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SHANGHAI CLIMATE WEEK
上海气候周

CLIMATETECH IN FOCUS
ARTIFICIAL INTELLIGENCE FOR SUSTAINABILITY

Contents

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Shanghai Climate Week is a global platform dedicated to advancing climate action and sustainable development through innovation and international cooperation, guided by the principles of “China Action, Asia Voice, Global Standard.” This year, we are pleased to continue to present ClimateTech in Focus, which discusses Artificial Intelligence as a key enabling infrastructure for sustainability, offering deeper insights to policymakers, industry leaders, and practitioners on how AI can strengthen energy systems, supply chains, and climate governance.

Shanghai Climate Week

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The Sino-International Entrepreneurs Federation is committed to helping public- and private-sector leaders achieve their goals by advising on strategy, policy, and delivery. As the Presenting Partner of this year’s ClimateTech in Focus, we underscore the critical role of aligning AI-driven innovation with measurable, real-world sustainability impacts – empowering entrepreneurs and investors across regions to scale trusted, practical solutions that accelerate the transition to a low-carbon, resilient global economy.

Sino-International Entrepreneurs Federation

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Preface I

Dr. Tshilidzi Marwala
Under-Secretary-General, United Nations
Rector, United Nations University

Ten years after the adoption of the 2030 Agenda for Sustainable Development, the international community continues to confront the widening gap between our ambitions and our collective progress. Climate impacts are accelerating, and while no region is spared, their effects are felt most acutely among those with the fewest resources to respond. These realities underscore the urgency of strengthening resilience, expanding access to sustainable energy, and ensuring that all countries have the capacity to participate meaningfully in the global response to climate change.

In recent years, science, technology, and innovation have offered new avenues for advancing this work. Artificial intelligence is becoming an increasingly significant tool for improving how societies anticipate climate risks, plan for changing conditions, and manage natural resources. We see its growing role in early warning systems, climate modelling, renewable energy integration, agriculture, water management, and urban planning. These developments point to AI's potential to support more effective and equitable climate action.

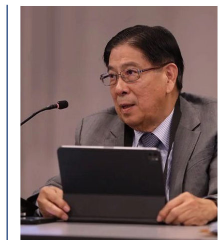
However, the benefits of AI will only be realized if countries have the skills, infrastructure, and institutions required to use these technologies responsibly. I often highlight the importance of "closing the digital divide" by strengthening national capacities so that all countries – particularly those in the Global South – can access the increasing opportunities emerging from digital transformation. Access and opportunity must be available to all. This principle is essential not only for fairness, but also for the credibility and effectiveness of the global climate action.

United Nations University's growing portfolio of initiatives illustrates a clear and urgent recognition: digital innovation must be mobilized in the service of climate objectives. As the research and education arm of the United Nations, United Nations University is committed to bridging science, policy, and capacity development to build a sustainable, inclusive, and digitally empowered future. Our work supports the UN system, governments, academic institutions, and communities in translating ambition into implementation: by developing the skills needed for data-driven decision-making, strengthening institutional readiness, advancing ethical and inclusive governance of emerging technologies, and fostering cooperation across sectors, disciplines, and regions. This integrated approach reflects not only the demands of our time but also the values at the heart of sustainable development.

This new edition of *ClimateTech In Focus*, dedicated to AI for Sustainability, offers timely insights into how technological innovation is reshaping climate and development pathways. Through case studies, expert dialogues, and analysis across energy, agriculture, finance, education, and environmental management, the report highlights both the opportunities and the responsibilities associated with deploying AI in support of sustainable development. It also draws attention to the essential enabling conditions required to scale these solutions, including reliable energy systems, coherent governance frameworks, adequate financing, and the continuous development of human capital.

The years ahead will be decisive. The choices we make now will determine the trajectory of our shared future. I remain confident that meaningful progress is possible when governments, the private sector, academia, and civil society work together with a shared commitment to inclusion, equity, and long-term sustainability. The United Nations will continue to play its part by supporting countries to harness the benefits of AI and digital innovation in ways that are safe, ethical, and aligned with the vision of the 2030 Agenda.

Preface II



Antonio Basilio
Director, APEC Business Advisory Council
Chairman, Pacific Economic Cooperation Council
Philippine National Committee

Across the Asia-Pacific and the world, one message is unmistakably clear: the twin forces of technological innovation and collective action will define our ability to confront the climate crisis. Among these technologies, artificial intelligence stands out as a catalyst of unprecedented potential – reshaping how we predict risks, optimize resources, and design the low-carbon systems of tomorrow. AI is rapidly transforming economies and "holds immense potential to unlock innovation, drive productivity, and promote inclusive growth" – if we guide its use responsibly and inclusively.

The urgency of our shared mission has not diminished; if anything, it has become more immediate as climate impacts intensify each year. What continues to evolve are the tools at our disposal – and the partnerships that strengthen our response. At the forefront of this new era, AI offers an extraordinary opportunity to accelerate sustainable innovation, enhance efficiency, and deepen cooperation. However, we must ensure that this progress benefits all and leaves no one behind.

Through initiatives such as the Seminar on Responsible Adoption of General-Purpose AI and the Asia-Pacific AI Governance Accelerator, PECC has been fostering frank dialogue on responsible AI governance – highlighting the importance of ethics, transparency, and trust in AI deployment. Likewise, ABAC's continued engagement with APEC Leaders has underscored that technological progress must go hand-in-hand with economic resilience, growth finance, and human-centered development. We have consistently emphasized that innovation should not come at the cost of equity or sustainability. Public-private collaboration is key: by working together, governments and businesses can transform emerging technologies like AI into engines of sustainability and shared prosperity.

Building on our previous report, *ClimateTech in Focus: Innovations for a Greener Supply Chain*, which explored how technology can strengthen supply chain resilience, this year's edition – *Artificial Intelligence for Sustainability* – examines how AI is reshaping the future of infrastructure, finance, and education. From smarter energy grids and climate-resilient infrastructure to growth finance innovation and personalized education for sustainability, AI is opening new frontiers. This report offers concrete, forward-looking recommendations to ensure that the AI revolution contributes not only to competitiveness but also to equity, trust, and climate action. Our goal is to harness AI to amplify what works in sustainability – optimizing resource use, democratizing knowledge, and accelerating low-carbon innovation – while safeguarding privacy, ethics, and inclusivity.

We stand at a pivotal moment where technology and responsibility intersect. The decisions we make today will define the legacy we leave for our children and grandchildren. I urge all stakeholders – businesses, governments, academia, and civil society – to seize this opportunity to harness the transformative power of AI, not as an end in itself, but as a powerful partner in building a sustainable, inclusive, resilient, and prosperous Asia-Pacific for all. By aligning innovation with stewardship and collective action, we can ensure that AI becomes a driving force in our quest for a future where economic growth and environmental well-being advance hand in hand.

Preface III

SHANGHAI CLIMATE WEEK 上海气候周

Zhou Yiping

Founding Director, United Nations Office for South-South Cooperation

Senior Strategic Advisor, Shanghai Climate Week

We are entering a decisive decade in which the trajectories of climate action and technological development are becoming inseparably intertwined. Climate risks are no longer abstract projections but lived realities across regions, economies, and societies. At the same time, artificial intelligence is rapidly evolving from a frontier technology into a foundational infrastructure shaping how we generate knowledge, allocate resources, and govern complex systems. The question before us is no longer whether AI will influence sustainable development, but whose priorities it will serve, and on what terms.

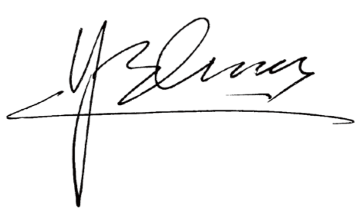
For the Global South, this moment carries particular weight. Many developing countries face the dual challenge of acute climate vulnerability and structural constraints in technology, finance, and infrastructure, yet these same countries also hold immense potential to leapfrog traditional development pathways. Artificial Intelligence, if designed and deployed with sustainability in mind, can become a powerful enabler of such a transition – supporting climate-resilient infrastructure, accelerating clean energy integration, improving agricultural productivity, and enhancing transparency in green finance. If misaligned, however, AI risks reinforcing existing asymmetries, deepening the divide between technology producers and technology recipients. From the perspective of South–South cooperation, this is a defining inflection point. What is required instead is a shift toward shared innovation, co-development, and collective capacity building.

This report argues that AI must be understood not merely as a tool, but as a system that embeds values, incentives, and power structures. Its integration into of inclusivity, sustainability, and long-term resilience. This means aligning AI development with low-carbon objectives, recognizing and addressing its environmental footprint, and ensuring that data, models, and computational resources do not become new sources of exclusion. It also requires respecting national development pathways and data sovereignty, while fostering mechanisms for trust-based cooperation across regions.

Yet technology alone is insufficient. Sustainable impact depends on people, institutions, and policies. Capacity building – from digital literacy to advanced technical expertise – must be treated as a strategic priority. Data infrastructure must be developed as a public good, not a private bottleneck. And global governance frameworks must evolve to reflect the realities and aspirations of developing countries, ensuring that international rules are not only technologically sophisticated, but also development-oriented and fair.

The coming ten years will be decisive. They will determine whether artificial intelligence becomes a catalyst for a more balanced, climate-resilient global development model, or whether it entrenches new forms of inequality. This report calls on policymakers, business leaders, and innovators to act with foresight and responsibility – to invest in cooperation rather than fragmentation, in shared capabilities rather than narrow advantages. By embedding AI within a framework of South-South solidarity and global inclusiveness, we can ensure that technological progress serves as a bridge toward sustainability, rather than a fault line of division.

Artificial intelligence should not be an exclusive asset of a few, but a shared instrument for collective resilience and green transformation. The opportunity before us is profound. The responsibility is even greater. How we choose to act now will shape not only the future of climate action, but the contours of global development for generations to come.



Executive Summary

Artificial intelligence (AI) is no longer a peripheral tool in sustainability efforts. Across energy systems, manufacturing, logistics, finance, certification, education, and public governance, AI is increasingly embedded as operational infrastructure – shaping how societies anticipate risk, allocate resources, enforce rules, and coordinate action at scale. This report examines how AI is already transforming climate mitigation and adaptation in practice, why progress remains uneven, and what institutional conditions are required to translate technical capability into durable public value.

AI's greatest contribution to sustainability lies not in breakthrough algorithms, but in its ability to reduce uncertainty, compress decision cycles, and align complex systems under real-world constraints. In energy and manufacturing, AI supports grid stability, renewable integration, predictive maintenance, and energy-carbon co-optimization, helping systems move along the spectrum between resilience and efficiency. In shipping and logistics, AI has become indispensable for navigating tightening emissions regulations, volatile operating conditions, and Scope 3 accountability, transforming logistics from a carbon blind spot into a governable lever for decarbonization. In finance, AI is shifting climate risk from narrative disclosure into decision-grade intelligence – embedding physical and transition risks into pricing, capital allocation, and supervisory frameworks. In certification and global trade, AI is reconfiguring compliance from document-driven procedures into data-driven trust infrastructure, enabling verifiable carbon transparency as a condition of market access.

Yet the report finds that technical readiness consistently outpaces institutional readiness. Many AI systems reach the pilot or MVP stage rapidly but struggle to scale to large-scale deployment. The binding constraints are rarely funding or model performance; instead, they arise from fragmented data ownership, legacy infrastructure, unclear regulatory pathways, limited operational capacity, and weak trust between innovators, regulators, and adopters. As a result, AI innovation in sustainability often stalls precisely at the point where real impact should begin.

To address this gap, the report argues for a shift in how AI innovation is incubated and governed. Effective incubation goes beyond capital provision and emphasizes deployment readiness: shared operational services, access to secure compute and data environments, domain-specific mentorship, predefined use cases with real buyers, and regulatory sandboxes that allow supervised learning before full-scale approval. Cross-border and networked incubation models are emerging as particularly effective, enabling talent, technology, and market feedback to circulate across regions rather than remaining siloed within national ecosystems.

Education and talent development are equally decisive. With AI already embedded in everyday learning, the question is no longer whether students will use AI, but how education systems guide its use. The report highlights a shift from rote knowledge reproduction toward critical thinking, interdisciplinary problem-solving, and project-based learning grounded in real sustainability challenges. Successful systems treat AI as a learning assistant rather than an answer machine, and they invest in institutional pathways that allow young people to move from education into public service, entrepreneurship, and policy influence. Countries competing effectively for AI talent combine flexible visas and incentives with meaningful roles, practical testbeds, and long-term integration into national innovation systems.

Equity and openness emerge as defining challenges of the AI era. While open data and shared models can accelerate innovation, poorly governed openness risks deepening data inequality, particularly for the Global South. The report emphasizes that openness must be conditional and governed – with clear usage rights, traceable provenance, and mechanisms that ensure local institutions retain control over locally generated data. Inclusive AI deployment is already visible in resource-constrained settings, where lightweight models, community data systems, and public-sector use cases deliver tangible benefits in mobility, disaster preparedness, public health, and agriculture. These experiences demonstrate that AI can support leapfrog development when paired with appropriate governance and infrastructure.

AI governance is not a brake on climate innovation but its enabling condition. Effective governance requires risk-proportionate oversight that builds trust, transparency, and accountability – distinguishing decision-support tools from systems exercising authority, and ensuring explainability, human oversight, and public legitimacy for high-impact uses. When treated as a learning system supported by capacity building and cross-border cooperation, governance enables AI to scale responsibly for climate action rather than constraining it.

AI EVOLUTION AT CROSSROADS: WHERE ARE WE HEADING?

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> *AI and other monitoring methods allow near real-time, transparent validation of carbon results, while strengthening disaster preparedness and enabling anticipatory action – saving lives, reducing costs, and building community resilience.*

H.E. Daniel Francisco Chapo

President of Mozambique

> *We are on the verge of absolute irreversibility of climate change. It's really now that it's being decided. In this decisive moment, the tools we choose to develop and deploy – including artificial intelligence – will inevitably shape our capacity to anticipate, to act, and ultimately to remain within planetary boundaries. In my eyes, we have no choice but to find a model of economic development compatible with those boundaries.*
>
> **H.E. Corinne Lepage**
> Former French Minister of the Environment & Former Member of the European Parliament

The Past, Emergence, and Destination of Artificial General Intelligence

Large Language Models (LLMs) mark a major change in AI. As these systems scale, especially Generative Pre-trained Transformer (GPT) models, they can develop skills like reasoning and problem-solving without being explicitly programmed, and these gains are still hard to fully explain. This has drawn strong interest from researchers and industry. Many report contributors and scholars agree that LLMs provide a clear substitutive advantage over traditional AI methods. As a result, LLMs have become a leading trend, changing how work is done across many fields.

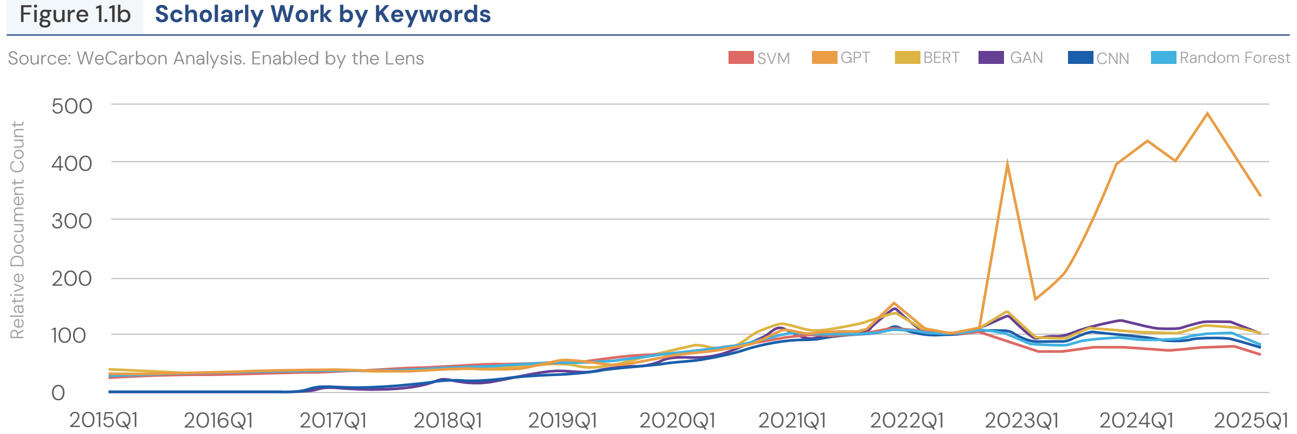
Figure 1.1a **LLMs vs. Traditional AI Approaches**

Feature	LLMs	Traditional AI Approaches	
Language Processing	Human-like, context-rich, emergent	Rule-based/statistical, limited	[5,6,7,10]
Adaptability	High (prompting, few-shot learning)	Low (task-specific training)	[2,4,5,10]
Application Scope	Broad, multi-domain	Narrow, domain-specific	[2,3,6,8,9]
Human Collaboration	Effective hybrid workflows	Limited	[1]
Interpretability	Basic with hallucinations / bias	Various	[5,10]
Computational Consumption	High	Various, usually low	

This growing interest has increased research into emerging technologies, shifting focus from traditional AI methods to advanced models. Researchers are applying a unified GPT and agent framework to large-scale language understanding, computer vision, reasoning, and multimodal generation. Industry leaders are using this approach to address high-impact problems in decision-making, optimization, market research, and evidence synthesis, indicating broader adoption of LLMs in real-world use.

Figure 1.1b **Scholarly Work by Keywords**

Source: WeCarbon Analysis. Enabled by the Lens



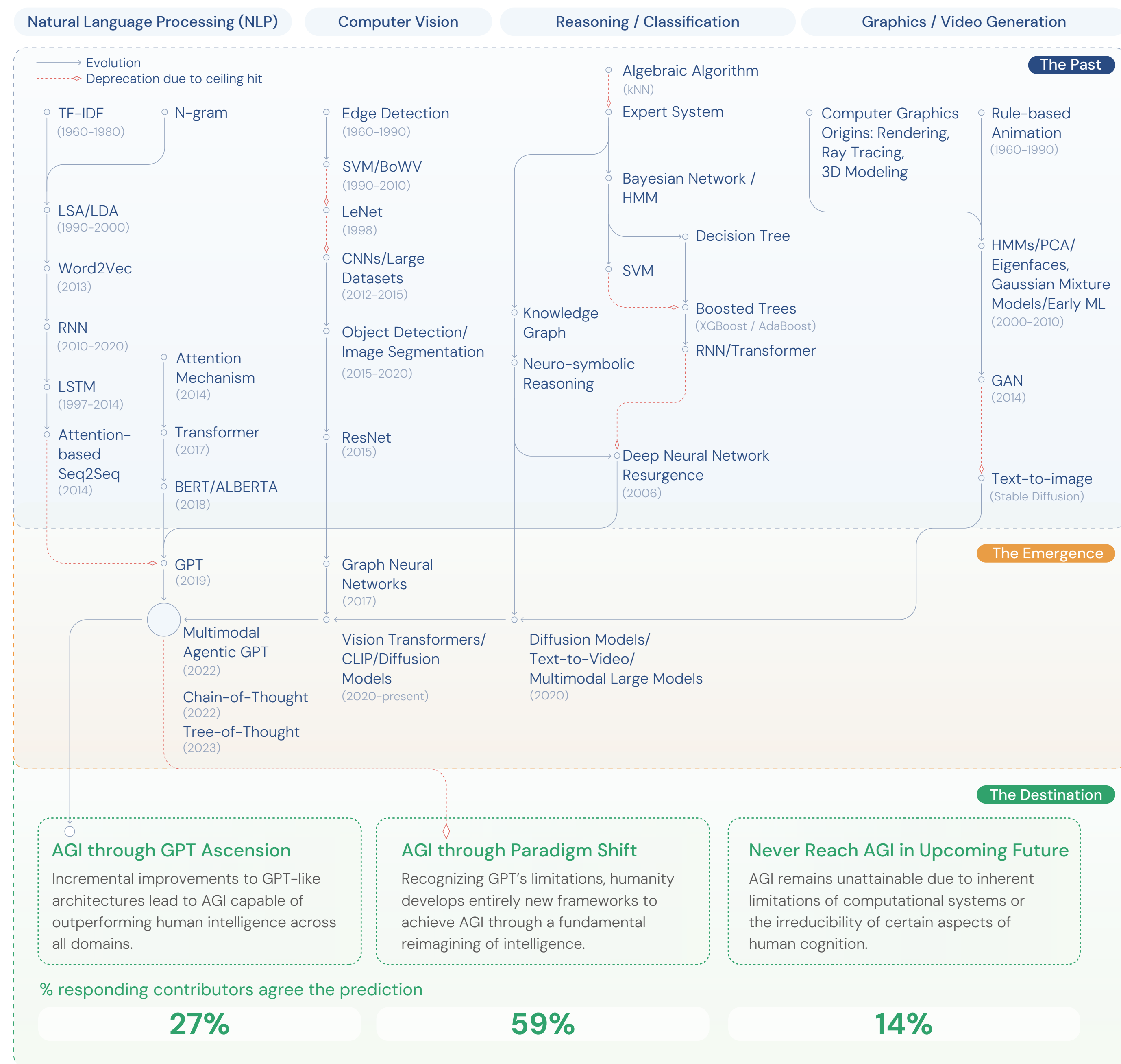
Following a monumental paradigm shift, the pressing question arises: where are we heading? Artificial General Intelligence (AGI) is the theoretical capability of machines to replicate human-like cognition, enabling them to understand, learn, and perform any intellectual task, unlike current narrow AI systems restricted to specific domains. First mentioned in Samuel Butler's Erewhon (1872) as fiction, AGI is now a serious research goal, and systems like GPT are seen as potential steps toward it. Public information shows some industry leaders from top AI companies speculate AGI will arrive by 2030 or sooner.

Many theoretical scientists outside the tech industry remain skeptical, arguing that current progress is not a viable path to AGI.

The history of AI is marked by cycles of optimism and disappointment, often referred to as "AI summers" and "AI winters." Each cycle shows both the promise of new breakthroughs and the limits that follow. The current excitement around LLMs may be a real step forward, but it also brings back concerns about overpromising and the need for realistic expectations.

Figure 1.1c **AI Evolution Pathways**

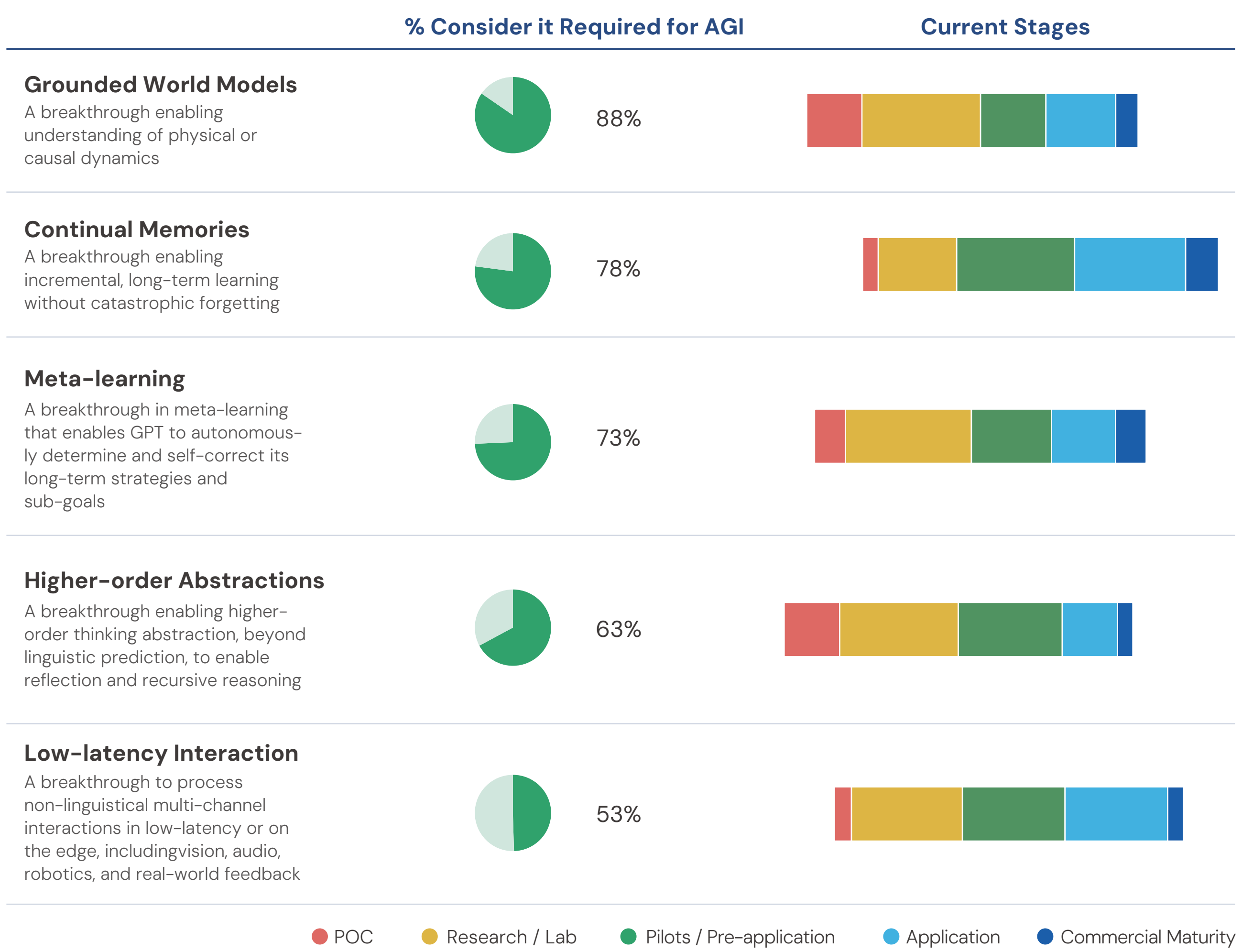
Source: WeCarbon Analysis



This report draws on cross-disciplinary research from a diverse panel of contributors. While perspectives across academia and industry remain divided, a preliminary consensus emerges: achieving AGI will require at least one major theoretical breakthrough beyond current approaches. Grounded world models and meta-learning are considered the most necessary among other technologies.

