-efficient**, and making the **physical infrastructure that powers AI lower-impact and more circular**.

Resource efficiency and optimization of AI itself: Advances in models, inference, software and computing hardware can increase the capability delivered for each unit of compute and energy consumed. AI can increasingly contribute to this optimization by selecting the right model for each task, adjusting inference frequency and allocating computational effort according to need rather than applying the same level of compute throughout.

Decarbonizing and circularizing the infrastructure behind AI: Even highly efficient AI depends on data centers, energy, cooling systems and physical hardware. Lower-carbon electricity, energy- and resource-efficient cooling technologies and intelligent infrastructure management can reduce the operational footprint of supplying compute. Across the lifecycle, servers and accelerators can remain in productive use for longer, be reused or refurbished where possible, and valuable materials recovered at end of life. Where technically and economically viable, computing infrastructure can also integrate more closely with surrounding energy systems through flexible demand and the productive use of waste heat.

Quantifying AI's net sustainability impact: Better measurement will make the resources consumed by an Industrial AI application visible alongside the sustainability benefits it enables. Comparing these effects across the lifecycle helps companies prioritize capabilities with a positive net impact, select the appropriate level of AI capability for each task, and avoid using resource-intensive AI where simpler approaches can achieve comparable outcomes.

What it takes and where we are: AI must deliver greater capability with fewer resources, while the infrastructure supplying it becomes lower-carbon and more circular. Progress is visible on each front. Systems now route tasks to the smallest model that can handle them, cutting energy per query without changing the answer. Autonomous cooling controls hold thermal targets while reducing data-center energy use, and new facilities are being designed to recover waste heat into district networks. Server operators are lengthening hardware life through remanufacturing and reuse. And LCA-based research begins to weigh an AI application's environmental cost against the benefit it delivers.

MORE EFFICIENT INTELLIGENCE

EFFICIENT MODELS
Smaller, smarter models that require less compute.

OPTIMIZED SOFTWARE
Better algorithms and systems that use less energy per task.

ADVANCED HARDWARE
Purpose-built chips and photonics that deliver more capability per watt.

EDGE INTELLIGENCE
Right-sized AI at the edge reduces data transfer and energy use.

+ SUSTAINABLE AI INFRASTRUCTURE

INTELLIGENT COOLING
AI optimizes thermal systems to reduce energy and water use.

GRID-RESPONSIVE COMPUTE
AI shifts and shapes workloads to support low-emission, reliable power systems.

CIRCULAR HARDWARE
Design for durability, reuse, refurbishment and responsible material recovery.

LOW-CARBON ENERGY
Procured and onsite renewable energy reduces carbon intensity.

Vision 3: Industrial AI connects and optimizes across industrial ecosystems

Despite ongoing scaling, most Industrial AI activity remains within company boundaries: **almost 90% of the 420 signals identified describe AI applied within an individual company's operations.** Even where multiple organizations collaborate, deployments typically connect a limited number of actors around a specific application. **Industrial AI today therefore predominantly optimizes what individual companies can see, influence, and control.**

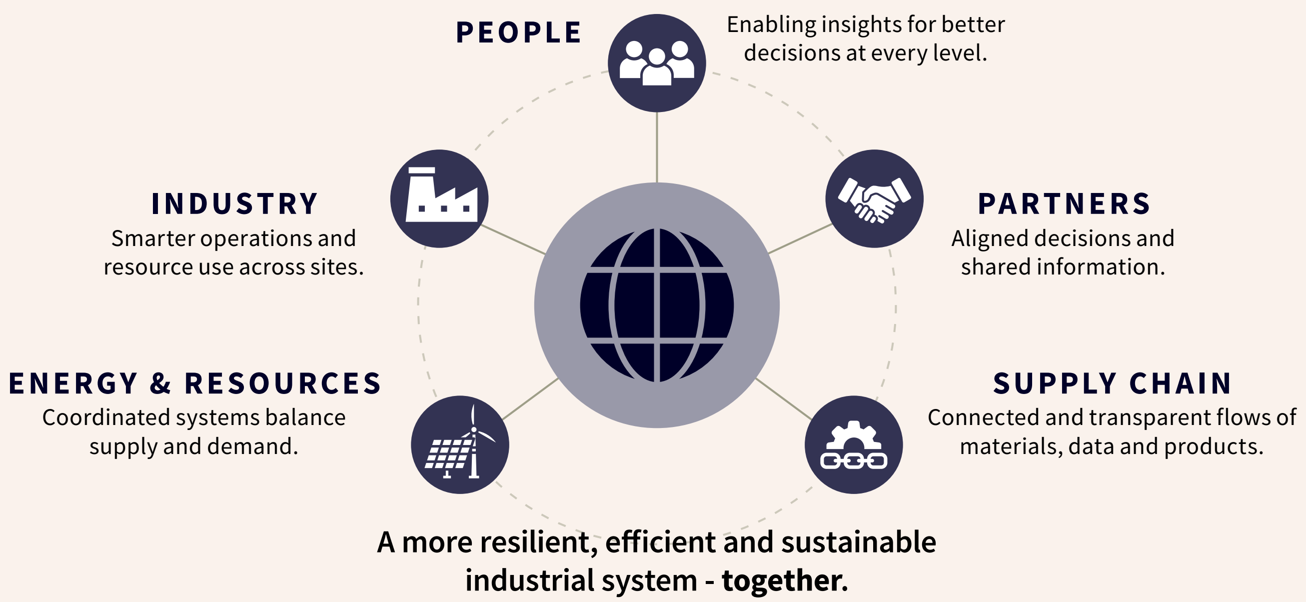
This matters because **many environmental outcomes extend beyond those boundaries**. **Optimizing each participant independently can improve individual performance, but it cannot systematically identify trade-offs and opportunities across the system as a whole.** This also explains why **Value-chain decarbonization accounts for only 7% of the signals identified, and circularity for 3%** (see Figure 4). Both require information and decisions to move across organizational boundaries more frequently than capabilities such as predictive maintenance or process control.

In the third vision, **Industrial AI expands its reach as data and decisions increasingly flow across organizational boundaries, shifting from optimizing individual machines, plants, and companies, towards optimizing the industrial ecosystem as a whole**. Shared intelligence links suppliers, manufacturers, energy systems, logistics providers, customers, and recyclers, allowing AI to optimize material, energy, and carbon flows across organizational boundaries and identify opportunities that no individual participant can capture alone.

This creates a path toward **system-level optimization of industry**. AI matches secondary materials with new demand, connects product information from design through use and end of life, and turns value-chain emissions data into sourcing, production, and logistics decisions. As intelligence becomes increasingly connected across the industrial lifecycle, sustainability optimization shifts from improving individual parts of the system toward improving how the system works together.

What it takes and where we are: System-level optimization requires interoperable data, aligned incentives, and trusted governance across organizational boundaries. AI platforms already turn fragmented feedstock, supplier and technology data into decision-ready intelligence, helping companies choose renewable and circular materials that would otherwise be hidden in the noise. Beginning to emerge alongside them are cross-industry marketplaces where AI matches excess materials from one sector to reuse opportunities in another, i.e., a plant's residuals routed to their highest-value next life.

Case Study #9 shows what this vision looks like in practice within energy systems.



CASE STUDY #9 (NON-SIEMENS)

Energy systems provide an early indication of what becomes possible when that boundary expands

- **Challenge:** As electricity systems incorporate more variable renewable generation, storage and distributed demand, optimizing individual assets independently becomes less effective. Decisions increasingly need to account for conditions across the wider network.
- **AI solution:** AI-based forecasting and real-time control can combine information on generation, demand, storage and network capacity to coordinate distributed resources and better match supply and demand across the grid.
- **Current scope:** Coordination already crosses ownership boundaries, not only single estates. Shanghai's State Grid reportedly aggregates 71 separate operators into 2.816 GW of dispatchable capacity, described by its operator as equivalent to a large conventional coal plant.
- **System impact:** No new generation was built. That capacity came from assets that already existed but were never dispatchable as one system, an early indication of how Industrial AI can move from asset-level optimization toward optimization across interconnected systems.

6 Turning Vision into Action: What Industrial Leaders Should Do Now

Capturing the full value of Industrial AI requires coordinated action from strategic direction through implementation. Boards and executives need to set priorities, functional leaders need to provide the conditions for scale, and operational owners need to translate them into deployment:

6.1 For the Board / CEO (Strategic Bets)

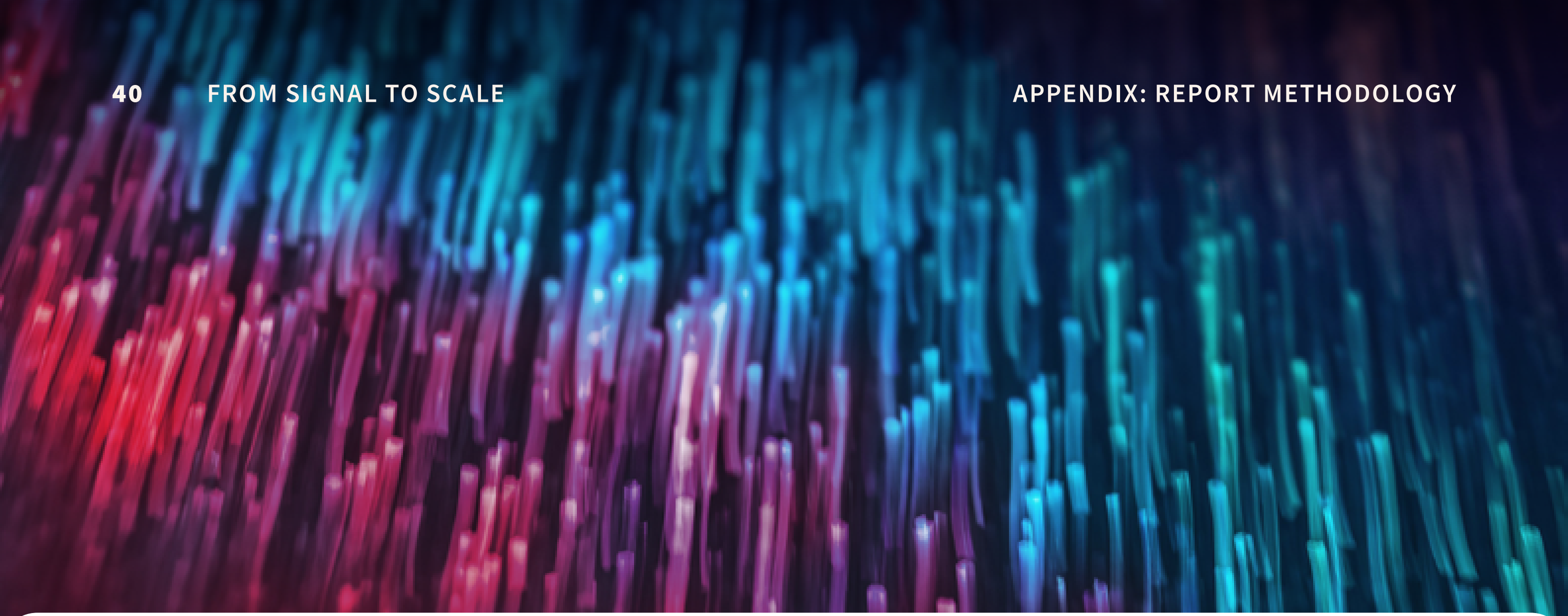
- **Take a holistic view of Industrial AI's value.** Evaluate initiatives across financial, operational, and environmental outcomes, including their contribution to sustainability targets. Integrating sustainability into AI investment decisions can strengthen the overall value case and provide a comparative advantage as regulation tightens and credible environmental performance is demanded.
- **Look beyond individual-company optimization.** Most Industrial AI today improves efficiency within individual products, processes, and companies. The next opportunity is to connect intelligence across organizational boundaries to identify system-level opportunities, from cross-organization energy efficiency/optimization and cleaner value chains to circular material flows. This requires collaboration and data sharing with value-chain and geographically proximate partners.

6.2 C-Suite/Function Head (Resourcing & Enablement)

- **Invest in organizational change alongside technology.** Scaling Industrial AI depends on people, processes, data, and technology working together. BCG's digital transformation framework allocates 10% of effort to algorithms, 20% to technology and data, and 70% to people and processes, reflecting the importance of organizational capabilities in moving from pilots to scale.
- **Build visibility into AI's net environmental effects.** Environmental benefits should increasingly be considered alongside AI's own energy, water, infrastructure, and hardware requirements. Application-level net assessment remains difficult today, but improving transparency provides a foundation for more complete and comparable assessments as methodologies mature.
- **For CSOs, join the business case.** Industrial AI initiatives already carry operational budgets and executive attention. Embedding sustainability KPIs alongside operational measures can make environmental value part of the existing investment case rather than requiring a separate sustainability case.

6.3 Operational Owners (Execution)

- **Start where deployment evidence is strongest.** Predictive maintenance, quality control and machine vision, and energy efficiency and optimization show some of the deepest deployment evidence in this study. Use this as a starting point while testing each capability against the specific operational context.
- **Define KPIs from the outset.** Track relevant operational and sustainability outcomes from deployment onward. Establishing measurement early provides a stronger basis for demonstrating the full value created as applications scale.
- **Match AI and hardware to the task.** Use the model, compute, sensors, and additional hardware required to achieve the intended outcome without unnecessary complexity or resource demand.