Figure 1.1d **Top 5 Critical Breakthroughs Expected Before Reaching AGI**

Source: ClimateTech In Focus Responding Contributors



Advances in computational capacity and bandwidth remain decisive constraints on more advanced adoption of AI services. Contemporary deployments typically operate within service-level throughput limits of roughly 500,000 tokens per minute for text generation and approximately 2 MB/s for image data, which restrict interactive applications to modalities that can be streamed within these bounds. As a result, commercially available video generation remains predominantly non-interactive and computationally intensive, while domains such as autonomous driving continue to depend on traditional methods because portable compute and low-latency infrastructure remain insufficient. Whether these constraints can be fully resolved is uncertain, yet continued progress in computational capacity is widely regarded as the central enabler for overcoming them and moving toward more general forms of intelligence.

The AI & Sustainability Paradox

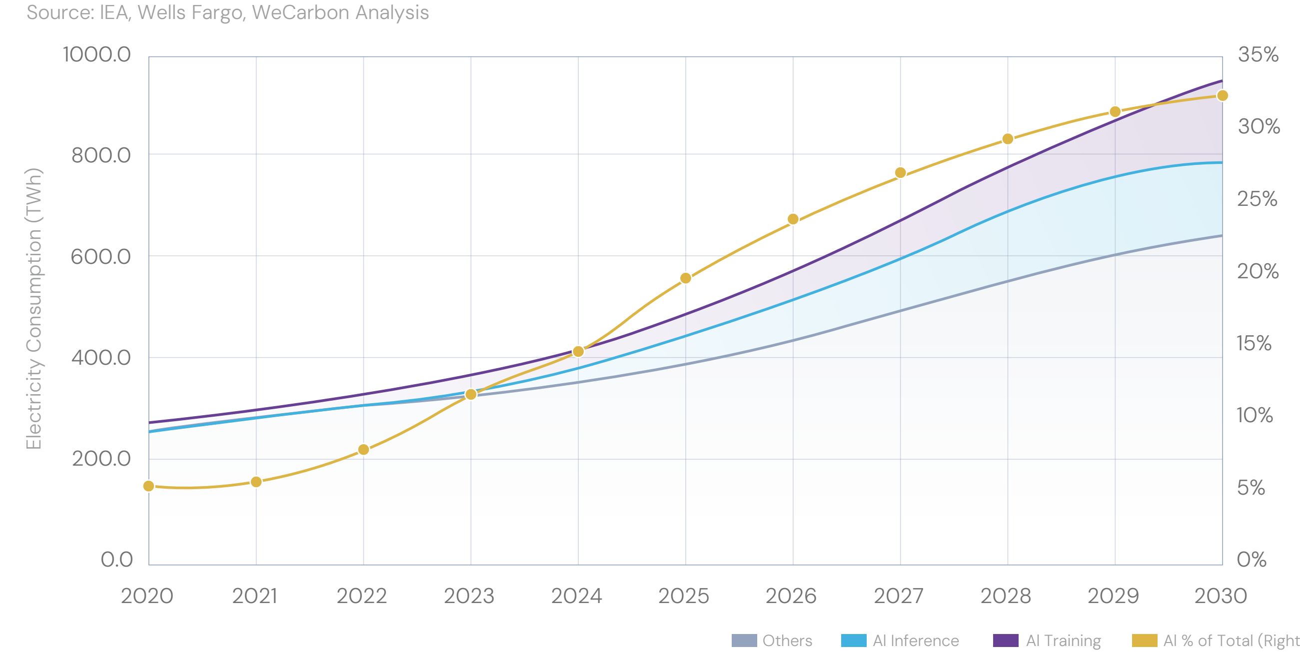
> *AI is becoming an enabler across every major sustainability objective, from lowering emissions and improving resource efficiency to strengthening the resilience of essential systems like food, water, and even how we live in cities. AI helps us optimize how we produce and consume energy, manage natural resources, and operate entire value chains more efficiently.*
>
> **Dr. Lamya Fawwaz**
> Executive Director, Masdar

Sustainability, defined as meeting human needs today without compromising those of future generations, requires that technological progress remain within environmental limits. Scaling up AI will inevitably increase the energy footprint, creating a paradox: both pressure on global net-zero goals and a powerful solution to a leaner supply chain.

Training the GPT-3 model with 175 billion parameters, which is no longer considered state-of-the-art as of now, created a footprint of over 1 GWh of electricity. [11] Contributors to the report believe AI is driving the expansion of cloud infrastructure and leading to the energy footprint of data centers becoming even more critical. The IEA and the report's contributors project at least a 30% year-on-year growth in electricity consumption for the world's AI-enabled servers , as a baseline scenario assuming the current level of AI growth sustains. [12,13,14,15,16]

Figure 1.2a **Electricity Consumption for AI-enabled Servers**

Source: IEA, Wells Fargo, WeCarbon Analysis



1.3%

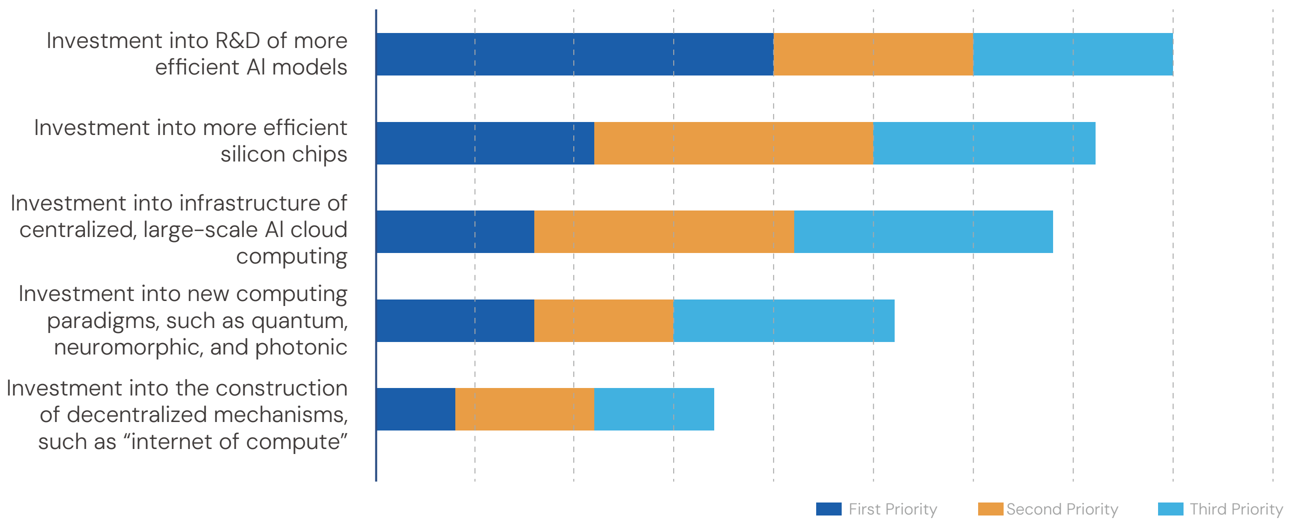
AI-related energy use in global electricity use in 2030

Inference will become the primary driver of electricity demand once AI is deployed on a global scale. In a single year, inference can emit more than 25 times the emissions of total training. If the forecast still shows that training dominates emissions totals, it suggests training demand is growing even faster rather than slowing. Contributors expect this gap to continue through 2030 because models keep getting larger, pushing training needs to rise as fast as, or faster than, global inference use.

AI's sustainability paradox is the conflict between its rising energy use and the need for its benefits to support climate and human development goals. AI can improve human welfare, but it may also contribute to global warming or resource depletion. It is the mandate of the human beings to align AI research, infrastructure, and governance so AI delivers more positive impact than environmental costs. The next sections explain how to reduce the environmental footprints of AI through advances in computing architectures, energy systems, and policy design.

Contributors to this report generally view model downsizing as the most effective approach over the next 5-10 years for easing compute and sustainability constraints, ahead of improvements in chip efficiency and further expansion of large-scale centralized AI cloud infrastructure.

Figure 1.2b **Investment to Address Compute Challenge**



Moore Law, or More Cloud?

Balancing AI's rapidly escalating compute demand and sustainability requires rethinking about where computing happens and how efficiently it runs. Specifically there are two distinct pathways:

Figure 1.2c **Optimization & Hyperscaling Goals**

Optimization (OPEX-driven)	Hyperscaling (CAPEX-driven)
• Maximize operational efficiency by more efficient chips, models, architecture, and encapsulation • More efficient chips with near-memory computing, quantization, and specialized GPU / ASICs • Smaller AI models through architectural efficiency (model downsizing) • Scale via more efficient units and smaller models	• Maximize capital efficiency by higher throughput and lower latency for centralized AI datacenters • More massive data centers with massive GPU / TPU clusters, high-speed backbone connection, and centralized scheduling • Scale via more hardware and larger models

Moore's Law began as Gordon Moore's observation that the number of transistors on an integrated circuit would roughly double every two years, leading many to expect ongoing gains in performance and lower costs. That trend is now slowing at advanced nodes around 3 nm and below, where further scaling faces increasing physical and economic limits from quantum tunneling, power density, leakage currents, and the rising complexity and cost of extreme ultraviolet (EUV) lithography. As a result, scaling no longer reliably delivers proportional reductions in energy per operation or cost per unit of compute. Most performance gains now come from architectural specialization, such as tensor cores and advanced packaging, which increase system throughput but often add design complexity and can raise total system power use at scale.

This More-than-Moore regime shift fundamentally reshapes the sustainability landscape of AI hardware: as single-device optimization approaches its physical and architectural limits, further scaling of AI performance becomes an engineering, energy, capital, and societal coordination challenge predominantly, pending the next breakthrough in fundamental science.

Smarter, Greener, but Not Bigger Model

Model downsizing in the More-than-Moore regime is one of the few ways to grow AI services without matching increases in energy use, carbon emissions, and material demand. Most real-world tasks, especially on edge devices, do not need general-purpose intelligence. They require focused, task-specific performance, so smaller models are often sufficient and more energy-efficient. Knowledge distillation, pruning, and quantization reduce parameter count, memory usage, and compute load, delivering similar performance at much lower computational cost. [17,18]

Figure 1.2d **Key Methods for Model Downsizing**

	Knowledge Distillation	Pruning	Quantization
Technology	• Downsize to smaller parameter count • Maintain accuracy by reasoning traces, intermediate layers, and other distilling techniques	• Downsize by removing redundant weights and channels • Maintain accuracy by preserving the model's effective expressive subspace	• Downsize by reducing precision from FP32 to INT8/FP4 • Maintain accuracy by calibration and Quantization-aware-training (QAT)
For Sustainability	Reduces compute, memory, and inference energy; enables on-device and edge deployment	Reduce FLOPs to enable lightweight edge inference	Reduce arithmetic energy and bandwidth to enable high-throughput low-power execution

40-70%
Lowered energy consumption by shifting to INT8/FP8 quantization

Empirical measurements show that INT8 or FP8 inference typically reduces energy use per inference by 40 to 70% compared with FP32 in compute-bound workloads, depending on the workload and memory behavior. Pruning can enable sub-watt neural inference on embedded platforms. [18,19] Because inference typically accounts for most lifecycle emissions of deployed AI systems globally, these per-inference savings will add up to a total reduction in CO_2 reductions. [19] Combined with edge deployment, compact models also reduce communication energy by replacing large raw-data transfers with smaller semantic outputs, delivering multiplicative energy savings across billions of devices. Model downsizing also lowers carbon footprint in hardware, reduces cooling water demand, and slows upgrade cycles for high-end accelerators. As a result, software compression is now a primary sustainability factor in large-scale AI, alongside energy-efficient hardware design and hyperscale infrastructure investment.

Recent advances in training efficiency show that improving training frameworks can reduce redundant computation and energy use, not just by compressing models for inference. Early stopping tracks loss curves and other convergence signals and ends runs that are unlikely to perform well, saving compute, energy, and emissions. In generative molecular modeling, early stopping can sometimes predict final performance using about 20% of the planned compute. Data-centric methods, such as subset selection and active learning, also reduce waste by identifying redundant training examples. By selecting the most informative, diverse, or uncertain samples, models can often reach similar quality with less data and computation. [20,21,22] This less-is-more approach helps limit growth in training energy use and makes algorithmic and data-efficiency methods key tools for sustainable AI, alongside inference compression, hardware efficiency, and edge deployment.

Edge-Cloud Hybrid AI as the Future

Michael Victor N. Alimurung, City Administrator of Quezon City, highlights that you can't talk about AI if edge infrastructure doesn't exist – AI assumes your cameras and sensors are connected. In an edge cloud hybrid system, each workload must determine where to be placed in the appropriate environment and architecture. The report outlines four functional regimes in a four-quadrant model: reflexive, embedded, systemic, and applicable. It does not aim to fully categorize AI. It offers a practical way to classify AI-enabled systems based on two deployment constraints: latency tolerance and aggregate compute demand.

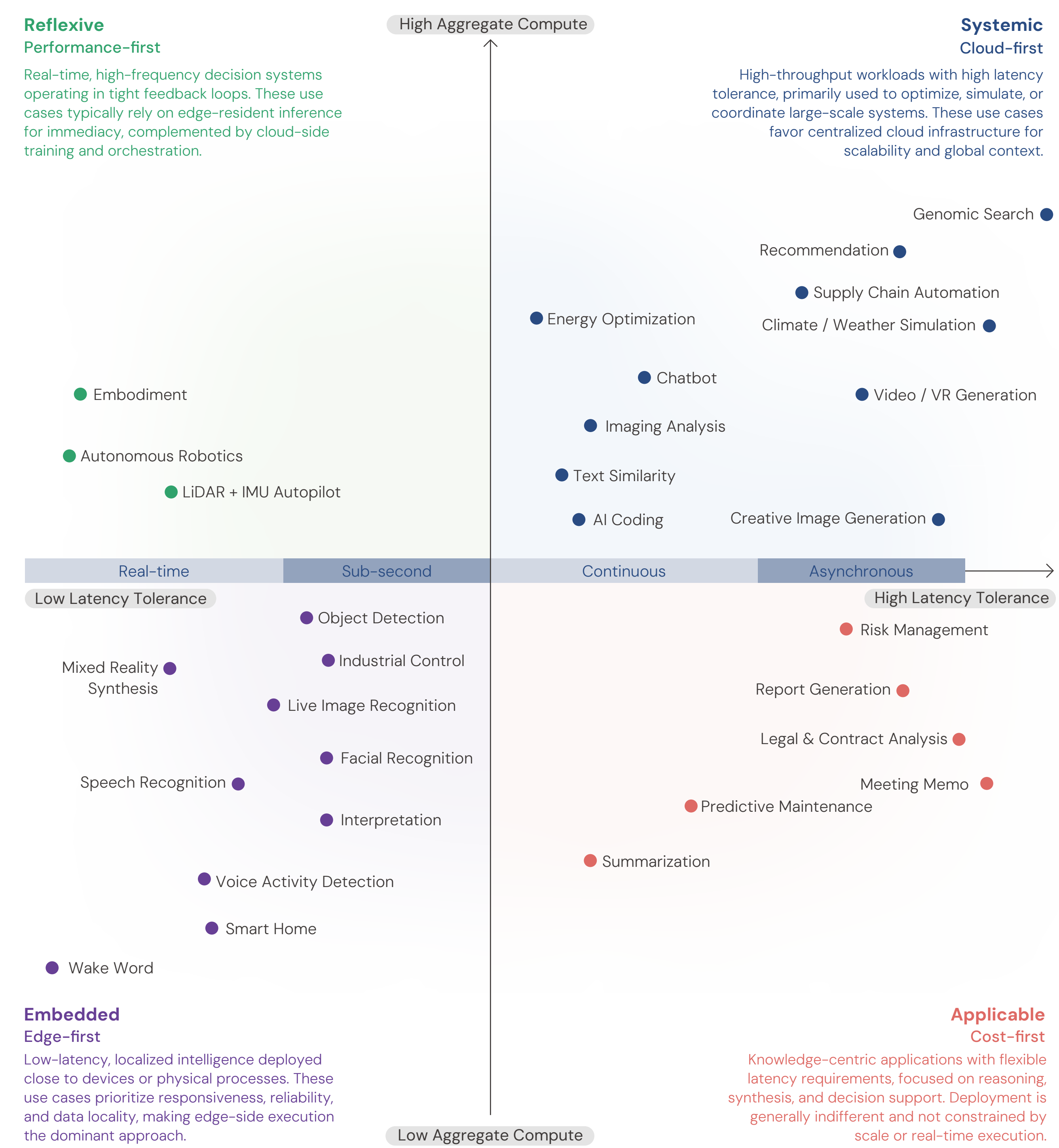
Point positions indicate dominant operational regimes under typical deployment assumptions. Many AI-enabled systems span multiple regimes across different stages of their lifecycle, including training, inference, and orchestration. Deployment is often flexible and primarily shaped by cost, governance, or organizational constraints rather than real-time or scale requirements.

This report classifies latency tolerance in terms of response coupling modes rather than absolute time thresholds:

- **Real-time** denotes tightly coupled control loops where delayed responses invalidate system correctness.
- **Sub-second** refers to interactions where small delays are tolerable, but perceptible latency degrades usability or performance.
- **Continuous** systems allow delayed computation but require progressive, streaming outputs to maintain situational awareness or interaction flow.
- **Asynchronous** systems decouple request and response entirely, allowing results to be retrieved after extended delays without impacting task execution.

Figure 1.2e **Main Patterns of AI Use Cases by Throughput and Latency Tolerance**

Source: WeCarbon Analysis



Hyperscale Sustainable AI Data Center

Hyperscale facilities demonstrably outperform distributed computing in energy efficiency per unit of computation. Best-in-class hyperscale data centers report site-level PUE values approaching 1.10 under favorable climatic and operational conditions, compared to a global industry average of 1.55, implying a 40% reduction in non-compute energy overhead through centralized optimization.[23] Leading examples of AI-focused facilities colocated with renewable generation achieve 90–95% hourly carbon-free electricity matching in selected regions, significantly reducing Scope 2 emissions relative to carbon-intensive regional grids. Cooling innovations are comparable: liquid immersion and free-air cooling reduce cooling energy demand by 30–50% relative to conventional chiller-based systems.[24]

Figure 1.3a **Map of Selected Renewable-powered Hyperscale Data Centers**

Source: WeCarbon Analysis

Note: Energy icons indicate primary renewable energy sources associated with each site.
Symbol size do not represent installed capacity, electricity output, or actual energy consumption.

CASE STUDY 1 | **Compute–Power Co-Optimization Platform**

As AI adoption accelerates, computing demand and electricity use rise together, making energy efficiency a core constraint. SenseTime's "Compute Power and Electricity Coordination Platform" in Lingang, Shanghai, China, improves both compute utilization and power management at the SenseTime Lingang Intelligent Computing Center.

- **Compute Management**
  An integrated training and inference architecture boosts utilization. The platform monitors total, real-time, and available compute plus training and inference workloads, enabling fine-grained, cross-region scheduling and energy-aware operating strategies. Off-peak workload shifting reduces idle waste and raises effective compute output per MW by 150%. In inference, it delivers a 4x increase in QPS at the same compute and electricity cost, with elastic, on-demand scaling to reduce large-scale inference cost.
- **Power Management**
  An energy large model monitors and predicts electricity use, real-time load, adjustable load, and PUE, and optimizes dispatch and efficiency. Built on SenseTime's large model and partnering energy algorithm architecture, it predicts the next 15 minutes of power demand and generates optimal dispatch strategies automatically. Reported performance: 90% to 95% demand forecast accuracy and 95%+ decision accuracy. Results at Lingang AIDC show annual PUE below 1.28 and 3,000,000 kWh of electricity saved per year.

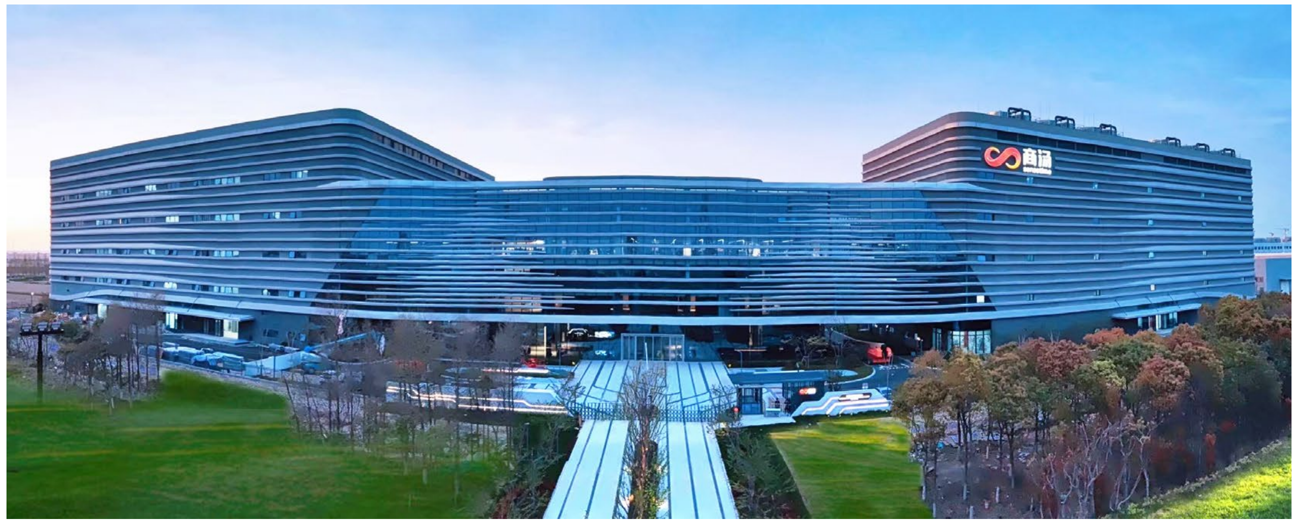
> *Compute infrastructure is not only the foundation of artificial intelligence; it is becoming a critical node in the energy transition and climate action. We are working to translate 'green sustainability, ethical governance, and inclusive empowerment' from industry aspirations into measurable, operational standards for next-generation infrastructure. In doing so, we are putting into practice our mission of staying committed to original innovation and enabling AI to lead human progress.*
>
> **Dr. Xu Li**
> Chairman and Chief Executive Officer, SenseTime

Beyond data centers, SenseTime's grounded world model, Kaiwu, provides an efficient, controllable synthetic data generation method to reduce dependence on real-world data in assisted driving and embodied intelligence, lowering energy use from physical-device training and reducing real-world intervention.

Since 2022, SenseTime has completed energy-saving retrofits in its office building, reducing greenhouse gas emissions such as CO_2 by nearly 95 tons per year, and includes sustainability requirements in supplier evaluations, such as environmental management, hazardous substance control, labor rights protection, and employee training.

When AI learns to manage its own electricity use carefully, we move closer to a greener digital future.

Source: SenseTime



AI Datacenter as a Strategic Asset

Hyperscale data center growth is highly concentrated and requires major capital. Global investment is projected to reach $6.7 trillion by 2030, including about $5.2 trillion for AI-capable compute facilities. This continues to concentrate infrastructure in a small group of large firms and in markets with low-cost electricity and enough grid capacity. [23] Many hyperscale sites already use about 100 MW or more per facility. Several new projects are requesting 100 to 300 MW at the grid interconnection stage, adding significant new demand to regional power systems. [24]

USD 6.7 trillion

Global investment in hyperscale data centers by 2030

If clean generation and transmission do not expand fast enough, electricity demand from hyperscale facilities could grow faster than the decarbonized supply. This can push grids to rely more on existing fossil generation or delay plant retirements, increasing local carbon intensity and adding operational strain to power systems. [25] Increased centralization also concentrates computing capacity in a limited number of countries and firms. Where renewable buildout cannot keep up with AI-driven demand, the gap between compute growth and clean energy scaling increases pressure on host-region energy systems. [26]

Governments and utilities therefore treat AI cloud infrastructure as strategic and are intervening in energy procurement, grid expansion, and interconnection rules to manage reliability and security risks. [27] Leadership in AI computing is widely seen as a strategic asset, prompting state-backed hyperscale cloud growth in the United States, the Gulf, and East Asia. The UAE's Stargate program in Abu Dhabi is a partnership involving G42 and global leading tech firms. It plans about 5 GW of AI data centre capacity, starting with an initial phase of about 1 GW powered by nuclear, solar, and gas. The program positions AI infrastructure alongside power plants and industrial zones in national development planning. Sameer AI Shethri, Vice President of the National Industrial Development Center, indicates that AI has become a primary driver and the heartbeat of industrial competitiveness and sustainability in the Kingdom of Saudi Arabia. China is taking a similar approach through its state-coordinated "East-to-West Computing" strategy. It links extensive AI use cases in East China with data centre clusters in West China powered by large-scale wind, solar, and hydropower, integrating sustainable AI computing into long-term grid and regional planning.

Geographical, Power, and Financing Archetypes

Geography and grid design strongly affect the carbon intensity of hyperscale data centers. Zhou Yiping, Founding Director of the United Nations Office for South-South Cooperation, notes that the snowballing growth of AI energy use is driving potential conflicts between AI development objectives and sustainability, creating hidden costs for society. Recent studies find that hyperscale data centers are becoming long-term, stable "super offtakers" of electricity, tying AI infrastructure closely to regional power systems.[28]

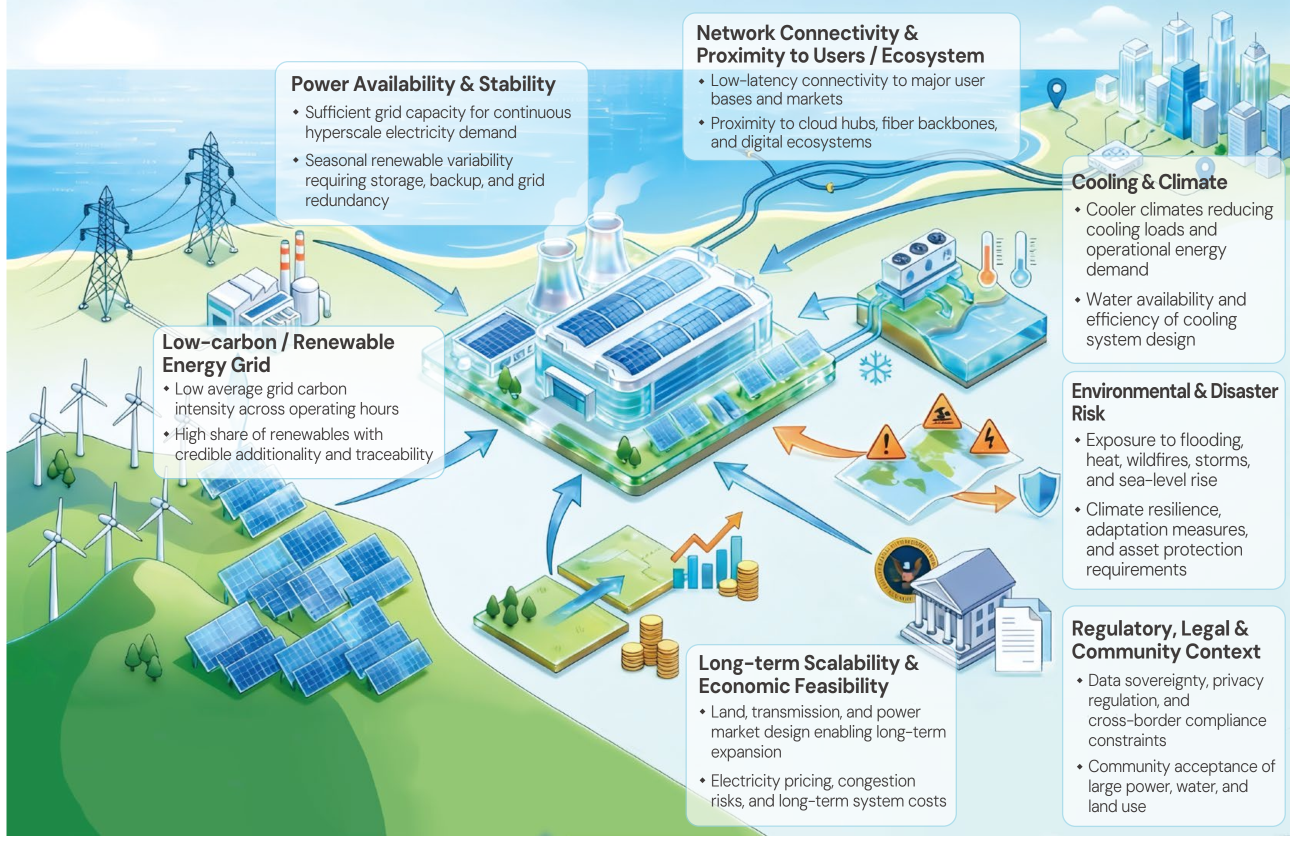
Over 60% of global hyperscale data center capacity, measured in commissioned IT power (MW), is concentrated in approximately 20 major metropolitan markets worldwide, making location a key decarbonization factor shaped by climate conditions, energy supply, climate risk, and power-market design. [29] Cooler climates reduce cooling demand, which partly explains why leading operators frequently select Nordic countries and northern North America. However, low-carbon electricity alone is insufficient. Even regions rich in hydro, wind, or solar can face pronounced seasonal variability, including winter wind fluctuations in Nordic systems or hydropower output linked to rainfall and snowmelt. As a result, energy storage, backup generation, and grid redundancy remain critical to ensuring an uninterrupted power supply.

Climate risk further constrains siting decisions. A 2025 global assessment of nearly 9,000 data centers reports widespread exposure to flooding, storms, wildfires, extreme heat, and sea-level rise. [30] Where flood protection, fire mitigation, and climate-adaptive design are inadequate, outages, repairs, and asset replacement can offset the benefits of cleaner electricity and favorable climate conditions.

Sustainability objectives also interact with regulatory and operational constraints. Multinational operators must comply with data-sovereignty regimes such as the General Data Protection Regulation (GDPR), introducing trade-offs between minimizing carbon intensity and meeting legal, latency, and business requirements. In some cases, low-carbon regions are geographically distant from major user bases, increasing latency or straining network capacity, which can be particularly limiting for latency-sensitive AI and cloud workloads.

Figure 1.3a **Hyperscale AI Center Location Factors**

Source: WeCarbon Analysis



AI date centers have a distinct electricity profile. Once built, they run at a steady, near-continuous load and can operate for decades. Their scale, scarcity, and stable demand make them attractive for renewable energy financing. For developers and lenders, long-term predictable electricity demand lowers revenue swings and demand risk, which improves project bankability and reduces the cost of capital for new renewable generation. [31] Mohammed Abdul Mujeeb Khan, Project Manager at Clean Rivers, also added that, to mitigate AI's carbon footprint, regulatory frameworks should require full-life-cycle emissions reporting for AI projects and enforce the use of renewable-powered data centers.

Peng Yucheng, Chief Executive Officer of Midas Innovation Group, notes that AI is shifting from a cost center to a responsibility center and that its carbon footprint is no longer a hidden cost. AI data centers are also becoming anchor customers for clean energy projects. These structures strengthen the case for large solar and wind projects and align digital infrastructure growth with energy system expansion. In practice, this accelerates financing and creates a feedback loop in which reliable, clean power supports AI deployment and AI demand helps expand renewable energy systems. [32]

CASE STUDY 2

Power-to-Compute at Hyperscale

Chindata Group is a leading carrier neutral hyperscale data center solutions provider and a pioneer in next generation AI-ready infrastructure across China. Guided by its mission to "Efficiently Convert Electrical Power Into Computing Power", the company plans, designs, builds and operates hyperscale data center clusters located in strategically important computing hubs, including major nodes in the Northern China region under the national "East-to-West Computing" initiative. Chindata's leadership is reflected in global recognitions such as the LEED Building Design and Construction (BD+C) Platinum certification for Huailai Headquarters Park Building One D, which is the only data center project in China to earn Platinum in the year 2025.

Chindata's coherent, infrastructure design archetype aims for increasing density, efficiency, and lifecycle performance requirements of the AI workloads, including modular construction, simplified power design, hybrid cooling and intelligent operations.

- Modular prefabrication allows the delivery of a 36 MW hyperscale project in approximately 6 months 50%-75% shorter than traditional cycles.
- Their "X-Power" system supports a high-reliability, extensive range of workloads from 12kW per rack for edge inference applications to 150kW per rack for hyperscale GPU clusters used in AI training. It achieves this through the application of 800V high voltage direct current architecture, multilevel energy storage and higher voltage grades that increase power delivery efficiency and help to alleviate power bottlenecks associated with AI cluster deployment.
- Their "X-Cooling" solutions integrates air cooling, cold plate liquid cooling and immersion liquid cooling into a unified system capable of achieving PUE levels between 1.12 and 1.14 during live operation, which is validated across diverse environments. The water-free and wastewater recovery features have saved an estimated 250,000 metric tons of freshwater and reused as much as 60% of total water in the cooling systems.

> *AI has become a powerful engine to reshape the world. Our responsibility is not only to support its growth but also to ensure that this growth is clean, efficient, and sustainable. Chindata integrates AI technologies across the full lifecycle of our businesses to continuously reduce energy consumption, lower carbon emissions, and advance long-term sustainable development.*
>
> **Nick Wang**
> President, Chindata

- Their operation & management platform, named Kunpeng, enhances these gains by analyzing thousands of real time data points and adjusting cooling load, equipment staging, and airflow patterns to maximize the use of natural cooling and reduce mechanical energy consumption.

Looking forward, Chindata continues to build a scalable and environmentally responsible pathway for high-performance computing in the AI era. Documented outcomes from their main campuses demonstrate significant improvements in energy and water efficiency, including cooling energy reductions equal to approximately 24,000,000 kWh annually and substantial enhancements in both PUE and WUE at the cluster level. These metrics confirm the effectiveness of integrating AI-driven operational intelligence with advanced engineering design.

Source: Chindata Group

Risk of Infrastructure Concentration

Hyperscale AI data centers create concentration risk in three connected areas: infrastructure resilience, privacy and data sovereignty, and reliance on a small number of firms for core economic and government functions.

Cloud infrastructure is already concentrated. The five largest technology firms control more than half of global cloud capacity, and the top three are projected to approach two-thirds within the next few years. [33,34] At the hardware layer, roughly 90 percent of advanced GPU processors come from a single firm, creating strong upstream dependence. [35] This produces vertical concentration across chips, cloud platforms, and model layers, leaving systemically important AI infrastructure controlled by very few firms. [36,37,38]

This concentration reduces operational resilience. Hyperscale platforms use tightly linked control planes and automation, so changes in security policy, traffic routing, or resource allocation can spread quickly across regions. Local configuration errors or overloads can trigger cascading outages that affect multiple sectors simultaneously, especially in high-load regions operated by dominant providers. [39,40] As AI training and inference become more centralized, these failures can act like shocks to other critical infrastructure, disrupting payments, logistics, energy dispatch, public services, and government operations. [36,41,42,43,44]

Geographic clustering increases the risk. Studies show that existing and planned data centers are concentrated in a small number of national and metropolitan hubs, many of which are exposed to flooding, storms, wildfires, earthquakes, or extreme heat. [45,46] In California, analyses indicate that median pollution-burden scores for data-center locations fall within the worst statewide quintile, with nearly one-third in the highest decile for diesel-related exposure. [47] As hyperscale AI facilities increase local electricity demand and cooling-water use, grid disruptions, water limits, or climate extremes can simultaneously impair multiple sites, increasing the risk of region-wide digital outages.

Concentration also increases privacy and data-sovereignty risk. When governments and companies rely on a small set of cross-border cloud providers, conflicts among domestic privacy rules, extraterritorial access laws, and provider security commitments become harder to manage.[48] In many countries, access to critical AI capabilities depends more on a few firms' choices about compute allocation, model governance, and infrastructure security. This can limit inclusive innovation, weaken economic sovereignty, and reduce regulatory flexibility, especially in developing economies. [36,49] As AI systems become embedded in financial, administrative, and public-service infrastructure, concentration risk becomes systemic risk, supporting calls for oversight frameworks similar to those used for other critical third-party infrastructure. [39,41,50,51,52]

AI in Climate Mitigation & Adaptation

> *Predictive asset management stands as the most significant and immediate application of AI in the energy sector. Extra investment in AI will deliver significant long-term operational savings.*
>
> **Nabil Al-Khowaiter**
> Former Chief Executive Officer, Aramco Ventures

Artificial intelligence training and climate mitigation share a key similarity. Both reach stable, efficient outcomes only with sustained, clear signals that guide optimization. In climate mitigation, incentives for decarbonization are fragmented. Signals are split across many actors, shaped by inconsistent policies, exposed to market volatility, and limited by long investment payback periods. This leaves most participants without a clear goal to optimize, and market forces alone do not reduce emissions at a socially optimal pace. Reflecting the scale of unrealized opportunity, Kristian Flyvholm, Chair & Chief Executive Officer of the Institute of Sovereign Investors, indicates that long-term investors could capture up to USD 9 trillion in value by addressing climate-related investment gaps.

AI can help by turning scattered signals into actionable optimization. By combining real-time data on supply and demand, weather and climate, asset health, and user consumption, AI can continuously improve operational decisions and make mitigation efforts more consistent and efficient. Instead of relying on fixed incentives or slow policy updates, AI supports adaptive, system-level optimization across complex energy and industrial systems.

~35%

Unplanned downtime reduced through AI-powered predictive maintenance and operational optimization

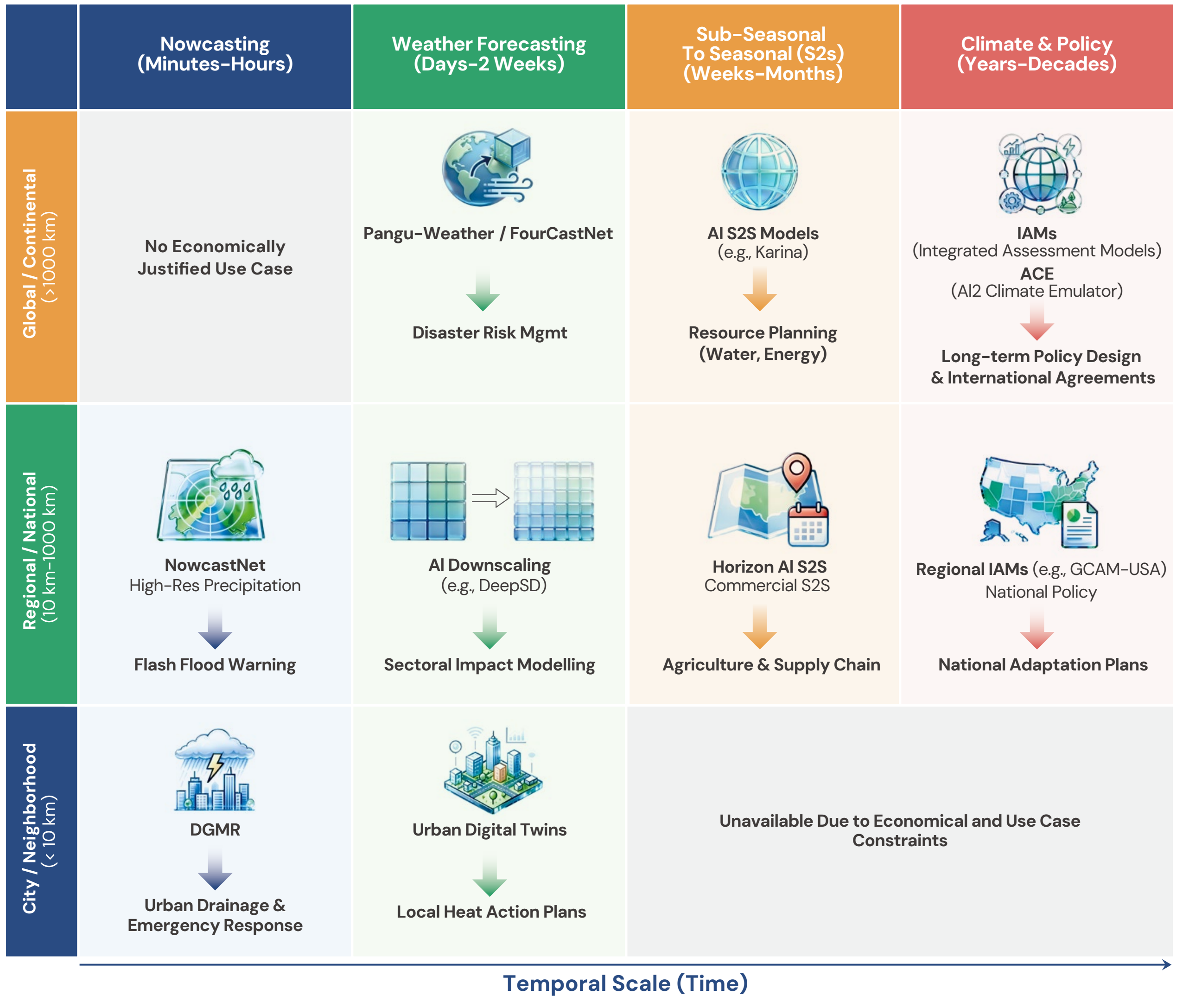
Empirical studies show in certain settings, AI in renewable energy systems, including solar, wind, and hydropower, uses predictive maintenance and real-time operational optimization to cut unplanned downtime by about 35% and raise total energy output by about 8.5%.[53] This shifts management from reactive fault response to condition-based intervention, improving reliability and asset use. More broadly, AI-enabled forecasting, smart-grid coordination, dynamic load scheduling, and data-driven maintenance create an integrated optimization framework that adapts to changing conditions and supports a more stable, efficient, low-carbon energy supply.[54,55]

Scenario Analysis and Climate Change Adaptation

Eric Chan, Chief Public Mission Officer of Cyberport, indicates that Climate AI is the fastest-growing part of the AI investment boom. He adds that climate impact should be built in during incubation, not added after scaling. By forecasting weather and climate across areas from neighborhoods to nations and timeframes from minutes to decades, AI improves policy design, land-use planning, and disaster risk management.

Figure 1.4a AI Methods for Climate-Change Adaptation across Spatiotemporal Scales

Source: WeCarbon Analysis



New transformer and deep learning weather models are improving operational forecasting and supporting adaptation planning. Pangu-Weather uses a three-dimensional "3DEST" architecture that represents the atmosphere across latitude, longitude, and pressure levels. It also uses hierarchical temporal aggregation to reduce forecast error. Benchmarks show it outperformed a leading operational numerical weather prediction system on geopotential, humidity, wind, and temperature from one hour to one week. FourCastNet produces global forecasts at 0.25° resolution. It matches numerical models on large-scale fields and often outperforms them on high-variance variables such as precipitation and surface wind. It also generates a week-long global forecast in seconds, making low-cost ensemble forecasting practical.

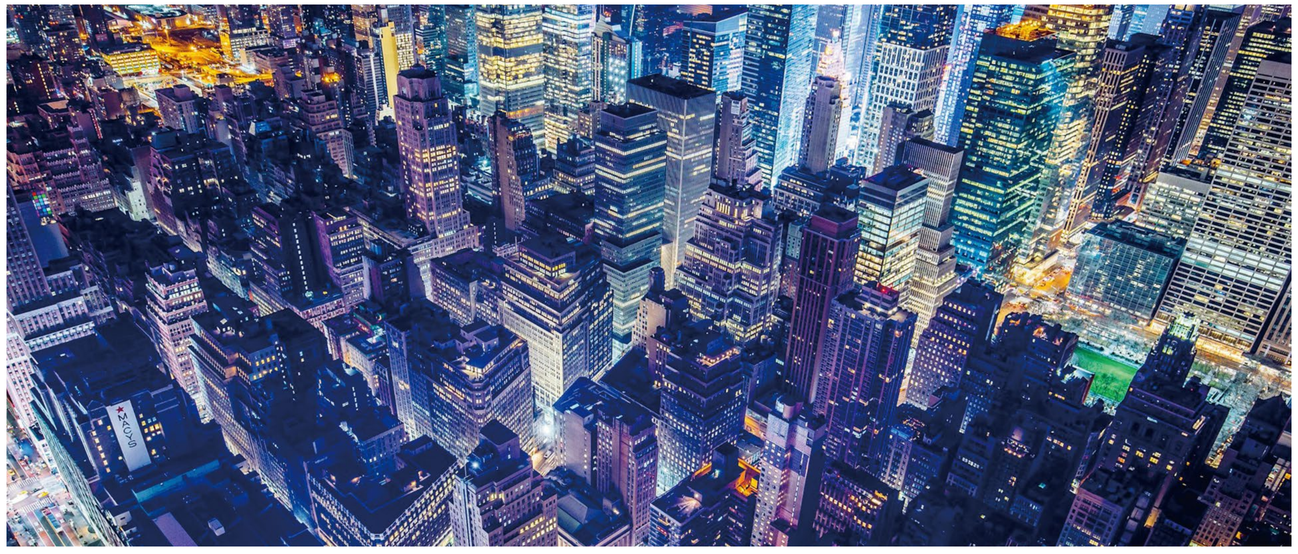
UAE and GCC countries have increasingly used AI in planning, scneario building, and comparing socioeconomic policy options.

Dr. Mohamed Bashir Kharrubi
Board Member, Abu Dhabi Investment Group

These advances deliver practical benefits. Faster, cheaper forecasts reduce reliance on supercomputers and help under-resourced national agencies, local governments, and institutions in developing regions access high-resolution global forecasts. More frequent and higher-resolution local forecasts improve water management, farm scheduling, infrastructure planning, and early warning systems.

These results are often delivered through digital twins that let decision-makers test scenarios and policy options. Guillermo M. Luz, Chairman of Liveable Cities Philippines, notes that a "digital twin" of a city can be built to test various scenarios and events during the planning stages before construction. Using AI to build scenarios may be more cost-effective than building physical infrastructure which fails to address "real-world" problems.

AI forecasting and simulation expand decision options by combining global coverage, fine spatial detail, fast inference, and scalable probabilistic outputs. This supports climate adaptation and mitigation planning. Model complexity should match decision risk and input data quality. AI forecasts and long-term projections should be used as probabilistic guidance, combined with local knowledge and flexible policy tools, and applied within multi-model, multi-scale decision frameworks. [56,57,58,59,60]



Monitoring and Forecasting

AI climate applications fall into three main areas: monitoring, forecasting, and optimizing. This section covers monitoring and forecasting, which provide the evidence base for mitigation and adaptation in energy, agriculture, land use, disaster risk management, and environmental governance.