Appendix: Report Methodology

Signals Database

The analysis of ***"FROM SIGNAL TO SCALE"*** is based on a structured signal database of publicly disclosed Industrial AI capabilities in the sustainability field. The database and resulting analysis are not specific to Siemens, while several of the use cases featured throughout the report draw on Siemens deployments to illustrate Industrial AI applications in practice. The signals database is used to identify where activity is concentrating across industrial sectors, sustainability outcomes and AI capabilities. The insights developed based on the analysis of this data are cross-referenced against the 24 interviews conducted with experts and practitioners of Industrial AI and sustainability.

Scope

The signal database covers more than 100 companies across process industries, discrete manufacturing, energy, transportation and infrastructure. The company set provides broad coverage across major industrial sectors and geographies and includes leading industrial companies and technology providers.

The database contains 420 verified signals published from 2023 onward. A signal is a publicly disclosed example of a specific AI solution linked to an industrial application, customer or measurable outcome. Signals include active deployments as well as announced deployments and deals that meet the study criteria. Broad statements of AI ambition are excluded, as are consumer and back-office applications and cases where AI plays only an incidental role.

Data collection and classification

An AI-supported web-scraper is used to systematically identify and structure potential signals from publicly available information, with each retained signal traceable to an identifiable public source. Signals are classified by sector, sustainability impact (operational decarbonization, value-chain decarbonization, resource efficiency or circularity), AI capability, and reported KPIs. The two resource domains are separated by what happens to the material rather than by lifecycle stage: resource efficiency covers material never consumed, such as yield gains, scrap and defect reduction and asset life extension, while circularity covers material consumed and then returned to use through sorting, recovery, remanufacturing or secondary input substitution. Where a signal fits multiple categories, the single most representative classification is retained to avoid double counting.

Quality control

Every signal and classification was independently checked before being included in the analysis. All 420 cases were reviewed to confirm that the reported information matched the original source, with a false positive rate held below 10%, and separately were manually reviewed to confirm correct classification.

Interpretation and limitation

The database indicates **where publicly visible Industrial AI and sustainability activity is concentrating**. The number and share of signals can therefore be used to compare observed activity across sectors, sustainability outcomes and AI capabilities. The database is not an exhaustive or statistically representative sample of global Industrial AI deployment. It captures publicly disclosed activity among the companies studied, making companies that disclose more activity more visible, while private, failed or undisclosed deployments are not observed. The findings therefore describe **patterns in publicly visible market activity, rather than total market adoption or aggregate environmental impact**.

Note on transparency & replication

The complete list of sources, the full set of organizations researched, and the tools used to collect and manage the data are not published here, consistent with the confidential nature of the underlying research process. What is disclosed is sufficient to interpret the report's findings and to understand the rigor behind them.

Report Findings

Please note that the data in the figures presented in this report are rounded to whole numbers, so totals may not sum as a result.

Additionally, to go further on the findings of Chapter 3, please find below an example of translation logic from operational KPIs to Sustainability ones, to capture the gross environmental benefits of Industrial AI:

APPENDIX TABLE 3

From operational metrics to sustainability KPI[ix]

OPERATIONAL KPI →	SUSTAINABILITY KPI	TRANSLATION LOGIC
Energy consumption / intensity	**GHG emissions**	Apply the relevant electricity or fuel emissions factor to the measured change in energy consumption.
Water use	**Water withdrawal & consumption**	Report the physical reduction in liters. Where relevant, assess the significance of the reduction in its local water-scarcity context.
Waste / e-waste	**Avoided waste & Amount of waste recycled**	Report avoided waste directly. For recovered material, account for recovery rates and material quality when estimating the amount of virgin material substituted.
Avoided material volume	**GHG emissions & Avoided material used**	Measure the reduction in material input required for the same output. Where lifecycle data are available, translate the avoided material into associated GHG emissions.
Downtime reduction / asset lifetime extension	**GHG emissions & Avoided waste & Avoided material volume**	Where longer asset life delays replacement, estimate the material, waste, and embodied emissions associated with the avoided or delayed replacement.

Source: *Quantis and BCG analysis*

ix. Avoided-emissions claims raise complex methodological questions (i.e. how the counterfactual is defined, where the system boundary sits, and the risk of double-counting against Scope 1, 2 and 3), which are not resolved in this report.

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We work with organizations around the world to connect sustainability ambition to real business outcomes by bridging insight with practical action. Our work, jointly with BCG, focuses on enabling solutions that improve profitability, reduce risk, increase efficiency, spark innovation, and build long-term resilience.