Figure 1.4b **Monitoring, Forecasting, and Optimizing across Sectors**
Source: WeCarbon Analysis

	Monitoring	Forecasting	Optimizing
Energy	• Real-time grid asset health monitoring • Smart meter anomaly detection	• Renewable generation prediction • Grid load and peak demand forecasting	• Dynamic grid balancing and frequency regulation • Battery energy storage system charge/discharge scheduling
Transport	• Real-time vehicle emissions tracking • Traffic flow and congestion pattern recognition	• Public transit ridership volume forecasting • EV charging station demand prediction	• Autonomous driving maximize energy efficiency • Eco-routing for logistics
Industry	• Detecting defect of production lines • Monitoring energy consumption	• Demand forecasting to prevent overproduction • Predicting supply chain disruptions	• Generative design for material efficiency • Real-time tuning of furnaces/ HVAC
Agriculture	• Satellite and drone-based crop health assessment • Automated pest and disease identification	• Hyper-local weather and frost risk prediction • Crop yield estimation and harvest timing	• Precision irrigation • Targeted fertilizer and pesticide application
Forests & Oceans	• Real-time deforestation alerts • Biodiversity presence verification	• Carbon stock sequestration potential projection • Wildfire risk and spread path modeling	• Optimizing large-scale ecosystem restoration • Identifying optimal planting sites for survival rates
Urban Infrastructure	• Automated analysis energy comsumption • Real-time carbon & pollution accounting	• Extreme weather impact simulation • Long-term resource security and asset maintenance	• Dynamic utility distribution • Waste collection route optimization

Dr. Shahid Mahmud, Senior Advisor of OIC-COMSTECH, summarizes that AI will be used to rebuild human relationships with nature, better understand it, better mind it, better guard it, and better reutilize it. In monitoring, AI enables continuous tracking of Earth's vital signs across scales that were not previously possible.

According to Ivan Mozharov, Co-founder and Managing Partner of Offset8 Capital, advanced analytics can support more robust baseline assessment, permanence, and delivery risk modelling, and performance tracking across geographies and methodologies. Importantly, he has already observed a pricing premium emerging for projects in the carbon market that deploy these advanced digital MRV tools. Satellite monitoring has existed for decades, but limited staff time and computing power have meant analysis has often been infrequent and local. Recent advances in deep learning, particularly transformer-based models, can process multispectral and radar data streams continuously. This supports near-real-time detection of environmental change. Tools like Global Forest Watch's deforestation alerts combine optical and radar signals to detect vegetation disturbance and tree-cover loss across large areas much faster than manual or rule-based methods. [61,62]

AI monitoring also improves the detection of major emissions. In 2024, the CH4Net model detected methane plumes in Sentinel-2 imagery with much higher recall than non-AI baselines while keeping similar false-positive rates. It can detect emissions around 200 to 300 kg CH_4 per hour, which is relevant for point-source leaks in oil and gas infrastructure. As a result, it detected about 84% of methane plumes in testing, compared with about 24% for a state-of-the-art non-AI baseline, with similar false-positive. [63,64] This shows data-driven methods can outperform band-ratio and purely physical retrieval approaches for large-scale methane monitoring. [63,64] China developed "MAZU," a nationwide AI early warning system for disaster prevention, and donated it free to countries including Djibouti and Mongolia to improve local responses to weather-related hazards. During earthquake rescue efforts in Myanmar, a multilingual real-time translation system based on Chinese large language model technology supported international humanitarian aid by providing key information. [65,66]

While monitoring provides the diagnosis, forecasting provides the prognosis. Climate systems are nonlinear and change across timescales from hours to decades. AI can learn from large, mixed datasets and generate fast probabilistic simulations, improving forecast accuracy and detail in key areas.

A major example is Arctic sea-ice prediction. IceNet, developed by the British Antarctic Survey with The Alan Turing Institute, trained on climate-model simulations (1850 to 2100) and satellite observations (1979 to 2011) to produce probabilistic sea-ice concentration forecasts up to six months ahead. At 25 km resolution, IceNet outperforms leading physics-based seasonal systems for summer Arctic sea-ice conditions, especially for extreme events. [67,68,69] This longer lead time helps indigenous communities, shipping operators, policymakers, and adaptation planners.

More broadly, AI forecasting supports renewable-energy output prediction, wildfire and drought risk assessment, crop yield forecasting, water-resource planning, and urban management. Providing predictions from hours to decades gives decision-makers practical guidance for both short-term action and long-term adaptation.

AI-driven monitoring and forecasting are becoming core parts of climate-resilience infrastructure. They shift climate information from periodic reporting to continuous awareness and forward-looking risk assessment, supporting later optimization and intervention. [70,71]

Optimization for Efficiency and Resilience

Beyond monitoring and forecasting, optimization provides actionable insights. Tomy Lorsch, Founder and CEO of ComplexChaos, pointed out that AI's biggest climate impact won't come from predicting the future – it will come from helping humans agree on how to shape it. In many cases the gains are immediately quantifiable: lower energy consumption, higher renewable energy utilization, reduced waste, and smaller carbon footprints.

Frank Wouters, Chairman of MENA Hydrogen Alliance, noted that AI is increasingly important not only for designing optimal configurations of complex systems, but more critically for operational optimization. AI-driven optimization works best for systems that are complex, change over time, have many parameters, and can't be managed well with heuristics alone. These systems are common in modern energy grids, urban infrastructure, manufacturing, logistics, and resource management. In these settings, small inefficiencies accumulate over time and at scale, leading to significant waste or emissions. AI controllers and optimization algorithms help by continuously processing sensor data, forecasting near-term behavior, and adjusting controls in real time, handling many interacting variables faster and more accurately than human operators or rigid rule-based control.

What defines the "optimization" archetype is not the specific sector, but these shared features:

- Many interacting variables (weather, supply, demand, system loads, environmental conditions) that change in real time or near real time
- Sufficient data from sensors, historical logs, and forecasts to support adaptive algorithms
- A control interface, such as actuators, scheduling systems, infrastructure controls, or decision protocols, that AI can influence
- Efficiency and timing gains that compound over time or at scale, where small percentage improvements produce large total savings
- High-impact inefficiency areas such as cooling, heating, energy generation, material use, transport, resource distribution, and manufacturing, where optimization can cut resource use or emissions

In these contexts, AI optimization can deliver fast, measurable benefits, often sooner than major structural changes like building new infrastructure, policy shifts, or behavior change in many domains, such as wind farms, data-center cooling, industrial plants, building air conditioning, water networks, traffic flow, and waste management.

AL FOR SUSTAINABILITY LANDSCAPE

II

> "
> *Artificial intelligence does not embody the thinking of an individual, but rather humanity's collective intelligence; therefore, the ethical and governance issues arising from its application must be approached with great care.*

H.E. Jin Liqun

President and Chair of the Board of Directors, Asian Infrastructure Investment Bank

Roles by Automation Level

Level of automation describes how much initiative and independent decision-making an AI system has, from passive data monitoring to full control and governance. As AI capabilities improve, systems shift from supporting decisions to making and executing them independently within defined risk and accountability limits. Yang Ming, Board Secretary of TusStar, recognizes that AI has a dual nature: it requires robust enabling services and infrastructure, and it can reshape innovation services by redefining productivity and the relationships that underpin it.

This classification does not reflect the technical "strength" of AI models, but rather the degree of decision responsibility and initiative delegated to the system. Razann Al Ghussein from the Office of Development Affairs, UAE Presidential Court, suggests that climate resilience requires a dual approach: utilizing AI while maintaining robust traditional emergency-preparedness systems. The same underlying model – such as a forecasting or optimization model – may function merely as an Advisor in a decision-support architecture yet become an Orchestrator when embedded within a closed-loop control system. As AI roles progress from Advisor to Governor, the primary challenge shifts away from incremental gains in predictive accuracy toward governance-critical concerns, including decision explainability, clearly defined risk boundaries with robust fail-safe mechanisms, and unambiguous accountability and regulatory auditability.

The automation-level framework should be used as a decision-allocation tool, not a technology maturity ladder. Its purpose is to determine which categories of decisions can be delegated to AI systems, under what constraints, and with what residual accountability. The shift from Observer to Governor reflects an expanding decision-making initiative, not stronger models. Consequently, the binding constraint in AI-for-sustainability deployment is rarely predictive accuracy, but institutional capacity to absorb failure, assign liability, and audit decisions ex post. Contributors to this report do not recommend treating higher automation as the sole objective in AI adoption, as it introduces transition risk without guaranteeing proportional sustainability gains.

Figure 2.1a **Roles by Automation Level**

Level	Automation Level	Decision Scope	Core Function	Typical Use Cases	Human Involvement
L6	Governor	Full control	Directly executes decisions through closed-loop sensing, control, and execution	Fully automated grid dispatch, industrial process control, autonomous plants	Rule-setting, auditing, ex-post accountability
L5	Orchestrator	Bounded control	Makes decisions within predefined constraints and coordinates multiple actors and resources	Local grid balancing, port and logistics coordination, adaptive traffic control	Boundary definition, emergency override
L4	Arbiter	Exception-based	Intervenes only during conflicts, anomalies, or extreme events to resolve or override	Disaster response, financial risk interception, system safety shutdowns	Normal operations, strategic design
L3	Advisor	Recommendation	Analyzes scenarios, ranks options, and allocates resources across multiple variables	Portfolio optimization, climate risk pricing, supply-chain planning	Final decision-making
L2	Interpreter	Interpretation	Classifies, explains, and attributes observed data and phenomena	Remote sensing analysis, fault diagnosis, text interpretation	Judgment and validation
L1	Observer	Data handling	Collects, structures, and visualizes data without interpretation	Sensor aggregation, logging, monitoring dashboards	Analysis and decisions

AI Use Case Landscape by Automation Level

Figure 2.2a **AI Use Case Landscape by Automation Level**

Wide Adoption · Innovations with Limited Adoption · Pilot / PoC Only

Sector	Observer	Interpreter	Advisor	Arbiter	Orchestrator	Governor
Energy *	Grid telemetry monitoring; Load & generation metering; Ancillary service monitoring	Short-term variable renewable energy (VRE) power forecasting; Load pattern inference; Asset condition diagnosis; Grid state estimation	Unit Commitment & Economic Dispatch optimization; Reserve margin planning; Storage dispatch optimization; Curtailment minimization	Fault Location, Isolation & Service Restoration (FLISR); Rate of Change of Frequency (RoCoF) event protection; Emergency load shedding trigger	Demand Response (DR) aggregation; Virtual Power Plant (VPP) orchestration; Microgrid coordination	Centralized autonomous grid dispatch
Manufacturing & Industrial Processes *	Industrial energy logging; Process telemetry; Emissions monitoring	Asset degradation diagnosis; Yield anomaly detection; Information Technology (IT) or Operational Technology (OT) data fusion	Predictive maintenance recommendation; Process parameter optimization; Energy–carbon co-optimization via digital twins	Safety shutdown override; Graceful degradation & fallback control	Energy–production coupling orchestration; Multi-line scheduling optimization	Lights-out manufacturing
Container / Seaside Shipping *	Vessel tracking; Fuel consumption logging; Emissions monitoring; Engine sensor telemetry	AIS behavior analysis; Emission attribution; Machinery anomaly detection; Methane slip detection	Voyage & weather routing optimization; Speed & engine load optimization; Wind-assisted propulsion control advisory; Reefer energy optimization	Abnormal berthing detection; AIS–SAR inconsistency detection; Incident rerouting & safety interception	Port call coordination (bounded); Fleet-wide scheduling (operator-internal)	N/A
Landside Logistics *	Fleet tracking; Fuel & energy logging; Cold-chain sensor monitoring	Driver behavior inference; Route delay detection; Vehicle health diagnostics; Load efficiency analysis	Route & speed profile optimization; Vehicle utilization optimization; Charging & refueling strategy	Safety risk interception; Incident rerouting; Driver intervention triggers	Fleet-level dispatch coordination; Urban last-mile orchestration; Warehouse–fleet scheduling	Autonomous mobility powered by autopilot
Certification *	Test data ingestion; LIMS/MES integration; Compliance document collection	Regulatory rule parsing; Test result interpretation; Evidence–rule matching	Certification readiness assessment; Test optimization recommendation; Document automation & verification	Non-compliance flagging; Dispute escalation trigger	Test workflow orchestration; Cross-system compliance data coordination	AI as Testing Inspector / Digital Engineer
Agriculture *	Weather, soil, and crop condition monitoring; Remote sensing data collection; Farm input and yield logging	Climate hazard interpretation; Crop stress and yield inference; Pest and disease recognition; Loss attribution	Climate risk early warning; Precision input recommendation; Intervention timing advisory; Market and price intelligence	Disaster alert escalation; Crop loss verification trigger; Insurance and relief eligibility flagging	Community-scale agriculture coordination	N/A
Financial Services *	ESG & exposure data aggregation; Asset-level climate exposure mapping	Physical climate hazard inference; Transition risk signal extraction; Greenwashing signal detection	Climate-adjusted PD/LGD estimation; Climate risk pricing; Portfolio optimization under climate scenarios	Credit approval interception; Insurance underwriting override; Fraud and greenwashing enforcement	Climate risk–aware capital allocation	AI as Digital Risk / Sustainability Officer
Urban Resilience	City sensor networks; Infrastructure monitoring	Flood & heat risk mapping; Impact attribution	Emergency resource allocation advisory	Disaster response decision support	Cross-agency coordination	N/A
Carbon Market & Nature Capital	MRV data collection; Geospatial data collection	Additionality & permanence analysis; Greenwashing detection	Credit quality scoring; Price advisory	Early warning for carbon market frauds	Automated market coordination	AI as Carbon Market Regulator / Trader
Waste Management	Waste flow monitoring; Collection logging	Image-based waste classification; Contamination detection	Collection route optimization; Treatment advisory	Hazardous waste interception	AI-managed city-scale waste control	N/A

* Sectors covered in this report

Automation Levels Beyond Technology

> *The best thing about AI is that it can be effectively used in projects. AI works with a precise target, and it has a targeted approach. AI allows us to faster analyze and make faster decisions, but the decision has to be made carefully, especially when we work with ecology and the climate problems.*
>
> **Sergey Kanavskiy**
> Executive Secretary, Shanghai Cooperation Organization Business Council

Automation as a Responsibility

The automation-level classification does not describe how mature an AI technology is; rather, it indicates how much decision-making initiative and responsibility are delegated to the system. The same underlying model may operate at different automation levels depending on system architecture, institutional context, and risk tolerance. As such, the automation level should not be read as a proxy for technical readiness, but rather as a lens that highlights where non-technical constraints bind most tightly.

The framework shows that progress beyond the Observer and Interpreter levels is mainly constrained by data access, organizational capability, public acceptance, and risk governance, not algorithms. As mentioned by Jonathan E. Savoir, Chief Executive Officer of Quincus, the biggest barrier in such a context is not technical but psychological and practical, as clients resist ceding full control to non-rule-based "black box" systems. Nan Junyu, Board Director and Vice President of CHINT Electric, gave a further example that, in critical scenarios such as power grid dispatching and equipment health management, even when AI performs well, we still need to take measures on interpretability, business model validation, expert knowledge, embedding quantifiable physical models into the algorithm, and adopt "Human-in-the-loop" to keep decisions controllable and trustworthy.

In climate applications, the absence of long-term, high-quality environmental data – particularly across large parts of the Global South – imposes a hard ceiling on automation. Dr. Hosni Ghedira, Senior Advisor of ai71, acknowledged that successful AI adoption requires a holistic approach that addresses data governance, cultural acceptance, local context, political cooperation, and long-term capacity building alongside the development of the technology itself. Without continuous, spatially resolved meteorological, hydrological, and ecological datasets, AI systems cannot reliably support advisory or control functions, regardless of model sophistication. In such contexts, the automation ceiling reflects structural data constraints rather than technological immaturity.

Conversely, the framework also exposes cases where technically mature AI remains trapped at low automation levels. In agriculture, for example, models for yield estimation, pest detection, and precision input recommendation are well established, yet adoption remains uneven. Here, automation is limited by social and economic risks, not by technical capability: trust deficits, asymmetric downside risk for smallholders, and the absence of mechanisms to absorb losses when AI-guided decisions fail. The above framework highlights a critical insight for decision-makers: low automation does not imply low maturity; it often signals unresolved social and distributional constraints.

Risk as the Upper Bound of Automation

The framework further clarifies how policy urgency can push technically immature AI into high-stakes decision chains. Applications such as carbon-sink quantification or natural capital valuation remain epistemically uncertain yet are increasingly embedded in regulatory instruments and market mechanisms due to climate policy imperatives. In these cases, higher automation levels do not necessarily reflect maturity, but rather a sense of urgency. The decision implication is not to exclude such AI, but to explicitly bound its role – treating outputs as provisional, uncertainty-bearing inputs rather than decision-authoritative signals and preserving strong human judgment at the Arbiter or Advisor levels.

As automation approaches the Governor level, the limiting factor is not data or social acceptance, but risk governability. Governor-level systems can directly actuate decisions affecting critical infrastructure and public welfare, such as electricity grids, water allocation, or urban systems. At this level, the relevant question is no longer what AI can do, but whether the new risks it introduces are themselves governable – whether failure modes are foreseeable, safety envelopes are enforceable, accountability is assignable, and intervention is feasible under stress. The automation-level framework, therefore, functions as a warning system: technical feasibility without governable risk constitutes systemic fragility, not progress.

Strategic Implications for Investment and Development Pathways

From a decision-making and capital-allocation perspective, this classification separates near-term opportunities from long-term structural change. Intermediate levels, such as Advisor and Arbiter, have already seen aligned technology, governance capacity, and economic incentives for deployment and scaling. These are the best fit for private capital, corporate investment, and mission-focused venture funding with moderate risk. In contrast, applications nearing the Governor-level automation point to institutional change, not product readiness, and require regulatory mandates, public coordination, and long timelines. These markets must be treated with special understanding, reasonable adoption forecasts, and clear awareness of governance complexity.

For the Global South, the framework points to a different strategy. Many regions may need to skip lower automation stages by leveraging open-source models, shared climate data infrastructure, and international cooperation. Options include treating environmental data as a global public good, building open-access foundation models tailored to local needs, investing through multilateral channels in sensing and monitoring, and supporting South-South knowledge transfer. Skipping stages does not mean skipping governance. It requires building governance capacity alongside the technology and placing AI systems in transparent, auditable, and cooperative institutions from the start.

FOCUS SECTOR DEEP-DIVE

III

© Windwoven Grid Cartography of the Gale, Jin Hailiang, Finalist of 2025 Climate and Sustainability Photography Awards

> *From a national strategic perspective, AI can support data-driven decision-making across upstream, mid-stream, and downstream operations by improving resource planning, forecasting demand, optimising infra-structure utilisation, and reducing operational losses.*

Rt. Hon. Dr. Ekperikpe Ekpo
Honourable Minister of State, Petroleum Resources (Gas), Nigeria

> “
> *All sectors in Saudi Arabia, we're always using artificial intelligence technology – especially environmentally, in water processing, and also in agriculture.*
>
> **H.R.H. Prince Khalid bin Saud bin Khalid Turki Al Saud**
> General Advisor, Saudi Arabia General Authority of Meteorology and Environmental Protection

Energy & Manufacturing

Optimization for Variable Renewable Energy

> “
> *AI-powered predictive dispatch on the supply side can reduce wasted wind and solar power and improve coordination between distributed resources such as solar PV and energy storage and the main power grid. On the demand side, AI can identify energy saving opportunities in industrial and other settings and speed up the shift to lower carbon energy use. Deeper integration of AI with energy management systems can deliver three benefits for companies: accurately identifying energy efficiency bottlenecks, intelligently optimizing resource allocation, and reducing energy costs and total carbon emissions.*
>
> **Yin Zheng**
> Executive Vice President of China and East Asia operations, Schneider Electric

48%
Cost increases due to backup capacity in the UK

The rapid rollout of VRE sources such as solar and wind can create significant grid stability challenges, especially when VRE exceeds 15% of total generation. To keep the system reliable and balanced in real time, grid operators need backup capacity, often from fossil-fueled peaker plants or hydropower, to provide ancillary services such as frequency regulation. This backup is often inefficient. Peaker plants, for example, may be used less than 10% of the time, running only a few hundred hours per year while producing relatively high emissions when operating. Dr. Li Zheng, President of the Institute of Climate Change and Sustainable Development at Tsinghua University, highlights that coal power and new energy will not be in a long-term either-or replacement relationship in the future, but need to work together. After the transition, coal power's role shifts from a primary source to one of flexible and reliable support.

Maintaining this rarely used infrastructure is expensive, and balancing cost increases in regions with high VRE penetration. In the UK, these costs rose by 48% in 2021. At 20% wind penetration, operating costs can increase by 1 to 4 euros per MWh of wind generation. The issue is compounded by limited visibility into consumption patterns. This forces utilities to dispatch generation reactively rather than use proactive, detailed demand-side management, which can improve efficiency and stability. [72,73]

Figure 3.1a **Electric Grids under Different VRE Levels**

Low VRE (<10%)	Medium VRE (10% - 30%)	High VRE (>30%)
• Aggregate impact on the power grid is negligible • Stability challenges being localized and manageable through minor operational adjustments or simple modifications to existing assets • Any disturbances, such as minor voltage fluctuations at the distribution level from residential solar installations, are generally contained and do not propagate to compromise the stability of the wider transmission system	• Inherent variability and partial predictability begin to exert a substantial influence on system-wide stability, necessitating more frequent dispatch of conventional generators to balance supply and demand • Increased operational tempo drives a higher demand for ancillary services, particularly for frequency regulation and the maintenance of reserve capacity to buffer against sudden changes in VRE output • High concentrations of distributed VRE, such as rooftop solar, can induce localized voltage fluctuations within distribution networks, compelling more sophisticated and precise voltage control mechanisms to maintain power quality	• The displacement of traditional synchronous generators by inverter-based VRE resources precipitates a critical decline in overall system inertia – the stored kinetic energy in rotating machinery that naturally dampens frequency deviations • A sudden disturbance, like a generator trip, can trigger a more rapid and severe drop in grid frequency (a high rate of change of frequency, or RoCoF), significantly elevating the risk of cascading failures and widespread blackouts • The diminished resilience to frequency excursions creates an urgent demand for rapid-response services and synthetic inertia, driving the deployment of advanced technologies such as battery energy storage systems, synchronous condensers, and grid-forming inverters, which can electronically mimic the stabilizing inertial response of traditional generators to ensure grid security

18%-20%
Suggested PRM targets for high levels of VRE

Managing VRE's connection to the grid is critical. When output is high, generation can exceed the grid's ability to absorb or transmit power. This can force curtailment, where operators intentionally reduce output to avoid instability. In some regions with high VRE, curtailment can waste more than 10% of available renewable generation. To keep the system reliable despite VRE variability, grid planners set a Planning Reserve Margin (PRM). PRM is a probabilistic buffer, often estimated using Loss of Load Expectation models, that reflects VRE's lower capacity value. For example, solar power's effective load-carrying capability (ELCC) can drop to 6% during evening peak demand, requiring substantial backup capacity. Recent studies of power systems moving toward high levels of VRE and storage suggest raising PRM targets to approximately 18%-20% to reflect changing risks and ensure sufficient resources are available.[74]

This structural demand for backup and ancillary services has historically been met by dispatchable generation, primarily simple-cycle gas turbines (SCGT), which, despite their rapid start-up times, operate at exceedingly low-capacity factors, often below 10%, and function as inefficient, high-cost "peaker plants" as a reliability insurance. Other measures are increasingly used but still in limited scope, such as long-duration energy storage (LDIR), industrial DR, due to higher system complexity and coordination cost. Furthermore, the displacement of synchronous generators by VREs drastically reduces system inertia, amplifying the grid's vulnerability to high RoCoF events and increasing blackout risk, necessitating the deployment of advanced grid-forming inverters capable of providing synthetic inertia and fast frequency response. The cumulative economic burden of these measures, encompassing curtailment losses, the capital and operational costs of underutilized reserve capacity, and the procurement of advanced ancillary services, constitutes the "system integration costs," a significant and growing financial challenge for renewable energy deployments.

The challenge of integrating VRE entails a fundamental divide in power grid operational philosophy, creating a spectrum bounded by two polar-opposite paradigms: the pursuit of absolute resilience through prophylactic redundancy at one end, and hyper-efficiency through dynamic optimization at the other. The position a grid occupies along this spectrum is governed by a complex calculus of regional climate risk, energy portfolio composition, and economic constraints.

Figure 3.1b **Poles of VRE Optimization Objectives**

Objective	Resilience-Priority	Efficiency-Priority
Mitigation Strategy	Prophylactic fortification through extensive physical redundancy, including substantial spinning and non-spinning reserves and parallel infrastructure (e.g., transmission lines, substations), to ensure N-1 security and absorb acute generation-load imbalances.	Dynamic optimization via a cyber-physical framework, leveraging high-fidelity AI-driven forecasting for predictive dispatch (Unit Commitment/Economic Dispatch) and market-based coordination of demand-side resources through mechanisms like real-time pricing and VPP aggregation; this substitutes temporal balancing with spatial smoothing achieved through large-scale interconnections ("supergrids") that exploit geographical and meteorological diversity.
Consequence	Substantial capital and operational expenditures from maintaining underutilized redundant assets and spinning reserves, coupled with elevated curtailment of available VRE as grid stability margins often take precedence over maximizing renewable energy absorption.	Inherent systemic fragility stemming from an acute dependency on the fidelity of stochastic forecasting models and the integrity of pervasive communication networks; the system is thus acutely vulnerable to high-impact, low-probability ("black swan") events, where forecast errors or network disruptions can trigger catastrophic, system-wide cascading failures in a grid stripped of traditional physical buffers.

Any objective should be based on reliable data. Peng Peng, Secretary General of China New Energy Investment and Finance Alliance, notes that forecasting models trained solely on historical data struggle to systematically address wind and solar curtailment caused by extreme climate events. The expert indicates that this makes data that can be used to infer energy use especially valuable, such as data related to production, charging, and discharging.

Algorithms matter as much as data. Dr. Wang Xin, Director of CGN Europe Industrial Innovation Company, predicts that as wind and solar capacity grows, power grids will require more upgrades to support sustained demand for battery energy storage. Grid flexibility and related trading require advanced algorithms, making AI well-suited for flexibility services and grid dispatch and management. AI can reduce the need for labor-intensive human oversight, improving efficiency and resilience. Alexander Kormishin, Chairperson of the BRICS Youth Energy Agency, has observed that AI's most immediate contribution is to automate routine monitoring, dispatch, and anomaly detection, freeing up limited staff time and budgets for innovation and further digital transformation.

At the same time, real-world deployment remains in its early stages. As Prof. Travis Bradford, Founder and President of the Prometheus Institute for Sustainable Development, explains, AI in today's energy systems primarily serves to "make the curves look smoother" by reducing forecast errors, limiting volatility, and optimizing day-to-day performance. As a result, the current impact is mostly incremental and focused on specific tasks rather than full-system autonomy.

The application of artificial intelligence in grid optimization is achieving transformative accuracy across these critical domains:

Figure 3.1c **AI Use Cases in Energy & Manufacturing**

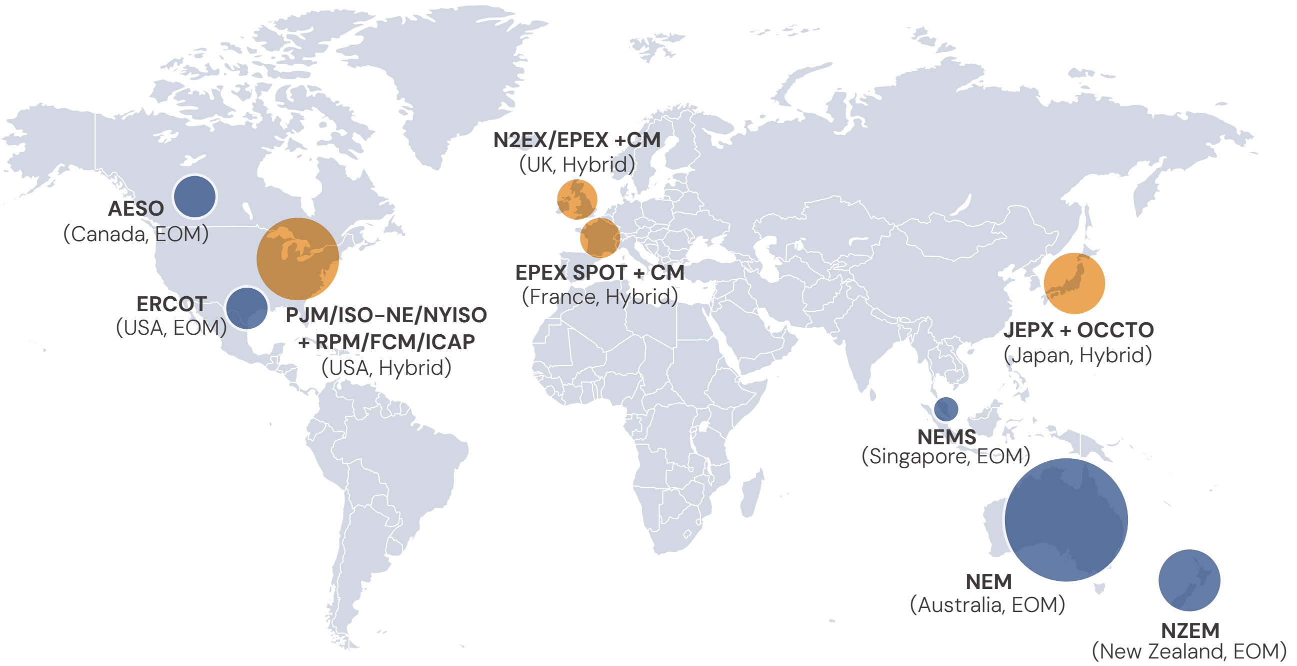
Domain	Use Case	Technology	Value Benchmark	Role of AI
Planning & Generation	VRE Power Forecasting: High-fidelity, short-term prediction of solar and wind output	Deep Learning: Time-series models (e.g., LSTM, Transformers) trained on meteorological, satellite, and historical generation data	Reduction in Mean Absolute/Root Mean Square Error (MAE/RMSE) over traditional statistical methods	Interpreter
	Unit Commitment/Economic Dispatch (UC/ED): Co-optimization of generation assets balancing fuel cost, emissions, and VRE stochasticity	Reinforcement Learning (RL) & Heuristic Optimization	Reduction in total system operating/adaptation costs	Advisor Orchestrator
	Energy Storage Optimization: Optimal charge/discharge scheduling for arbitrage and ancillary service provision	Stochastic Optimization & RL	Increase in revenue from arbitrage and grid services compared to simple rule-based control	Advisor Orchestrator
Transmission & Distribution (T&D)	Predictive Asset Maintenance: Proactive identification of incipient failures in insulators, conductors, and substation equipment	Computer Vision & Sensor Fusion: YOLO/CNN models analyzing drone-captured visual, thermal (IR), and LiDAR data streams	Reduction in maintenance costs and unplanned outages	Advisor
	Power Flow & Security Analysis: Real-time prediction of grid congestion and voltage violations to prevent cascading failures	Graph Neural Networks (GNNs) & Physics-Informed ML: Models that learn grid topology and physics to forecast power flows under contingencies	Reduction in redispatch costs and improved lead-time for corrective actions	Advisor Arbiter
	FLISR: Millisecond-level fault isolation and network reconfiguration to minimize outage duration	RL & Heuristic Search: Algorithms determining optimal switching sequences to restore power to non-faulted grid sections	Reduction in customer interruption indices	Arbiter
Demand - Infrastructure	DR & VPP Orchestration: Aggregation and control of distributed flexible loads (e.g., HVAC, industrial machinery)	Multi-Agent RL (MARL) & Distributed Control: A central "brain" coordinating thousands of IoT-enabled assets as a single dispatchable entity	Peak load reduction; provides MW-scale capacity for ancillary service markets	Orchestrator
	Energy & Carbon Co-optimization: Minimization of energy cost and carbon footprint for facilities (e.g., data centers) via digital twins	Reinforcement Learning & Digital Twin Simulation: AI agents controlling dynamic systems (e.g., cooling, server loads) within a physics-based simulation	Reduces data center PUE; substantial reduction in energy expenditure	Interpreter Advisor
Demand - Mobility	Vehicle-to-Grid (V2G/V1G) Aggregation: Orchestration of EV fleets as virtual batteries for grid services and optimized charging	Reinforcement Learning & Predictive Analytics: AI platform forecasting driving behavior and optimizing charging/discharging against market signals	Reduces EV charging costs; enables fleet participation in lucrative frequency regulation markets	Orchestrator

Integration Cost Market Distribution

Beyond algorithmic optimization, the design of electricity markets is a decisive force in allocating the integration costs required for grid resilience. In an "energy-only market" (EOM), where generators are remunerated solely for the energy they produce (MWh), there is no financial incentive to maintain costly, infrequently used capacity (MW) for future reliability, thereby systematically discouraging investment in low-frequency, high-impact events. While this model was once considered robust, operating on the free-market principle that price spikes during scarcity would naturally fund new capacity, the ascendancy of zero-marginal-cost renewables has systematically suppressed these critical price signals.

This creates an unsustainable paradox: the structural need for dispatchable backup capacity rises to offset VRE, yet the market revenue to support it evaporates, a situation compounded by the advent of large-scale storage, which invalidates the market's foundational premise of non-storability. The Electric Reliability Council of Texas (ERCOT), America's largest EOM, serves as a cautionary exemplar of this market inefficiency. Having chronically operated with dangerously low reserve margins (often below 13%), its vulnerability was catastrophically exposed during the 2021 Winter Storm Uri, when a highly coupled failure between un-weatherized natural gas infrastructure and power generators, a systemic risk unpriced and unmitigated by the EOM, precipitated a multi-day, statewide blackout.

Figure 3.1d **Global Electricity Market: EOM vs. Capacity**



Energy-Only Market (EOM)
Hybrid Market (Energy Market + Capacity Mechanism)

In response to these systemic vulnerabilities, a global policy pivot away from pure EOMs is underway, with many grid operators now implementing Capacity Markets or other hybrid structures that explicitly remunerate dispatchable resources for their availability. In these markets, providers are paid not only for generating energy but also for their commitment to be available to generate power in the future, creating a direct revenue stream for reliability. Beyond the binary of energy and capacity, a more granular suite of market products has emerged, including Ancillary Services such as frequency regulation, voltage control, and black-start capability, which are essential for grid stability in a low-inertia environment.

Even jurisdictions historically committed to the EOM model are now conceding to its limitations. Japan, for instance, which liberalized its electricity market starting in 2016, initially operated without a long-term mechanism to ensure resource adequacy. Faced with rising concerns over generator retirements and thinning reserve margins amidst its renewable expansion, the country introduced its first nationwide capacity market, holding its inaugural auction in 2020 to secure capacity four years in advance. This transition reflects a broader recognition that market design must co-evolve with the physical grid.

This programmatic shift towards market-based remuneration for grid services has, in turn, catalyzed a burgeoning ecosystem of AI-driven trading solutions designed to capitalize on price volatility, a rapidly expanding market segment. These systems deploy algorithms analogous to those used in high-frequency quantitative finance, which ingest vast, heterogeneous datasets – ranging from granular meteorological forecasts to real-time grid load information – to execute automated trading strategies. Crucially, the persistent competitive alpha in this domain is rarely derived from the proprietary nature of the trading algorithms themselves, which are often replicable, but rather from the superior acquisition and inferential analysis of high-resolution, often exclusive, load and grid constraint data, enabling a more nuanced prediction of localized supply-demand imbalances than can be achieved by competitors.

Looking forward, the evolution of electricity markets is poised to accelerate towards even more sophisticated, multi-layered designs. Future frameworks will likely integrate Flexibility Markets that value the speed and ramp-rate of a resource's response, and highly localized, distribution-level markets for non-wire alternatives. The conceptual frontier is Transactive Energy, a peer-to-peer framework where millions of distributed energy resources (DERs) – from electric vehicles and smart appliances to rooftop solar – can autonomously bid their services into a dynamic, integrated marketplace, thereby orchestrating a resilient and efficient grid from the bottom up.

Next-generation Electricity Grid Building

Nick Mabey, Chief Executive Officer of E3G, indicates that a key open question is whether AI will make the energy system more centralized or more decentralized. The design of a future AI-powered grid is not determined by technology alone. Instead, it depends on each country's context and a trade-off between two governance approaches: state-led, centralized models that use strong decarbonization mandates to speed up deployment but reduce operational flexibility, and decentralized, market-driven models that support innovation but can lead to underinvestment in long-term reliability unless capacity mechanisms are carefully designed. Muhammad Mustafa Amjad, Program Director of Renewable First, believes that future systems may price infrastructure rather than the energy commodity itself, and that AI and machine learning are essential for aligning supply and demand.

Figure 3.1e **Electricity Grid Archetypes**

Centralized China, France	**Market-driven** USA, Germany, Australia	**Hybrid / Transitional** India, Nigeria
Centralized power systems use top-down planning and dispatch by a national or regional operator. With AI, this can become a centralized "super-brain" where one authority aggregates real time data across generation, storage, grids, and loads, then optimizes system operation. Peng Peng, Secretary General of China New Energy Investment and Finance Alliance, highlights that China's power system has extremely high safety requirements and is currently adopting a steady strategy of taking small but fast steps. In the short term, it will still mainly rely on centralized human supervision to ensure stable and reliable grid operation. This model improves coordination but amplifies a data Matthew effect. Incumbent operators hold decades of proprietary operating data, enabling more accurate AI forecasting and dispatch. The advantage compounds, raising barriers for smaller firms and distributed energy players.	Market-driven power systems are organized around multiple Independent System Operators (ISOs) or Regional Transmission Organizations (RTOs), which coordinate generation and demand through competitive market mechanisms rather than centralized command. In an AI-enabled evolution of this model, the grid increasingly resembles a network of semi-autonomous microgrids – such as communities, campuses, or industrial parks – each capable of local balancing. Within each microgrid, AI optimizes generation, storage, and demand in near real time. Coordination with neighboring microgrids occurs through price signals and market-based energy exchanges rather than centralized directives. This distributed intelligence architecture reduces reliance on a single control center, lowers systemic concentration risk, and enables smaller actors to participate on more equal footing. However, it also places greater demands on interoperability standards, real-time market design, and localized forecasting accuracy to maintain system stability.	Hybrid or transitional systems occupy an intermediate state between centralized command and fully market-driven operation. These systems often retain strong central planning functions while gradually introducing market mechanisms, distributed generation, and localized control. In practice, AI deployment in such systems is uneven: centralized optimization may coexist with emerging microgrids and regional markets. This creates both opportunities and risks. On one hand, AI can accelerate grid modernization by improving forecasting, reducing losses, and integrating variable renewables. On the other, fragmented governance and uneven data access can exacerbate coordination challenges and slow institutional adaptation. The long-term trajectory of these systems depends on how effectively regulatory frameworks, data-sharing mechanisms, and market rules evolve alongside AI capabilities.

In regions of the Global South with profound grid infrastructure deficits, decentralized microgrids have become the most expedient and economically viable solution to alleviate energy poverty, effectively leapfrogging centralized grid expansion. One significant example is the "Pay-As-You-Go" (PAYG) model, an innovative asset-financing mechanism that promotes access to clean energy by amortizing the initial capital expenditure of a Solar Home System (SHS) into micro-payments.

Figure 3.1f **Pay-As-You-Go Financing Process in Africa**

Installation	Micro-Payments	Risk Control
The consumer pays a nominal initial deposit (e.g., $25-30) to receive an SHS unit, which typically includes a solar panel, battery, LED lighting, and a mobile phone charging port.	The user then makes regular micro-payments, often priced at parity with their previous daily expenditure on kerosene, via M-Pesa or other mobile money to purchase ongoing access to electricity.	• Each SHS is embedded with an IoT module that communicates with the provider's central cloud platform. • Upon receipt of payment, the system is remotely activated; in the event of non-payment, the system is remotely deactivated. • This digital collateralization effectively mitigates default risk in unbanked populations that lack formal credit histories, making the extension of asset financing scalable and commercially sustainable.

The limits of purely centralized or decentralized grid architectures show the need to move toward a hybrid, hierarchical model. The future power grid should combine centralized cloud intelligence with distributed edge computing in a cloud-to-edge system. This approach builds resilient, shared intelligence where each layer handles specific tasks. Sonia Dunlop, Chief Executive Officer of the Global Solar Council, highlights that AI can enable aggregation of small assets into VPPs, allowing decentralized producers to access markets, which is central to scaling solar and battery integration, improving grid efficiency and reliability.

The cloud layer acts as the system's "central brain." In its governor role, it handles large-scale, compute-heavy optimisation tasks such as transcontinental energy trading, stochastic reserve planning, and system-wide weather forecasting. Dr. Lü Xuedu, former Deputy Director-General of China's National Climate Center, notes that AI can accurately predict power supply and enable grid peak shaving and demand-side regulation, thereby improving the efficiency of renewable energy utilization.

The edge layer embeds intelligence near the physical assets, executing time-critical functions that are computationally or geographically infeasible for the central cloud. Its primary roles include:

- **Sub-second Control** Orchestrator
  Executing latency-critical tasks, such as the fast frequency response of grid-forming inverters and protective relaying, operating on timescales inaccessible to the cloud.
- **Localized Prediction & Autonomy** Orchestrator Advisor
  Performing high-frequency, localized load and generation forecasting to enable autonomous control of discrete systems.
- **Resilience Through Disconnected Operation** Arbiter
  Crucially, the edge provides profound fault tolerance by maintaining autonomous local control during communication disruptions with the central cloud, thereby embedding resilience directly at the grid's periphery.

IT/OT Fusion: Pavestone for AI in Manufacturing

The foundation of manufacturing intelligence is breaking down the long-standing barrier between Information Technology (IT) and Operational Technology (OT). IT manages business systems like ERP, cloud platforms, and business logic. OT runs physical operations using PLCs, SCADA, and field devices. This split is built into industrial design and reflects a focus on predictable performance, stability, and physical separation. AI pushes IT and OT to merge. To deliver useful insights, AI must combine enterprise data with real-time sensor data and turn predictions into physical actions. This shift changes what industrial systems can do and introduces new risks.

A typical integrated IT and OT data architecture works like this. On the shop floor, PLCs, sensors, and actuators continuously collect high-frequency operational data through Industrial Internet of Things infrastructure. At the network and edge layers, edge gateways preprocess data and run real-time analytics near the source to enable millisecond responsiveness and reduce latency and bandwidth consumption. At the platform and application layers in IT and the cloud, protocols such as OPC UA support semantic interoperability across devices, while messaging protocols such as MQTT enable scalable data transmission to the cloud. In the cloud, AI models analyze data across the system to support predictive maintenance, production optimization, and supply chain orchestration. According to Johnson Chng, Asia Chairman of VenCap, AI can reduce energy consumption by 12% in industrial settings without adding new hardware; adding IoT sensors can increase savings to 20%.

Dr. Tyne Lin, CPO of Annto Logistics under Midea Group, highlights that linking operations directly to the sales and marketing system, called "production-sales integration", can cut unnecessary storage and transfers. The main barrier to adopting AI in manufacturing is organizational, not technical. Manufacturing is cautious because of how OT systems are built. Linking modern AI platforms from IT to legacy industrial control systems reveals interoperability gaps and introduces new risks. Combining IT and OT removes the separation that has long protected industrial operations. Evidence shows how serious this is, as up to 74% of incidents affecting critical infrastructure come from breaches in enterprise IT systems. Recent repeated incidents show this clearly. Attackers did not access OT networks directly, but disrupting IT systems alone was enough to stop physical operations. In AI-enabled manufacturing, this imbalance becomes even more important.

AI further expands the attack surface through its intrinsic opacity. Many industrial AI systems, particularly those based on deep learning, operate as "black boxes," with decision logic that is difficult to interpret or formally verify. This opacity enables novel attack vectors. In adversarial attacks, imperceptible perturbations to input data – such as sensor readings or images from visual inspection – can induce catastrophic misclassification, allowing defective products to pass quality control. In data poisoning attacks, malicious samples injected during training embed latent backdoors, enabling attacker-defined behavior when specific triggers arise in production. Between 2024 and 2025, reported incidents involving model theft, poisoning, and manipulation increased by approximately 180%, underscoring the rapid escalation of AI-specific threats.

Beyond malicious interference, industrial AI introduces a subtler but equally profound challenge: dynamic safety. Unlike conventional control logic, AI systems – particularly those employing adaptive optimization or online learning – do not remain behaviorally static. Their decision boundaries evolve over time, creating the risk of drift. Data drift arises when changes in raw materials, equipment conditions, or environmental factors alter the statistical properties of inputs relative to training data, degrading model reliability. Concept drift is more insidious: the underlying relationship between inputs and outcomes itself changes, as in chemical processes where catalyst degradation alters reaction behavior. Unchecked, such drift can push systems toward inefficient or unsafe operating regimes without any external attack.

180%

Increase in AI-specific cybersecurity threats in industrial scenario between 2024 and 2025

These risks are compounded by the objective functions typically assigned to AI systems. Models optimized for short-term throughput or energy efficiency may sacrifice long-term asset integrity, accelerate equipment fatigue, or erode safety margins. Such behavior is locally rational but globally unsafe, revealing a misalignment between algorithmic optimization and system-level resilience.

The challenge is compounded by the incompatibility between traditional DevOps practices and manufacturing realities. Testing AI models on live, high-value production lines is often infeasible. The solution lies in high-fidelity simulation platforms and digital twins, which serve as essential sandboxes for training, validating, and stress-testing AI models under a wide range of scenarios. These virtual environments enable systematic exploration of failure modes without risking physical assets or production continuity.

A successful transition, therefore, begins not with deployment, but with governance. Effective AI integration in manufacturing requires an integrated risk-management function spanning IT, OT, data science, legal, and compliance domains, guided by proactive frameworks. The first mandate of such a team is to classify system functions by criticality, rigorously distinguishing essential production pathways from auxiliary or non-critical features. This prioritization underpins architectures designed for graceful degradation under stress, ensuring that AI-enabled manufacturing systems fail safely rather than catastrophically.

CASE STUDY 3 | AI-Enabled Sustainable Manufacturing

As a global provider of intelligent energy system solutions, CHINT Group draws on more than four decades of manufacturing experience to embed digitalization, intelligence, and decarbonization across the entire production lifecycle. Through the integration of industrial internet platforms, big-data infrastructure, and AI technologies, CHINT has developed replicable zero-carbon factory and industrial-park models that improve total factor productivity while supporting high-quality industrial upgrading.

- **AI-based In-line Quality Control**
  CHINT has deployed adaptive AI vision inspection across low-voltage electrical equipment, smart meters, and photovoltaic module lines. The systems continuously learn defect patterns from production data, achieving >98% detection accuracy and 100% online inspection at critical steps. Manual inspection labor was reduced by ~75%, effective capacity increased by 115.4%, and outgoing quality variability was significantly reduced, establishing an industrial-scale zero-defect control baseline.

- **AI-driven Flexible Production Systems**
  In its electrical equipment future factory, AI-coordinated robotic welding, assembly, and material handling enable high-mix, low-volume manufacturing. On the miniature circuit breaker line, fully automated production reaches a cycle time of 1.2 seconds per unit. Compared with conventional workshops, operating costs fell by 43%, production efficiency increased by 335%, and product development cycles shortened by 22%.

- **Digital-twin Optimization of Energy and Production Coupling**
  At the CHINT metering industrial park, a digital twin integrating generation, grid, load, and storage uses real-time data from 1,681 sensors and dual-mode HPLC-Bluetooth communication. The system dynamically allocates production to lower-energy-intensity lines (>70% of output), optimizes photovoltaic generation, storage dispatch, and off-peak electricity use, delivering 8,500 kWh in electricity savings and an 8.47 tCO_2 reduction.

- **End-to-end Industrial Internet Integration**
  Through a proprietary cloud platform under a "one cloud, two networks" architecture, shop-floor equipment is connected to enterprise systems for real-time data ingestion and analysis. Production schedules are dynamically adjusted based on order inflow, enabling coordinated multi-line operation and direct integration with CRM and energy management systems, shortening delivery cycles and improving order fulfillment reliability.

> *We recognize that AI itself is an energy-intensive technology, and that making AI green is a prerequisite for achieving sustainable development.*
>
> **Nan Junyu**
> Board Director and Vice President, CHINT Electric

By positioning AI as a foundational production capability rather than a peripheral tool, CHINT has established an integrated "AI-enabled manufacturing" model that simultaneously advances efficiency, flexibility, and decarbonization. Driven by both digital transformation and dual-carbon objectives, the company continues to demonstrate how AI can underpin scalable, zero-carbon manufacturing pathways for the broader industrial sector.