Grounded in science and informed by data, we help leaders move beyond intent to implementation by embedding sustainability into core business decisions and scaling solutions that deliver measurable impact. Through our connection to BCG, we help accelerate and scale these solutions across organizations and value chains.

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References

1. Reuters Events. (2025). *From pilots to performance: How industrial AI is helping to scale sustainability impact.* In cooperation with Siemens. **https://1.reutersevents.com/LP=39274**

2. Siemens AG. (2025). *Infrastructure Transition Monitor 2025*. **https://static.sw.cdn.siemens.com/siemens-disw-assets/public/5kge2RFjL4FtK59FYzHPSJ/en-US/FULL_Siemens_ITM_Report-2025.pdf**

3. IoT Analytics. (2025). *Industrial AI market report 2025–2030*. **https://iot-analytics.com/product/industrial-ai-market-report-2025-2030**

4. Science Based Targets initiative. (2025). *SBTi trend tracker: August 2025.* **https://files.sciencebasedtargets.org/production/files/SBTi-Trend-Tracker-2025.pdf**

5. Circle Economy Foundation. *The Circularity Gap Report 2025.* Released 13 May 2025 at the World Circular Economy Forum (WCEF), São Paulo, Brazil. Available at: **https://www.circularity-gap.world**

6. Eurostat. (2025). *Over 12% of materials in the EU come from recycling.* **https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20251119-1**

7. Eurostat. (2025). *Circular economy – material flows. Statistics Explained*. **https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Circular_economy_-_material_flows**

8. International Energy Agency. (2026). *Key questions on energy and AI*. **https://www.iea.org/reports/key-questions-on-energy-and-ai**

9. Gröger, J., Behrens, F., Gailhofer, P., & Hilbert, I. (2025). *Environmental impacts of artificial intelligence: Evaluation of current trends and compilation of an overview study* (Öko-Institut, on behalf of Greenpeace e.V., Hamburg). **https://www.greenpeace.de/publikationen/20250514-greenpeace-studie-umweltauswirkungen-ki-eng.pdf**

10. Aczel, M., Chamanara, S., Matin, M., Farsi, A., Marwala, T., & Madani, K. (2026). *Environmental cost of AI's energy use: Carbon, water and land footprints.* United Nations University Institute for Water, Environment and Health (UNU-INWEH). **https://doi.org/10.53328/INR26RMA002**

11. De Vries-Gao, A. (2026). Recalibrating global artificial intelligence e-waste estimates. *Resources, Conservation and Recycling*, *229, Article 108872*. **https://doi.org/10.1016/j.resconrec.2026.108872**

12. Baldé, C. P., Kuehr, R., Yamamoto, T., McDonald, R., D'Angelo, E., Althaf, S., Bel, G., Deubzer, O., Fernandez-Cubillo, E., Forti, V., Gray, V., Herat, S., Honda, S., Iattoni, G., Khetriwal, D. S., Luda di Cortemiglia, V., Lobuntsova, Y., Nnorom, I., Pralat, N., & Wagner, M. (2024). *The global e-waste monitor 2024*. International Telecommunication Union (ITU) & United Nations Institute for Training and Research (UNITAR). **https://ewastemonitor.info/the-global-e-waste-monitor-2024**

13. Luccioni, A. S., Jernite, Y., & Strubell, E. (2024). Power hungry processing: Watts driving the cost of AI deployment? *In Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency* (FAccT '24). Association for Computing Machinery. **https://doi.org/10.1145/3630106.3658542**

14. Gupta, U., Kim, Y. G., Lee, S., Tse, J., Lee, H.-H. S., Wei, G.-Y., Brooks, D., & Wu, C.-J. (2022). Chasing carbon: The elusive environmental footprint of computing. *IEEE Micro, 42(4),* 37–47. **https://doi.org/10.1109/MM.2022.3163226**

15. Faiz, A., Kaneda, S., Wang, R., Osi, R. C., Sharma, P., Chen, F., & Jiang, L. (2024). LLMCarbon: Modeling the end-to-end carbon footprint of large language models. In *The Twelfth International Conference on Learning Representations* (ICLR 2024). **https://arxiv.org/abs/2309.14393**

16. AECOM. (2026). *Pioneering waste heat from data centres at scale in UK first*. **https://aecom.com/projects/pioneering-waste-heat-from-data-centres-at-scale-in-uk-first**

FROM SIGNAL TO SCALE

The Industrial AI
Sustainability Opportunity

In cooperation with