Source: CHINT

Safe and Responsible AI Transitions in Industries

While AI-driven optimization promises substantial gains in efficiency and sustainability across manufacturing – from energy management and digital twins to predictive control and operational orchestration – the central challenge lies not in the envisioned end state, but in the transition itself. It is during this pathway that tightly coupled technological opportunities and systemic risks co-emerge. Manufacturing systems, characterized by extreme dependence on production continuity and high capital intensity, exhibit greater structural conservatism toward AI adoption than the energy sector. In this context, legacy reactive governance and risk-control mechanisms are no longer adequate to manage the non-linear risks introduced by AI, including cascading downtime, latent quality deviations, and ambiguous returns on investment. Leadership is therefore compelled to confront a deeper question – not whether to upgrade, but whether it is safe to do so. Enabling a secure, resilient, and sustainable AI transition in manufacturing demands a fundamental reconfiguration of governance frameworks, system architectures, and operational safety models, shifting risk management from ex post mitigation to ex ante design.

An underestimated barrier to industrial AI adoption lies in the incomplete interoperability between modern IT stacks and legacy industrial control protocols, including IEC 61850, OPC UA, and proprietary fieldbus systems. This gap makes safety and reliability not an auxiliary concern but a foundational design constraint, governed by a non-negotiable principle: keep things running and never break them.

At the core of industrial AI safety lies the doctrine of graceful degradation. Rather than preventing outright failure, systems must be engineered to fail safely. When AI components malfunction, drift beyond acceptable bounds, or lose network connectivity, control must automatically and seamlessly revert to deterministic logic executed locally by programmable logic controllers (PLCs) or distributed control systems (DCSs), thereby preserving both production continuity and physical safety.

Operationalizing graceful degradation requires a deliberate separation between intelligence and control. AI must function as an advisor, not a sovereign decision-maker. This is achieved through a layered control architecture. At Level 1, PLCs and DCSs enforce hard-coded, deterministic safety and control logic. Level 2, comprising SCADA and human–machine interfaces, provides system visibility and operator interaction. Level 3 hosts AI-based decision and optimization engines, which generate recommendations and optimized setpoints without direct authority over actuation. In this "AI-as-supervisor" model, AI proposes, but deterministic control executes.

System integrity is maintained through continuous heartbeat and health-monitoring mechanisms, whereby PLCs or DCSs verify the availability, latency, and validity of AI outputs. Any anomaly – whether network interruption, stale inference, or statistically aberrant recommendations – triggers an immediate fallback. Crucially, this reversion must be bumpless: control transitions smoothly from AI-assisted operation to predefined safe control states using the last validated setpoint, avoiding abrupt disturbances that could damage equipment or destabilize processes.

To address the combined risks of model opacity and behavioral drift, decent degradation must be reinforced by two further design principles. First, a Human-on-the-Loop (HOL) operating model is essential for safety-critical manufacturing. Operators continuously supervise AI recommendations, retain immediate veto authority, and intervene whenever outputs conflict with operational judgment. Human decisions are not merely overrides; they form a feedback loop that informs subsequent model refinement. This represents a deliberate shift away from Human-in-Command paradigms, recognizing that accountability, rather than autonomy, is the governing requirement in industrial environments.

Second, AI systems must be constrained by immutable safety envelopes embedded directly within PLC or DCS logic. These hard limits – on temperature, pressure, speed, or chemical composition – are non-negotiable and inaccessible to AI modification. Regardless of model behavior or optimization objectives, any command that violates these boundaries is rejected at the control layer, providing a final, deterministic line of defense against both adversarial manipulation and endogenous drift.

This architectural pathway is critical for three reasons. It establishes operator trust by guaranteeing that, in the worst case, AI failure returns the system to familiar, validated control modes. It safeguards production continuity by preventing AI-induced faults from cascading into full-line shutdowns. Last but not least, it creates a protected operational environment where AI systems can be updated, retrained, or replaced without interrupting live production. In industrial manufacturing, resilience is not achieved by eliminating failure, but by engineering systems that absorb it without catastrophe.

Shipping & Logistics

Global Governance on Seaside Decarbonization

The shipping and logistics industry is facing two pressures related to decarbonization. A significant driver is regulatory mandates, including the International Maritime Organization's (IMO) ambition to achieve net-zero greenhouse gas (GHG) emissions by 2050, which aligns with various nationally determined contributions (NDCs). Concurrently, market-based pressure is intensifying as cargo owners and supply chain principals demand more stringent emission reductions from their logistics partners. As international emissions standards converge and demand for granular, real-time emissions management grows, the adoption of Artificial Intelligence (AI) has become an essential instrument for operational control and strategic compliance.

On the seaside, the IMO has committed to achieving net-zero GHG emissions from international shipping by or around 2050. Key interim goals, compared to 2008 levels, include reducing the carbon intensity of international shipping by at least 40% by 2030 and total annual GHG emissions by at least 70%, with a target of 80% by 2040. To enforce this trajectory, the IMO has instituted a multi-faceted regulatory regime within the MARPOL convention:

Figure 3.2a **Key Regulations on Seaside Decarbonization**

Regulation	Description
Energy Efficiency Existing Ship Index (EEXI)	A one-time technical certification requiring existing ships to meet a specific energy efficiency design standard.
Carbon Intensity Indicator (CII)	An operational measure that rates ships annually from 'A' (best) to 'E' (worst) based on their carbon intensity. A ship rated 'D' for three consecutive years or 'E' for one year must implement a formal corrective action plan.
GHG Fuel Standard (GFS)	A forthcoming technical measure that will mandate a phased reduction of marine fuel's GHG intensity, assessed on a well-to-wake lifecycle basis.
Maritime GHG Emissions Pricing Mechanism	An economic element to be implemented alongside the GFS, likely taking the form of a GHG levy, a feebate system, or a cap-and-trade scheme to incentivize accelerated emissions reduction.
Emission Control Areas (ECAs)	Established under MARPOL Annex VI, these designated zones enforce stricter controls on sulphur oxides (SOx) and nitrogen oxides (NOx), compelling operators to either use more expensive low-sulphur fuels or invest in exhaust gas cleaning systems (scrubbers), which carry high capital costs and face operational restrictions.

These regulations introduce significant operational and financial complexities. For instance, compliance with ECA standards is projected to add an estimated $1.31 per tonne of cargo in the Mediterranean, a cost increasingly passed to customers. As vessel operating costs depend on multiple dynamic variables – including fuel price, carbon pricing, weather, and ocean currents – traditional human-led optimization of voyage planning and vessel performance becomes exceedingly difficult.

USD 1.31 / ton

Cost added by compliance with ECA standard in the Mediterranean

Artificial Intelligence is emerging as a transformative technology to navigate this complex landscape, unlocking substantial efficiencies and emissions reductions across multiple domains.

Figure 3.2b **Seaside Decarbonization Use Cases**

Use Case	Description	Automation Level
Voyage and Vessel Optimization	AI platforms can synthesize real-time data on weather, ocean currents, sea ice, and vessel-specific performance to dynamically optimize route planning. This continuous adjustment surpasses human capabilities and can yield fuel savings of up to 20%. Further, by analyzing sensor data from onboard machinery, AI-driven predictive maintenance algorithms can preempt equipment failures, ensuring engines and auxiliary systems run at peak efficiency and preventing excess fuel consumption and emissions.	Advisor
Wind-Assisted Propulsion	AI is critical for maximizing the potential of hardware like Flettner rotor sails and wing sails. AI algorithms perform real-time control, adjusting rotor rotation speed or sail angle to generate maximum thrust from prevailing wind conditions, directly reducing engine load and fuel burn. Trials have demonstrated verified fuel and CO_2 savings of 8.2% from rotor sails alone, with combined savings from AI-driven voyage optimization reaching up to 28% on transatlantic routes.	Governor
Refrigerated Container Efficiency	By fusing multi-source sensor data – including internal and ambient temperature and humidity, container stacking density, and door-opening frequency – AI dynamically optimizes set-point temperatures and defrost strategies, safeguarding cargo integrity while reducing energy consumption and enabling early detection of equipment anomalies to prevent cold-chain failure.	Orchestrator
Robotic Removal of Hull Fouling	Timely removal of hull fouling effectively reduces the navigation resistance of ships. According to Alexander Peng, Vice President, Shanghai Humanoid Robot Innovation Incubator, this can also lower fuel consumption, and indirectly contributes to energy conservation and emission reduction in the shipping industry.	Governor
Real-Time Methane Monitoring	Advanced sensors, including Fourier-Transform Infrared Spectroscopy (FTIR), Non-Dispersive Infrared (NDIR) sensors, and quantum cascade lasers, feed real-time exhaust gas composition data into AI models. These models provide immediate emission insights, predict periods of high methane slip based on operational parameters, and can actively manage methane abatement catalysts, which can convert over 95% of slipped methane into less harmful CO_2 .	Advisor
Engine Load Optimization against Methane Leakage	Data shows methane slip varies significantly with engine load, decreasing from 6.8 g/kWh at 10% load to 2.2 g/kWh at full load. AI can recommend optimal engine RPMs and load profiles for different conditions to minimize emissions, demonstrating the granular control necessary for effective decarbonization.	Advisor

This synthesis of regulatory pressure and technological capability underscores a paradigm shift in the maritime industry. Achieving the ambitious 2050 net-zero target depends not only on new fuels and hardware but also on the intelligent, data-driven optimization of every aspect of fleet operations – a domain where AI is proving indispensable.

AI-driven Fleet Management

Road freight and last-mile distribution fleets are among most structurally entrenched and analytically intractable sources of Scope 3 emissions in global supply chains. For large manufacturers, retailers, and energy companies, logistics activities routinely account for 30–60% of total Scope 3 emissions, with road transport dominating due to its high energy intensity, fragmented asset ownership, and limited real-time observability. As a result, last-mile operations have long been a blind spot in carbon accounting, limiting both emissions attribution accuracy and mitigation effectiveness. Jeffrey Wang, GCA Supplier Operations Manager of Maersk, further notes that compared to traditional diesel trucks, electric trucks have very different operational characteristics. If we try to manage electric trucks using the same mindset and methods as diesel trucks, we will run into many problems. What's needed for a fleet company or even a driver is an open mindset and a willingness to change existing operational behaviors.

Smart AI fleet management fixes this structural deficit with a data-driven control system for logistics. Zhang Junyi, CFO of Sense Auto, recognizes that AI can boost vehicle energy efficiency through smart route planning, optimize EV charging time and location, support renewable energy use, and help the grid manage peak demand, making the auto industry smarter and more sustainable.

By integrating satellite positioning, vehicle telematics, IoT sensing, artificial intelligence, and cloud-scale analytics, these platforms enable continuous monitoring, optimization, and governance of vehicles, drivers, and logistics workflows. No longer confined to isolated efficiency tools, mature fleet systems increasingly operate as embedded control nodes within urban mobility infrastructures and low-carbon logistics ecosystems. At full maturity, such platforms are organized into four tightly coupled layers: data acquisition, real-time analytics, decision intelligence, and enterprise-level integration.

Economic pressure remains the dominant catalyst for fleet digitalization. According to Abdelrhman Hatem, Founder of Electrify, AI is not just a layer of optimization, but the backbone of how we scale sustainable mobility – turning raw data into operational intelligence that works in real, resource-constrained markets. In logistics operations, last-mile delivery alone can absorb more than 50% of total delivery costs, driven by fuel price volatility, labor intensity, vehicle downtime, and coordination inefficiencies. AI-enabled fleet management mitigates these pressures through three interdependent operational mechanisms.

- **Route and Speed Profile Optimization** Advisor

  By learning from historical and real-time traffic conditions, road topology, vehicle mass, and delivery constraints, AI systems optimize not only the shortest distance but energy-minimizing trajectories and speed profiles, reducing stop-and-go losses, idling time, and peak-load fuel burn.

- **Driving Behavior Correction** Advisor Arbiter

  High-frequency telemetry – engine load, throttle position, acceleration patterns, and braking intensity – enables attribution of excess fuel use to specific driving behaviors. Feedback loops and adaptive training programs translate these insights into sustained efficiency gains at the driver level.

- **Vehicle Utilization and Load Efficiency** Advisor Orchestrator

  Dynamic dispatching and demand-aware scheduling minimize empty mileage and suboptimal loading. By increasing payload efficiency and trip consolidation rates, equivalent logistics demand can be served with fewer vehicle-kilometers travelled, lowering both fuel intensity and emissions per unit of service.

Beyond efficiency, smart fleet management resolves a critical Scope 3 data deficit. For most corporations, emissions from third-party logistics providers are still estimated using generic emission factors because primary activity data are unavailable. Mandating standardized telematics deployment and trajectory data sharing from contracted carriers transforms this opaque segment into a directly measurable system. High-resolution activity data enable activity-based carbon accounting using harmonized methodologies, allowing logistics emissions to be natively integrated into enterprise carbon-management platforms. Data traceability further strengthens emissions verification, ESG disclosure credibility, and regulatory preparedness.

Advanced AI methods further enhance system-level optimization under real-world uncertainty. Traditional routing algorithms optimize the shortest distance or the lowest cost under static assumptions. Real logistics environments, however, are shaped by traffic dynamics, weather disruptions, and stochastic demand. Deep reinforcement learning (DRL) reframes routing as a Markov decision process, enabling agents to learn policies through interaction with dynamic environments and to optimize cumulative system-level rewards rather than local optima. Compared with classical approaches such as A* or genetic optimization, DRL explicitly models uncertainty, encodes multi-objective trade-offs – including time, cost, fuel use, and emissions – and generalizes across unseen scenarios. While training is computationally intensive, inference is near-instantaneous, enabling minute-level responsiveness at the urban scale. Jonathan E. Savoir, Chief Executive Officer of Quincus, observes that after extensive training, these agents can infer the optimal route for a new shipment in seconds, integrating real-time data such as weather, port congestion, and delays.

Human behavior remains the dominant risk vector in fleet operations, accounting for over 90% of serious road accidents. AI-based driver-monitoring architectures mitigate this risk through layered sensing and inference. Inertial sensors detect aggressive manoeuvres, driver-monitoring systems analyze facial dynamics and posture to identify fatigue and distraction, and advanced driver-assistance systems monitor lane deviation and headway to issue real-time warnings. Together, these systems reduce accident frequency, insurance losses, and liability exposure, contributing directly to social sustainability outcomes.

Deeper mechanical observability further extends AI control into the vehicle itself. Telematics platforms integrated with vehicle CAN buses and standards such as J1939 unlock continuous monitoring of engine speed, coolant temperature, oil pressure, transmission load, brake wear, battery voltage, and state of health. AI models detect subtle anomaly drift well before failure thresholds are reached. Simultaneously, high-frequency fuel metrics enable precise attribution of inefficiency to specific driving behaviors, providing a quantitative basis for targeted intervention and training.

By integrating operational optimization, behavioral governance, and high-fidelity emissions measurement, smart AI fleet management transforms logistics from a passive Scope 3 liability into an actively governable lever for decarbonization. Its strategic significance lies not only in cost reduction, but in enabling scalable, auditable, and system-level emissions mitigation across one of the most structurally resistant segments of the global economy.

CASE STUDY 4 | Low-Emission Container Transportation Solution

Background

Maersk is a purpose-driven company. As global supply chains grow more complex, customers need integrated logistics. Maersk aims to meet this need by delivering sustainable, responsible, simpler, and more reliable logistics outcomes, supporting its mission to integrate the world.

Decarbonizing logistics is a core part of this vision. Maersk is working to lead the industry toward a carbon-neutral future. Its investments in low-carbon technology have reduced carbon emissions by 40% over the past decade, and the company is accelerating progress to reach net zero by 2040.

In addition to ocean decarbonization, Maersk is focusing on reducing greenhouse gas emissions from inland transportation. The company plans to expand low-emission inland solutions across transport modes so that by 2030, at least 30% of cargo is moved using low-emission fuels or energy. To reduce greenwashing risk and provide transparent decarbonization services, Maersk has developed Low-Emission Inland Transportation Services (Alternative Technologies and/or Fuels with GHG Emission Visibility) globally, using alternative technologies or fuels with visible GHG emissions data.

Solution: Low-Emission Inland Transportation Services

In Maersk Great China Area, we have launched the Low-Emission Inland Transportation Services based on electric heavy-duty container trucks, offering a comprehensive solution that includes low-carbon vehicle deployment, GHG reduction accounting, and data visibility. Based on test data and operational experience, the Energy Transition Execution team developed a platform for the service, including raw data collection, GHG accounting, environmental attributes transfer and data visibility. This platform is verified by third-party to ensure transparency and credibility. GHG accounting follows widely recognized industry standards such as the Global Logistics Emissions Council (GLEC) Framework and the Greenhouse Gas Protocol (GHG Protocol), covering the full lifecycle of GHG emissions from well to wheel. After electric truck transport operations, the platform collects transport raw data and calculates emissions. The equivalent amount of renewable electricity certificates (GEC-China Green Electricity Certificate) can be coupled with the service according to the customers' needs.

Key Achievements and Next Steps

Since the service launch, Maersk has continuously collaborated with partners in the ecosystem to push vehicle and infrastructure development. Over the past few years, Maersk GCA EV capacity and cargo volume using EV container trucks have grown exponentially. By Q3 2025, the service has been deployed across 9 ports in North, East, and South China, covering 38+ cities. The service has also attracted lots of market attention and received positive feedback from customers. For instance, a major multinational e-commerce retailer signed a logistics service contract with Maersk, using the low-emission inland transportation service to handle approximately 7,000 containers (40') for port-related operations.

Recently, together with partners, we launched a pilot program - "Low-Emission Container Transport Routes around Shanghai Port,"covering the areas within 250 km from Shanghai port, once the pilot finished, we will copy the experience to other ports. Looking ahead, Maersk is willing to work with ecosystem partners to explore the new models and technologies and accelerate the landside low-emission transportation.

> *AI can help increase the vehicle utilization ratio and provide optimized routes based on commercial needs and fuelling/charging stations, which could increase operation efficiency, reduce the energy consumption, improve the service quality, helping turn EV trucking from 'possible' into 'productive, efficient, and reliable'.*
>
> **Jeffrey Wang**
> GCA Supplier Operations Manager, Maersk

Source: Maersk

Finance & Investment

Climate-related Financial Risks Management

Artificial intelligence has been widely deployed in sustainable finance across carbon markets, green electricity trading, and ESG investment analytics. However, in most institutions, its functional role remains confined to the advisor layer, improving disclosure, reporting efficiency, or qualitative assessment. The decisive frontier for AI adoption lies not in producing better narratives, but in enabling climate and transition risks to be transformed into quantifiable, comparable, and auditable financial risk factors that can be directly embedded into pricing, capital allocation, and balance-sheet governance. This shift marks the transition of AI from an advisor to an arbiter, and ultimately to an orchestrator of financial decision-making.

A 2025 industry survey found that 61% of banks incorporate climate factors into their probability-of-default (PD) models, 43% into loss-given-default (LGD) estimates, and 36% into IFRS 9/CECL expected-loss estimates. By contrast, only about 18% had integrated climate into their internal-rating (IRB) credit models. In a 2020 European banking survey, 70% of banks reported integrating climate risk into traditional risk assessments, and roughly 85% had performed climate scenario analysis. These figures mirror a broader shift: for example, ECB supervisors now report that >90% of banks consider themselves materially exposed to climate risks (up from ~50% in 2021). [75,76,77]

70%

Banks reported integrating climate risk into traditional risk assessment

Climate risk is well positioned to migrate from advisory analytics to decision-critical financial infrastructure, as it already intersects with binding control points in the financial system. Physical and transition risks are explicitly embedded in credit approval and expected credit loss provisioning under IFRS 9, in insurance underwriting and premium setting, in portfolio risk limits, and in supervisory stress-testing regimes administered by the ECB, PRA, and MAS. Despite this institutional penetration, operational integration remains constrained by the design of legacy risk models, which were built for low-dimensional, stationary financial variables rather than spatially explicit, non-linear, and path-dependent risk drivers.

Conventional credit and market risk frameworks are optimized for historical cash-flow projections, leverage ratios, and short-horizon volatility measures. Climate risk, by contrast, emerges from interacting physical processes, infrastructure exposure, energy systems, and policy trajectories; it varies sharply across geographies, and propagates through threshold effects and cumulative damage. Its observables are heterogeneous and frequently multimodal, spanning physical climate signals, geospatial exposure, economic structure, and regulatory dynamics. This structural mismatch – rather than a lack of conceptual recognition – constitutes the primary barrier preventing climate risk from being priced in financial markets.

CASE STUDY 5 | Empowering Business Resilience with Climate Risk Monitor

In an era defined by intensifying climate uncertainty, the imperative for organizations is not merely to respond, but to anticipate and adapt. Climate Risk Monitor exemplifies a shift in how businesses engage with climate intelligence – offering not just data, but actionable insights that inform strategic decisions.

As climate uncertainty intensifies, organizations are shifting from responding to anticipating and adapting climate risks. Aon's Climate Risk Monitor exemplifies a shift of climate intelligence from data to actionable insights that inform strategic recommendations.

Developed by Aon's Climate Hub in Singapore, with support from the Singapore Economic Development Board, Climate Risk Monitor integrates historical climate data, IPCC emissions scenarios and CMIP6 global climate model outputs across multiple time horizons and climate scenarios. The tool screens risk for seven climate perils, both acute and chronic, including drought, extreme rainfall, heat stress and cooling demand, freeze, wildfire potential, tropical cyclone, inland and coastal flooding. Once location, value, and occupancy data is submitted, the tool generates immediate information at asset and portfolio levels with reporting for up to 15,000 locations globally for any one entity, with heatmaps and hazard maps to visualize spatial patterns of geographically diverse risk.

Climate Risk Monitor provides users insights across four foundational domains:

- **Asset Resilience**
  By pinpointing the most vulnerable locations within a portfolio, organizations can move beyond reactive measures and proactively strengthen their assets against the forces of change.
- **Due Diligence**
  Integrating climate analysis into acquisition strategies ensures that long-term financial health is not undermined by hidden exposures, reflecting a more holistic approach to value assessment in an evolving risk landscape.
- **Risk Transfer**
  As insurance markets recalibrate in response to new climate realities, robust, data-driven insights become essential for negotiating terms that reflect genuine risk, fostering resilience through tailored coverage.
- **Regulatory Reporting**
  Supports disclosures aligned with regulatory requirements, helping organizations meet stakeholder expectations and compliance standards.

Climate Risk Monitor uses machine learning to process huge climate data, interpolate downscaled climate projections and granular historical climate data to deliver high resolution and detailed information about current and future climate conditions for each location.

When scientific rigor is paired with practical business insight, the resulting clarity enables leaders to navigate uncertainty with greater confidence. With its global reach and deep insights, Climate Risk Monitor is a vital resource for risk and sustainability managers across multiple sectors. As climate risk becomes a defining factor in long-term business viability, this tool offers a strategic path to resilience.

> *Climate change is no longer a distant threat — significant and escalating climate risks are reshaping business strategy across the globe. Aon's Climate Risk Monitor equips organizations with the deep insights needed to successfully manage these risks, seize emerging opportunities, and build resilience in the face of future climate-related challenges.*
>
> **Jennifer Richards**
> Chief Executive Officer, Asia Pacific, Aon

Source:

The central challenge is therefore quantitative translation. Climate impacts unfold over long horizons, while financial decisions require forward-looking, scenario-consistent estimates that can be mapped to balance sheets, income statements, and cash-flow dynamics. Artificial intelligence addresses this gap by functioning as a computational interface between physical climate processes, economic exposure, and financial risk parameters. Rather than supplanting established financial models, AI augments them by resolving data integration, dimensionality, and non-linearity constraints that were previously prohibitive at scale.

At the physical-risk layer, AI transforms climate hazards into probabilistic, asset-level risk signals that are compatible with financial transmission. These signals represent hazard-intensity distributions rather than losses, and therefore parameterize downstream vulnerability and damage relationships. Transition risk follows a complementary pathway in which AI converts unstructured information on corporate strategy, policy exposure, and capital allocation into structured indicators that can be projected into revenue, cost, and investment trajectories under alternative policy and technology pathways.

Climate impacts become financially operative only when translated into core risk parameters. In credit risk, climate-adjusted losses affect both the probability of default and the loss given default. In structural credit models, projected climate damages reduce expected asset values and increase asset volatility, thereby compressing distance-to-default and raising climate-adjusted default probabilities. In parallel, climate exposure metrics derived from physical and transition pathways can enter statistical default models as additional explanatory variables, allowing their marginal contribution to default risk to be estimated and back-tested alongside conventional financial ratios.

Loss given default is particularly sensitive to climate risk through its effect on collateral valuation. Acute hazards generate immediate physical damage, while chronic exposure progressively erodes market liquidity and insurability, altering recovery expectations even in the absence of a discrete shock. By quantifying climate-adjusted liquidation values net of insurance recovery and time-to-sale effects, AI transforms LGD from a static assumption into an exposure- and scenario-dependent function, enabling differentiated collateral haircuts, covenant triggers, and pricing adjustments consistent with observed risk.

At maturity, these components converge into an orchestrated risk-pricing architecture. Hazard scenarios, exposure mappings, and financial transmission models are continuously updated and propagated into climate-adjusted default probabilities, loss rates, and expected losses that directly inform credit pricing, portfolio limits, capital allocation, and supervisory stress testing. Governance is preserved through versioned data pipelines, model documentation, and audit trails, ensuring interpretability and regulatory traceability. In this configuration, AI functions not as a forecasting overlay but as a computational layer embedded within the core machinery of financial risk management.

Figure 3.3a **Management Measures by Climate Risk Domain**

Risk Domain	Primary Data Input	AI / Model Approach	Auditable Intermediate Output	Financial Risk Output
Physical climate risk (acute)	Satellite imagery, SAR data, climate reanalysis, disaster tracks, asset geolocation	CNN-based spatiotemporal models, event detection networks	Asset-level hazard intensity, damage probability distributions	Asset impairment, business interruption losses, PD and LGD adjustments
Physical climate risk (chronic)	Sea-level rise indicators, heat stress indices, drought metrics, insurance availability	Statistical–ML hybrid models with vulnerability curves	Long-term loss rate trajectories, insurability thresholds	Collateral haircuts, tenor adjustments, regional exposure limits
Climate downscaling	GCM outputs, historical high-resolution observations	GAN-based or physics-informed generative models	High-resolution, scenario-consistent hazard maps	Forward-looking PD/LGD under regulatory stress scenarios
Transition risk	Corporate disclosures, policy texts, Capex data, emissions and energy profiles	Topic modeling, sentiment analysis, Transformer-based NLP and relation extraction	Strategy-capital consistency scores, policy exposure indicators	Revenue and cost pathway adjustments, credit spread and valuation impacts
Financial transmission	Financial statements, asset registers, insurance coverage	Structured transmission models calibrated with ML	Climate-adjusted BS/IS/CF projections	Climate-adjusted PD, LGD, ECL, capital consumption

CASE STUDY 6

Making ESG and Climate Claims Auditable at Scale

BlueOnion, an ESG innovator in the Cyberport community, is a climate and green-finance platform that enables banks, asset managers, and corporates to evaluate ESG and climate claims with the same discipline applied to financial data. Operating across Asia-Pacific and Europe, the platform focuses on a persistent failure point in sustainable finance: sustainability disclosures are abundant, but evidence is fragmented, inconsistent, and difficult to verify across products, portfolios, and issuers.

What the Platform Does

At the investment product level, BlueOnion applies a holdings-based, bottom-up approach across equities, corporate bonds, sovereign debt, and other instruments. Instead of relying on aggregated ESG scores, the system ingests primary disclosures directly from issuers, structures them into standardized datapoints, and validates them against external sources to surface inconsistencies, missing data, and potential greenwashing signals that are often invisible in top-down assessments.

Funds and portfolios are assessed across three integrated dimensions – sustainability performance, consistency between stated environmental and social characteristics or objectives, forward-looking climate risk. A key differentiator is that these assessments are fully traceable. Users can move from portfolio conclusions back to individual holdings, disclosures, and validation checks, enabling defensible internal decisions and regulatory-facing documentation.

Beyond analytics, BlueOnion standardizes how banks and distributors conduct sustainability due diligence on funds and asset managers. Asset managers can reuse validated responses and keep information current, while gatekeepers can assess not only portfolio composition, but also whether stated sustainability approaches are reflected in actual investment and engagement practices.

Corporate and SME Use Cases

BlueOnion applies the same evidence-driven structure to corporate sustainability reporting. Climate scenario analysis and stress testing can also be layered into the same environment, allowing management to link transition plans and decarbonization targets to quantified risk and forward-looking assumptions rather than narrative commitments.

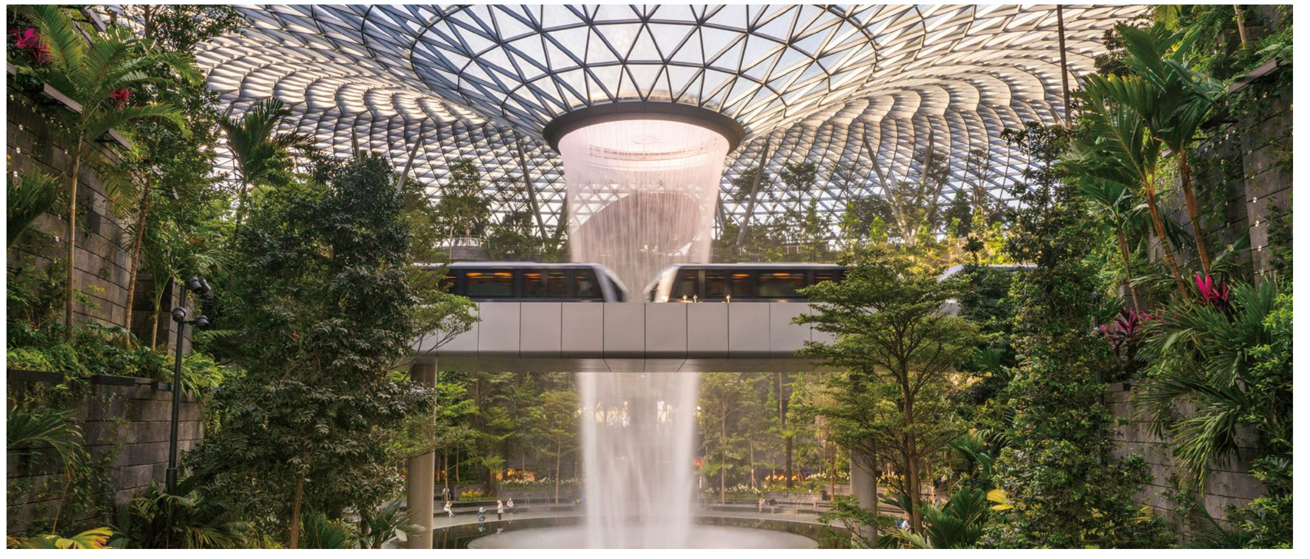
Green FinTech innovators complement this ecosystem by providing sophisticated digital platforms for ESG reporting, green asset tokenization, climate risk modelling, AI-powered wealth management and sustainable finance instruments.

Eric Chan
Chief Public Mission Officer, Cyberport

Impact and Validation

In early deployments, BlueOnion has demonstrated that sustainability assessment can be both more rigorous and more operationally efficient when built as digital infrastructure rather than advisory processes, supporting approved green-fintech projects across asset managers, private banks, and retail banks. Together, these implementations position BlueOnion as a practical assurance layer between issuers, financial institutions, and regulators, shifting sustainable finance from narrative-based signaling toward auditable, comparable, and continuously updated, evidence-based capital allocation.

Source: BlueOnion



Frauds and Greenwashing Detection

> *Innovation in climate finance and market mechanisms is essential to ensure credible and sustainable technology transfer. AI-enhanced transparency enables investors to distinguish substantively low-carbon projects from narrative-driven claims, reducing greenwashing risk and strengthening the integrity of sustainable finance.*
>
> **Zhou Yiping**
> Founding Director, United Nations Office for South-South Cooperation

As climate finance scales, fraud and greenwashing are increasingly driven by the disconnect between narrative disclosure and verifiable physical or operational reality, particularly in shipping, logistics, energy infrastructure, and port-based transshipment. AI enables a shift from disclosure-driven trust to evidence-based verification by fusing independent data streams across space, time, and modalities. According to Kristian Flyvholm, Chair & Chief Executive Officer of the Institute of Sovereign Investors, AI can screen vast unstructured datasets to surface credible projects, estimate missing emissions, and distinguish real transition plans from greenwash, improving engagement with governments and MDBs.

At the operational level, AI integrates satellite optical imagery, synthetic aperture radar (SAR), radar-shadow analysis, and vessel Automatic Identification System (AIS) data to detect inconsistencies between reported activities and observed behavior. SAR enables the identification of vessel presence and infrastructure activity under cloud cover and at night, while AIS pattern analysis exposes anomalies such as signal gaps, improbable trajectories, or repeated offshore rendezvous. When combined with port call records and emissions factors, these signals enable automated detection of false berthing claims, undeclared ship-to-ship transfers, and emissions laundering through nominally "low-carbon" port transshipment.

At the corporate level, AI detects greenwashing by quantifying divergence between strategic narratives ("Talk") and observable actions ("Walk"). Natural language processing models identify vague commitments, passive constructions, and non-operational climate language, and systematically cross-reference these signals with capital expenditure, R&D intensity, asset-level investments, and supply-chain behavior. Persistent misalignment is converted into probabilistic greenwashing risk indicators suitable for due diligence, monitoring, and portfolio oversight. Dr. Fu Xiaolan, Founding Director of the Technology and Management Centre for Development, observes the revolutionary efficiency boost for AI in valuations. She noted that traditional valuation and due diligence processes are extremely costly and take weeks or months, whereas the AI valuation tool can significantly reduce costs and time by delivering results quickly with high accuracy.

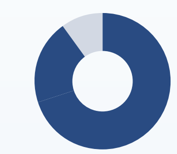
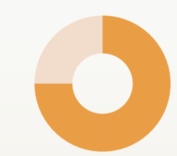
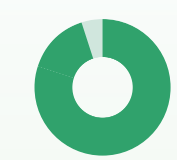
By embedding multimodal verification into financial workflows, AI shifts greenwashing detection from an ex post reputational assessment to an ex-ante risk management approach, directly affecting eligibility, pricing, and risk allocation for green bonds, sustainability-linked loans, and carbon market instruments.

In this configuration, AI-based fraud and greenwashing detection functions as trust infrastructure rather than auxiliary compliance, anchoring climate claims in independently verifiable evidence and reinforcing market discipline across climate-aligned financial systems.

Certification & Global Trade

Figure 3.4a **Manpower Replaced in Certification & Global Trade Activities**

Source: WeCarbon Analysis

Activity in Certification & Global Trade	Corresponding Challenge of Activity	Replaced with Agentic AI Feature	% of Manpower Estimated to Be Replaced
From Laboratory to Data Factory	**Manual, Artisanal Workflows & Information Asymmetry** • Testing is organized around labor-intensive, physical workflows involving shipment queues and serial re-testing cycles that create significant time latency. • Data remains trapped in static PDF reports, limiting real-time visibility and creating information asymmetry that slows down design feedback loops.	• Automated test generation • Dynamic resource orchestration • Self-healing execution • Real-time analysis and feedback • Automated data ingestion and quality control • Contextualisation through metadata • Cryptographic anchoring and distributed ledger notarisation	 70-90%
From Expert Judgement to Control Systems	**Subjective, Opinion-Driven Expert Review** • Relying on manual interpretation of thousands of pages of ambiguous, frequently changing standards (e.g., ISO, IEC). • The subjective process is hard to audit, prone to human inconsistencies across jurisdictions.	• Regulatory rule parsing • Semantic disambiguation and governance • Evidence-rule matching	 50-75%
Cross-border Compliance Documents Automation	**Fragmented, Manual Document Assembly** • Relying on manual search, transcription, and reconciliation of data across siloed systems to create Technical Files, Declarations of Conformity, and CBAM filings. • The process is costly, error-prone, and creates high compliance risk.	• Automated data extraction • Data cleaning and cross-validation • Semantic structuring and linkage • Schema and logic parsing • Data orchestration and generation • Consistency assurance and version control	 80-95%

In contemporary global trade, compliance certification is no longer a procedural formality but a non-negotiable condition for market access, constituting the infrastructural rule system governing cross-border circulation of goods. Regulatory regimes such as the EU Carbon Border Adjustment Mechanism (CBAM), the Digital Product Passport (DPP), and long-established conformity frameworks, such as CE, IEC, and ISO, converge on a single principle: without certification, products cannot legally circulate. These regimes span product safety, electromagnetic compatibility (EMC), radio equipment (RED), chemical compliance (REACH, RoHS), energy efficiency, carbon footprinting (LCA/EPD), and enterprise-level ESG performance, collectively forming a dense but fragile global trade governance architecture. Frankie Chang, CEO of Forbes China Group, observes that the market increasingly rewards measurable decarbonization today. Investors, customers and regulators are aligned in demanding verifiable data and tangible outcomes. Technologies with intrinsically MRV-compatible features such as CCUS, high-efficiency storage and green hydrogen are taking center stage.[78]

Despite their systemic importance, certification and testing remain organized around labor-intensive, document-centric workflows that exhibit structural inefficiencies and escalating failure risks. Key bottlenecks include:

- **Time Latency and Iteration Drag**
  Physical sample shipment to third-party laboratories, fixed testing queues, and serial re-testing cycles caused by minor design nonconformities routinely extend certification timelines by weeks or months, delaying market entry and eroding competitive windows.
- **Documentation Burden**
  Technical Files – encompassing design drawings, risk assessments, Declarations of Conformity, and multi-jurisdictional translations – are manually assembled, versioned, and archived for up to a decade, making them costly, error-prone, and difficult to maintain.
- **Cost Escalation**
  Laboratory testing, retesting after failure, and reliance on external compliance consultants collectively impose significant financial overhead, particularly for hardware-intensive products.
- **Information Asymmetry**
  Test data are generated and retained within laboratory systems, while manufacturers typically receive only static PDF reports, limiting real-time visibility, root-cause diagnosis, and design feedback loops.
- **Coordination Friction**
  Communication with certification bodies, particularly EU Notified Bodies, relies heavily on asynchronous email exchanges across time zones, leading to prolonged clarification cycles and regulatory uncertainty.
- **Consistency and Regulatory Risk**
  Manual aggregation across design, production, and testing pipelines often leads to internal inconsistencies; regulatory updates (e.g., RED revisions) require exhaustive manual audits across product portfolios, exposing firms to fines, shipment holds, or forced inventory write-offs.

Certification requirements are rising in both volume and rigor. Dr. Robert Slone, Senior Vice President and Chief Scientist and Innovation Officer at UL Solutions, notes that people trust certifications when outputs are reproducible, data sources and assumptions are clear, and independent experts have vetted the underlying methods, with AI serving as a facilitator, not a replacement, for robust assurance. As sustainability-linked regulations expand and evolve, products must demonstrate not only technical compliance but also verified carbon footprints, supply chain ESG attributes, and lifecycle transparency. In this environment, certification services that rely mainly on manual work will soon consume greater economic and operational resources.

From Laboratory to Data Factory

AI-driven certification reconfigures this paradigm by transforming laboratories from artisanal testing units into programmable data factories. At its core lies test orchestration, an AI-mediated control layer that plans, executes, monitors, and optimizes testing workflows end to end:

- **Automated Test Generation** Interpreter
  AI agents parse regulatory knowledge graphs to derive test requirements directly from declared product functionalities, automatically generating compliant test plans and cases aligned with specific directives and standards.
- **Dynamic Resource Orchestration** Orchestrator
  Containerized test environments and AI schedulers allocate workloads across instruments and cloud resources based on priority, duration, and availability, enabling parallel execution and maximized equipment utilization.
- **Self-healing Execution** Arbiter
  Adaptive AI testing systems detect interface changes or environmental anomalies during execution and autonomously adjust scripts, reducing manual intervention and maintenance overhead.
- **Real-time Analysis and Feedback** Orchestrator
  Test outputs are continuously analyzed, with defects automatically classified, root causes inferred, and remediation guidance generated, compressing development-test-fix cycles.

Beyond efficiency gains, AI fundamentally redefines trust in sustainability and trade by shifting certification from human-reviewed documentation to machine-verifiable fact streams. Its critical contribution lies in converting physical testing processes into tamper-resistant digital evidence, a prerequisite for regulations demanding lifecycle-level transparency such as battery DPPs:

Automated Data Ingestion and Quality Control

Raw data streams are continuously captured from LIMS, MES, BMS, and IoT-enabled instruments, with AI models performing anomaly detection, drift correction, and intelligent imputation to ensure baseline data integrity.

Contextualization Through Metadata

Each data point is enriched with precise timestamps, device identifiers, standard versions, operator context, and environmental parameters, and is bound to a unique product or batch identifiers.

Cryptographic Anchoring and Distributed Ledger Notarization

Standardized data packages are hashed using cryptographic algorithms (e.g., SHA-256), and the resulting fingerprints are recorded on distributed ledgers, creating immutable, time-stamped proof of test occurrence and content without exposing raw data.[79]

Certification automation therefore functions not merely as a productivity enhancement but as foundational infrastructure for sustainable trade, enabling material and energy efficiency gains through test reuse and optimized sampling, expanding safety and performance coverage by making large-scale and high-frequency testing economically viable, and supplying credible, high-granularity upstream data for carbon accounting, lifecycle assessment, and digital product passports – without which higher-level sustainability models lack empirical grounding. In this transition, AI does not simply accelerate certification processes; it fundamentally restructures how evidence is generated, how trust is established, and how compliance is enforced in the global economy.

From Expert Judgement to Control Systems

Interpreter

Conventional certification regimes are fundamentally opinion-driven, relying on expert interpretation, narrative justification, and manual review of evidence. AI-driven certification replaces this paradigm with a deterministic control system grounded in verifiable data streams and executable rules, transforming compliance assessment from a subjective judgment process into a repeatable, auditable decision workflow.

- **Regulatory Rule Parsing**
  Using advanced document intelligence and natural language processing, AI systems decompose thousands of pages of ISO, IEC, and sector-specific standards into machine-executable logic by extracting normative thresholds, test methods, conditional clauses, and cross-references, and encoding them into structured knowledge graphs that convert qualitative regulatory language into quantitatively verifiable constraints.
- **Semantic Disambiguation and Governance**
  Ambiguous regulatory expressions and recursive references are resolved through probabilistic confidence scoring and human-in-the-loop escalation, ensuring that low-certainty interpretations are reviewed by domain experts and continuously fed back into model training to reduce hallucination risk and improve rule fidelity over time.[80]
- **Evidence-rule Matching**
  Parsed regulatory rules are automatically matched against cryptographically anchored digital test evidence, enabling AI systems to locate relevant sensor streams, timestamps, and test conditions and to verify compliance deterministically – for example, validating surface-temperature rise limits directly against calibrated thermal data rather than narrative test summaries.

In this architecture, certification ceases to be a static expert opinion captured in a report and becomes an executable control system in which rules, evidence, and decisions are continuously aligned, traceable, and reproducible across products, jurisdictions, and regulatory updates.

Cross-border Compliance Documents Automation

Advisor Orchestrator

Global trade runs on paperwork. Each transaction depends on completing, verifying, and reconciling documents such as customs declarations, certificates of conformity, LCA and EPD disclosures, CBAM filings, and due diligence records required by banks, insurers, and buyers. This document-first setup still relies on manual searches, data entry, and reviews, which slows work and increases compliance risk. Rembrandt Koppelaar, Lead for Global & EU DPP Regulations Observatory, CIRPASS-2, highlights that digital battery passports and similar products should use the same data format to scale without format-to-format translation, supported by modular templates, consistent access rules across operators, and standardized presentation so shoppers see the same information regardless of the manufacturer.

> *AI can automate and monitor trade compliance, tracking carbon, water, and energy, so companies can meet audit and certification requirements with less red tape.*
>
> **Hon. Karim Fatehi OBE**
> Chief Executive Officer, the London Chamber of Commerce and Industry

AI-powered document intelligence shifts this from a people-driven process to a data-driven model. A unified data backbone can feed different regulatory, commercial, and financial documents as needed. Instead of asking staff to find and retype information, AI builds a programmable compliance layer that generates documents from validated data. This shift happens in two closely linked stages.

The foundation of document automation is consolidating fragmented internal and external data into a unified, auditable data model that supports regulatory-grade outputs. AI platforms ingest structured data directly from enterprise systems and simultaneously extract key variables from unstructured sources – including PDFs, scanned supplier declarations, emails, invoices, and test reports – using OCR, NLP, and multimodal machine-learning techniques.[81] Extracted data are automatically normalized across formats and units, reconciled against business rules and transactional records and flagged for anomalies or contradictions that would otherwise propagate compliance errors downstream. Cleaned data are ingested into a central data model or knowledge graph that explicitly links products to their documents and to energy or emissions data, forming a traceable, end-to-end view of product compliance.

Once an SSoT is established, AI-driven document intelligence and generative models automate the creation and maintenance of regulatory and trade documentation at scale.

- **Schema and Logic Parsing**
  Modern multimodal document intelligence models interpret not only the textual content of regulatory templates but also their layout, tables, and visual structures, allowing AI systems to infer field semantics and validation logic even as official forms and schemas evolve.
- **Data Orchestration and Generation**
  Using retrieval-augmented generation frameworks, AI systems query the SSoT for authoritative data, perform required calculations (e.g., emissions aggregation or recycled content ratios), populate structured fields with precision, and generate compliant narrative disclosures when free text is required.
- **Consistency Assurance and Version Control**
  Because all documents are drawn from a shared SSoT, cross-document consistency is enforced by design. When upstream data are updated, affected documents are automatically identified, versioned, and regenerated, with complete audit trails preserved for regulatory inspection.

Document automation provides straightforward support for sustainable global trade. It helps small and medium-sized enterprises meet compliance requirements by replacing manual paperwork with low-cost, automated workflows. It also reduces trade friction by cutting delays, penalties, and re-audits caused by documentation errors or inconsistencies. It increases the flow of genuinely sustainable products by turning verified environmental performance into faster, more reliable market access rather than leaving it as a static label. Liao Shuanghui, Chairman of the Shanghai Jinsinan Institute of Finance, highlights that AI-driven smart compliance systems can automatically check whether products meet international green certification requirements, reducing manual review costs and lowering error rates.

CASE STUDY 7

AI-Enabled Carbon Compliance for Global Green Trade

Carbon transparency is now required for market access as climate rules reshape global trade. The EU Carbon Border Adjustment Mechanism (CBAM) and the Digital Product Passport (DPP) make carbon data a regulated, auditable production factor. Siemens China responds with a full-cycle digital approach that embeds AI-driven carbon intelligence into industrial and supply chain systems.

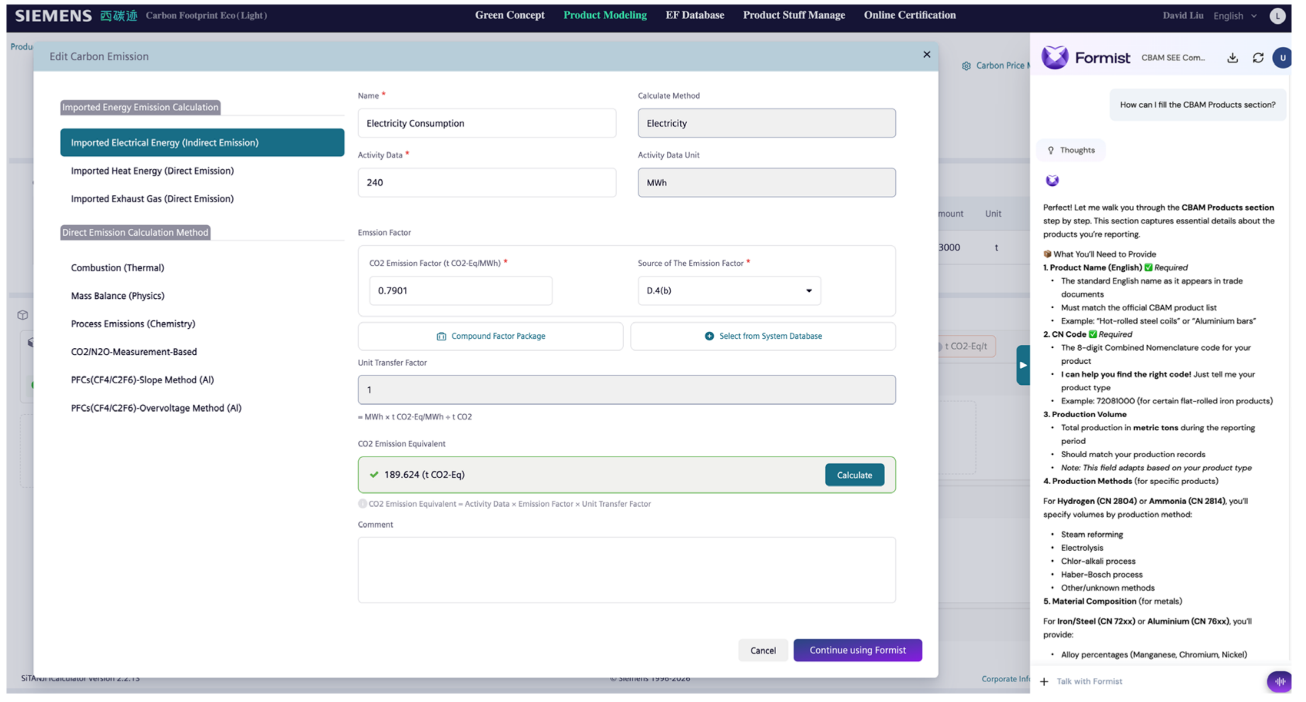
Siemens uses a closed-loop model of data transparency, accurate accounting, trusted certification, and decision support to move compliance into daily operations. The foundation is SiTANJI, Siemens' carbon portfolio management platform, which integrates industrial data streams, digital twins, blockchain-based traceability, and AI analytics to deliver full lifecycle emissions accounting aligned with international standards. Digital twins tie emissions to physical processes and product flows, while blockchain enables secure, auditable data exchange across supply chain partners and third-party verifiers, reducing manual reconciliation and strengthening cross-border compliance readiness.

Siemens integrates WeCarbon's Formist™ AI Agent on SiTANJI to provide a joint AI Form Solution for sustainability reporting, primarily CBAM, that transforms reporting from a months-long, consultant driven effort to a largely automated process completed in hours. The AI guides submissions step by step, maps uploaded operational data to templates, auto-fills required fields, parses historical records, and flags anomalies with corrective recommendations. This enables non-experts to complete submissions without specialized carbon or legal expertise, significantly shortens reporting cycles, reduces reliance on external consultants, lowers compliance costs, and improves internal control of carbon data while maintaining traceability and audit readiness. By embedding regulatory logic in live production data, enterprises can monitor exposure, test sourcing or production changes, and identify compliance risks earlier.

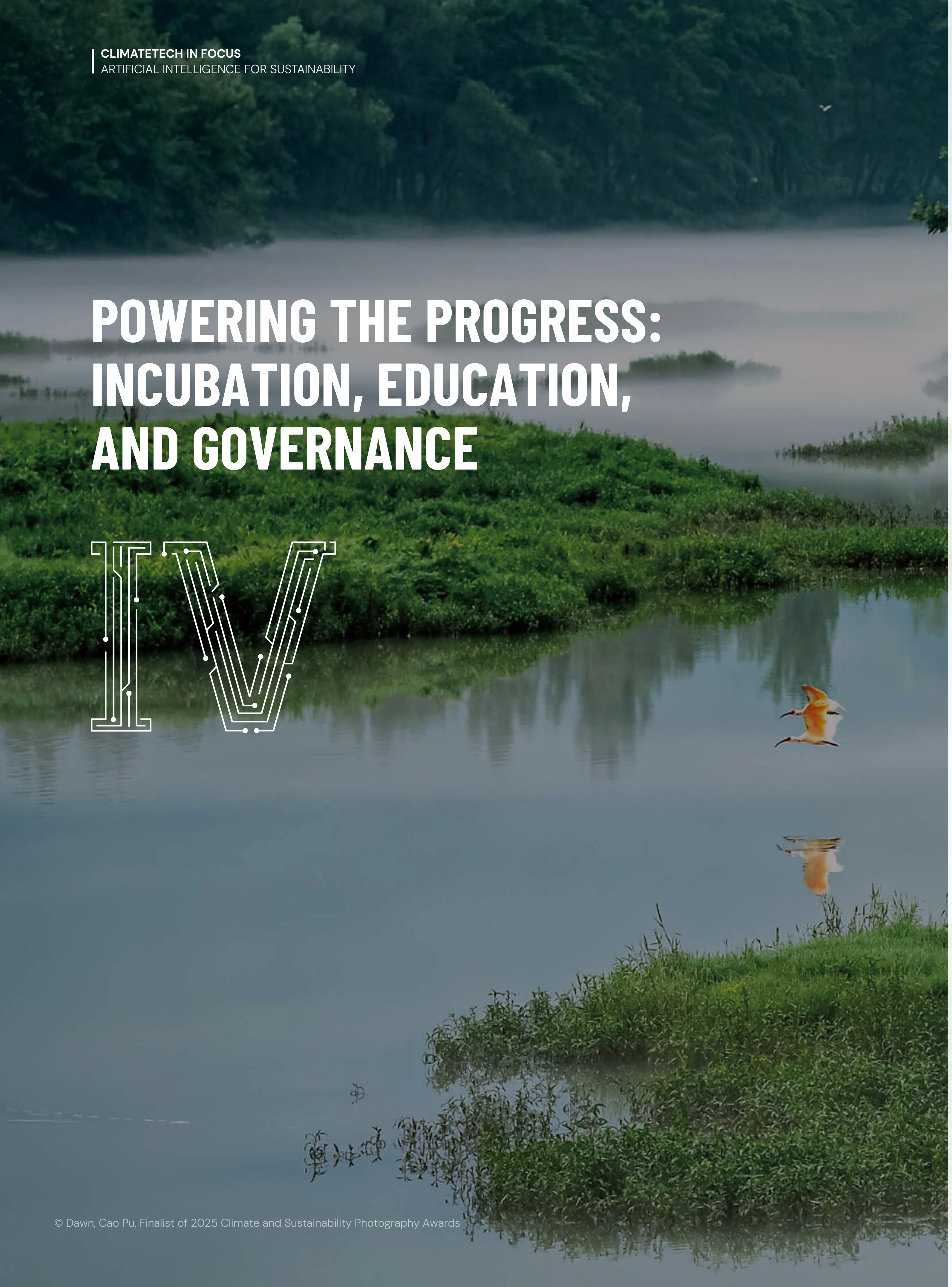
> *In the face of increasingly complex international green trade barriers such as the EU's CBAM and battery passport, many export-oriented SMEs are trapped in a compliance dilemma of 'not knowing what to do' and 'not being able to do it'. Siemens, in collaboration with leading innovators, lowers these barriers through technological innovation, delivering inclusive solutions that significantly reduce both technical complexity and adoption thresholds for enterprises.*
>
> **Hu Jianjun**
> Vice President, Siemens China

The practice is amplified through the Siemens Xcelerator ecosystem, which combines industrial AI, IoT, automation, and partner solutions into an interoperable, scalable platform that helps enterprises of different sizes meet green trade requirements while controlling total compliance costs.

Source: SIEMENS



The global trade ecosystem, the circulatory system of the world's economy, stands at a critical juncture. Traditional mechanisms for certifying and verifying climate-related claims – largely reliant on static documentation and periodic audits – can no longer meet the speed, complexity, and transparency required amid rising greenwashing risks and new regulations. This chapter examines how a powerful synergy of artificial intelligence (AI), blockchain, and advanced data capture technologies is creating a new framework for global trade – one built on dynamic, data-driven trust and verifiable climate credentials.



POWERING THE PROGRESS: INCUBATION, EDUCATION, AND GOVERNANCE

IV

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Australia can be sort of pro innovation and pro integrity, by scaling obligations with risk and impact, but by still keeping our guardrails compatible with our norms.

Hon. Matt Kean
Chair of Climate Change Authority, Australia

Incubation for AI Innovation

Incubation Beyond Capital

AI has changed how sustainability solutions are built and scaled. Many AI-native startups now use pre-trained foundation models, cloud infrastructure, and modular software stacks, reducing the need for large in-house R&D teams and rigid organizational structures. Xu Jieping, Chief Executive Officer of Plug and Play China, identifies that many leading entrepreneurs are born global today, focusing from the start on real pain points and global markets with the end goal in mind, and using profitable business models to keep addressing climate and sustainability challenges. As a result, many AI-native companies reach an MVP and early market validation with fewer than 30 people, sometimes launching across regions within months. This trend appears in accelerators and early-stage funding programs worldwide, where AI-native startups account for a growing share of new entrants.

However, faster MVP cycles have not translated into proportionally higher rates of large-scale deployment. Yukio Sakaguchi, President of Clean Energy Research Lab, highlights that what we really need is not another "shiny algorithm," but boring and painful yet essential upgrades and reforms in industrial use cases.

This gap between fast testing and slow deployment changes what limits AI innovation. Capital matters more for scaling, funding long deployment cycles, shared infrastructure, risk management, and coordination across multiple stakeholders. When raising capital for AI companies, three broad capital archetypes emerge. These categories are not strict or mutually exclusive, and many projects combine multiple forms of capital support.

Figure 4.1a **Main Capital Archetypes**

Opportunist Capital Driven by Financial and Equity Exit	**Patient Capital** Driven by Vision and Strategy	**Purpose Capital** Driven by Mission and Mandate
• Incentivized by portfolio-level IRR maximization through accelerated valuation growth and liquidity events • Target at a pipeline of VC-ready companies optimized for scale, growth metrics, and follow-on financing • Favor projects with fast execution speed, large addressable markets, and fast monetization over scientific depth • Low risk tolerance • Shorter exit-driven value realization	• Incentivized by platform dominance, ecosystem lock-in, and long-term corporate competitive positioning • Target at a pipeline of startups that expand cloud workloads, data gravity, and vertical market penetration • Favor projects with strong strategic fit to internal infrastructure, product roadmaps, and hardware stacks • Medium risk tolerance conditional on strategic alignment • Platform expansion and acquisition-option time horizon	• Incentivized by public-interest missions of translating frontier research into societal and economic application • Target at a pipeline of deep-tech spin-offs and licensable frontier technologies • Favor projects with high scientific novelty, technical depth, and long commercialization horizons • High risk tolerance for technical, regulatory, and financial uncertainty • Long research-to-commercialization time horizon

> *Hub71 concentrates capital, corporates, and government entities that are interested in global ClimateTech solutions in one place to speed up the time to market for ClimateTech innovators. This also sheds light on the importance of ClimateTech solutions for the future of the UAE economy.*
>
> **Ahmad Ali Alwan**
> Chief Executive Officer, Hub71

Xiao Jie, General Manager of New Energy Nexus China, highlights that what's often missing in this field isn't capital – it's trust infrastructure: an environment where startups, corporates, financiers, and regulators can test ideas safely and learn from failure. Leading practice recognizes that other supports beyond capital are essential to scale up an AI business.

Building on that point, a key reason many top incubators, such as Hub71 and Plug and Play, succeed is that they create an all-in-one ecosystem: they bring startups, corporates, investors, government and regulators, pilot opportunities, and shared services into a single, coordinated platform. This reduces coordination friction, makes experimentation safer, accelerates learning, and shortens the path from proof-of-concept to scale.

Figure 4.1b **Incubation Support Beyond Capital**

Area	Observations	Leading Practice
Operational Support	• Early AI teams lack HR, procurement, security, and compliance capacity • Founders spend disproportionate time on non-core operations • Operational friction delays pilots and customer onboarding	• SAFE-based funding combined with in-kind operational support (workspace, legal, hiring, compliance, market access) • Centralized back-office services shared across portfolio companies
Services & Infrastructure	• GPU access and secure environments constrain post-MVP development • Small teams lack bargaining power with hyperscalers	• AI-as-a-Service packages providing GPU credits, secure cloud, and deployment tooling • Shared national and regional compute platforms
Knowledge	• Most deployment failures are domain-driven rather than model-driven • Generic founder mentorship shows limited impact after MVP • Sustainability applications require cross-disciplinary coordination	• Mentorship structured by deployment roles (operators, buyers, regulators) • Co-development tracks linking founders, engineers, industry partners, and research institutions
Use Case	• Many AI tools lack defined buyers or adoption pathways • Pilots fail without predefined data access, KPIs, or budgets • Horizontal AI accelerators overproduce non-deployable tools	• Challenge-based programs with predefined datasets, metrics, evaluation criteria, and pilot budgets • Application-specific tracks focused on AI tied to concrete use cases rather than generic AI • Thematic roadshows and matchmaking between innovators and use case owners
Regulatory & Compliance Support	• Regulation is a late-stage failure point for sustainability in finance, healthcare, transport, and energy • Unclear compliance blocks commercialization • Buyers require regulatory assurance before adoption	• Regulatory sandbox participation covering data governance, model transparency, and human oversight • Limited-scope supervised commercial deployment prior to full approval

New financing models are expanding funding options for early-stage AI and sustainability projects, lowering dependence on traditional venture capital and institutional grants. In addition to equity investment, decentralized funding pools, crowdfunding, and revenue-based financing provide flexible capital that aligns with the risk and cash flow needs of applied AI development. These models can support data- and compute-intensive projects, helping teams move from research and prototyping to deployment without scaling prematurely or relinquishing unnecessary ownership.

Regional cross-border institutions are reshaping AI incubation. The China-ASEAN Artificial Intelligence Innovation Cooperation Center links complementary strengths across locations: advanced R&D in East and South China, system integration and industrial coordination in West China, and application development plus market validation across ASEAN. This "R&D-Integration-Application" structure creates continuous feedback across technology development, talent development, and real-world deployment. Yang Ming, Board Secretary of TusStar, described an "Incubation + Investment" model built on "Two Countries, Twin Innovation Parks" and "Multi-country, Multi-node" networks. Under this approach, innovation parks in China and the UK are paired to support two-way flows of talent, technology, and capital. Key resources, including incubation teams, mentorship, client connections, and financing, are coordinated across regions. This setup helps innovations reach international markets and creates opportunities for expansion.

Win Hearts Above Growth

> *For collaboration to be genuinely generative rather than symbolic, startups must be given real on-ground project opportunities where they can deploy and refine their solutions, generate measurable value, and prove themselves in live operational environments.*
>
> **Butti Almheiri**
> Co-lead Adaptation Negotiator, UAE Climate Change Special Envoy

Scalable AI products succceed beyond download, usage, or revenue targets. They become part of daily work and life by providing steady value, reducing friction, and earning trust. A 2025 global study found that many people use AI and expect broad benefits, but only 46% are willing to trust AI systems. Usefulness alone does not guarantee acceptance. [82]

Alejandro Diego Luis Giles R. Katigbak, Chief Risk Officer of PHINMA Corporation, believes that using AI in any business must first address users' hesitation to move away from manual processes. He highlights that training that requires people to sit down and use AI is especially valuable. People adopt AI when it saves time and fits their existing workflows. AI performs best when it is built into tools people already use, automates routine tasks, and gives relevant insights. Success should be measured by adoption and outcomes such as usage frequency, time saved, task completion, and satisfaction, not installs.

Founders should also earn employee trust and commitment. Metrics will not motivate teams if they do not see real user impact. Alice Ho, Chief Youth Officer of Global Alliance of Universities on Climate, has observed tech giants moving faster by splitting large departments into small squads with clear missions, giving them greater autonomy, and using AI for supporting analysis. She recognizes that empowered cross-functional teams often iterate faster, take more ownership, and respond to feedback better than rigid hierarchies.

Engagement with local government also matters. AI businesses operating globally should respect local laws and regulations, especially regarding data. Hon. Karim Fatehi OBE, Chief Executive Officer of the London Chamber of Commerce and Industry, advises that as small businesses scale, they should focus on their products and avoid involvement in geopolitical disputes and political themes.

Tales between Giants and Disruptors

Partnerships between large companies and startups look efficient: big companies offer distribution, data, and regulated operating environments, while startups offer speed and product focus. In practice, even as interest rises, many challenges remain. Surveys show about 27% of startups are satisfied with corporate engagements, often because progress is slow and internal coordination is weak. Startups also point to unclear goals, long decision timelines, and pilot projects that never scale. [83] These problems are worse in AI, where integration and compliance costs are high.

Platform giants create a different kind of pressure. As foundation model platforms add more features, they absorb many common functions that startups used to build. Startups cannot rely on a thin layer of API calls and a simple interface, and users and enterprises increasingly expect a single coherent environment where key capabilities are available by default. As Felix Ayque, Co-founder and Chief Executive Officer of Komunidad, notes, while AI is currently applied in a fragmented way across many tools and platforms, the long-term direction is toward a unified, AI-powered core system that delivers consistency, scalability, and intelligence across functions. This raises the bar for startups because value must come from clear use cases, domain-specific workflows, and outcomes that large platforms do not deliver by default. The main risk is not competing with the models, but becoming irrelevant: startups that do not define a clear problem, embed into real workflows, or deliver differentiated results may be replaced as platforms evolve, while those that own a specific use case and build around operating context, data, and execution can still grow.

Jason Ho, President of Macao Technology General Association, and Dr. Lu Gang, Co-founder of BEYOND Expo, both advise designing accelerators around guaranteed pilot commitments from corporate-funded PoCs with clear KPIs and timelines. Several alternatives matter for engaging giants with disruptors because they shorten the path from idea to real deployment signals and reduce integration work:

- Model competitions and challenge programs let large enterprises work with startups without committing to a single vendor too early. The enterprise publishes a dataset or a tightly scoped problem, sets shared constraints, defines benchmarks, and uses deployment-linked evaluation metrics. Multiple teams compete on the same task, ensuring comparable results. Startups invest significant effort because strong performance can lead to pilots, procurement opportunities, or paid commercial work, not just prize money. The enterprise reduces selection risk by observing which approaches survive real-world constraints before committing budget and integration capacity.

  This pattern is already common in energy and sustainability, where buyers want measurable accuracy, robustness, and operational fit before adoption. Examples include Elewit and Red Electrica using data challenges to improve renewable generation forecasting, Enel running open challenges and AI-focused contests tied to energy use cases, and Shell running its Shell.ai hackathon around real energy problems. Similar challenge formats have also been used by major energy players such as TotalEnergies and Iberdrola group entities, and by companies like GEN-I that run analytics-focused challenges in energy trading and forecasting contexts. The incubation impact is direct: challenge formats produce a deployment-shaped signal, shorten time to credible validation, and provide corporates with a structured path from open exploration to purchase without betting early on one vendor. [82,84,86,87,88,89,90]

- Platform marketplaces reduce procurement delays. With catalogs, rankings, discovery, and monetization, startups can validate demand through real usage before investing in expensive enterprise sales efforts. OpenAI's GPT Store provides usage-based proof and earnings. [84] The ChatGPT App Directory and Apps SDK improve distribution and discovery for third-party tools. [85] A new approach is to prove retention and workflow pull within the platform, then use that traction to sell to larger customers from a stronger position.

- Open protocols reduce integration friction, but the bigger point is that they change the go-to-market strategy. Instead of selling a standalone product and fighting procurement cycles, a disruptor can plug into giant platforms where users already sit. The Model Context Protocol (MCP) is an open standard for connecting AI systems to external tools and data sources consistently, reducing the need for one-off connectors. For incubation, this matters because distribution and integration move upstream: startups can ship as connectors, tool servers, or workflow extensions that run within a platform surface, access enterprise data through standardized interfaces, and demonstrate usage before negotiating heavyweight contracts. That lowers integration costs, shortens time-to-deployment signals, and enables enterprises to support more third-party capabilities without rewriting internal tooling for each vendor.

The tales of success between giants and disruptors depend less on who is stronger and more on whether they can move collaboration from slow, fragmented pilots to repeatable, standardized approaches using challenge-based evaluation, platform distribution, and open protocols to align speed, governance, and scale.

Educating for AI-Native Generation

AI in Classrooms: Not If, But How

Bringing AI into classrooms is no longer a question of whether education systems should respond, but how they do so responsibly and effectively. Traditional education can be conservative, institutional, and often slow to adopt emerging technologies. An estimated 86% of learners worldwide already use AI in their studies, with around 25% using it nearly daily. Yet many institutions continue to rely on restrictive responses – blanket bans, automated "AI-detection" tools, or policies that discourage AI use altogether. Such measures neither prevent widespread adoption nor address the underlying reasons students turn to AI: reducing manual workload, supporting complex reasoning, or meeting increasingly demanding academic requirements. As AI systems increasingly surpass human performance in test-based evaluation, assessing learning primarily through exam scores or answer reproduction becomes less meaningful.

According to Alice Ho, Chief Youth Officer of Global Alliance of Universities on Climate, this shift is especially important when addressing complex, interdisciplinary challenges such as climate change. Higher education should embrace the opportunities created by generative AI while remaining anchored in the core mission of teaching. AI tools can explain complex climate science concepts in intuitive, accessible ways, helping students build foundational understanding more quickly and lowering entry barriers through efficient information retrieval and idea generation. At the same time, it is worth cautioning against over-reliance on AI, which may weaken independent thinking. Rather than banning AI, it's better to guide its use – treating AI as a learning assistant rather than an answer machine. For example, students may be encouraged to use AI to gather sources or draft outlines, but are then required to verify, challenge, and expand upon AI-generated content, cultivating habits of questioning and validation alongside efficiency gains.

> "
> *AI has made knowledge acquisition fundamentally easier, rendering traditional teacher-centered instruction insufficient.*
>
> **Liu Qing**
> President, National Innovation Center par Excellence

From a sustainable development perspective, education should guide students to apply AI to real-world problems, not just abstract exercises. Project-based learning already helps students apply AI to practical sustainability use cases, such as campus carbon-neutrality monitoring and community support systems. These interdisciplinary projects develop technical skills while fostering sustainability awareness, social responsibility, collaboration, and problem-solving. Floriane Gusciglio, General Delegate at ParisTech, stated that educators should be committed to training a generation that can "speak both languages" – one is AI, and the other is sustainability and climate science. Instead of using AI as a shortcut to find information faster, students should use AI to create value and solve problems to support long-term sustainability.

Experiences from Southeast Asia further illustrate this approach. According to Zhou Yiping, Founding Director of the United Nations Office for South-South Cooperation, regional scholarship programs, online learning platforms, and investments in public data and digital infrastructure have significantly strengthened AI literacy among young developers, educators, and grassroots communities. AI itself can support digital inclusion through intelligent translation, adaptive learning, and personalized content delivery, helping to build inclusive, lifelong learning ecosystems.

China has supported similar capacity-building efforts through short- and medium-term AI training programs, joint education initiatives, and academic exchanges aimed at developing AI research and application talent in developing countries. In Cambodia's smart agriculture projects, for example, Chinese teams have provided on-site technical guidance and hands-on training, supporting local capacity development and long-term self-reliance. These experiences underscore a broader lesson: the educational challenge posed by AI is not one of control, but of direction – how to harness efficiency gains while preserving curiosity, critical thinking, and human agency.

CASE STUDY 8

Integrating AI into Climate Mitigation Research, Policy, and Education

Columbia University's School of International and Public Affairs (SIPA) has long been recognized as a global leader in climate, energy, and sustainability studies. This leadership is reflected institutionally through the school's Climate, Energy, and Environment (CEE) concentration, one of the most comprehensive climate-policy training programs among international affairs schools, and through SIPA's close integration with the Center on Global Energy Policy (CGEP) – a leading global think tank whose research regularly called upon to provide policymakers and global business leaders with the insights they need to make change happen. The Climate & Sustainability Alumni Network comprises over 4,000 climate, environmental and sustainability professionals worldwide. It includes graduates of the Climate School as well as its partner programs, which include degrees offered and conferred by Columbia College, School of General Studies, the School of International and Public Affairs, and the School of Professional Studies, as well as the Graduate School of Arts and Sciences.

Recent assessments, including the Innovation for Cool Earth Forum (ICEF) *Artificial Intelligence for Climate Change Mitigation Roadmap* reports, led by Professor Dr. David Sandalow, highlight the transformative potential of AI in global mitigation efforts. According to report, although the emissions generated by training and using AI currently account for less than 1% of global emissions, future growth is uncertain due to the rapidly increasing demand for data centers. The report also points out that the core bottleneck in realizing AI's climate potential is the lack of data and talent, and emphasizes that establishing trustworthy AI, expanding open data, developing open-source foundation models, and ensuring the widespread deployment of AI in emission monitoring, extreme weather forecasting, and materials innovation will have a potential "order of magnitude" impact on global climate mitigation.

> *SIPA is committed to educating the next generation of policymakers to help them shape and govern AI tools for climate change mitigation.*
>
> **Dr. David Sandalow**
> Co-Director of the Energy and Environment Concentration, School of International and Public Affairs at Columbia University

As a concrete institutional example of how AI research can be integrated into climate and public policy education, Columbia SIPA has taken significant steps to embed AI into its academic offerings. The school now provides 13 AI-related courses that span ethics, digital content provenance in the age of generative AI, and the application of AI to urban governance and conflict prevention. These offerings reflect SIPA's recognition that AI will be central to future policy work and ensure that graduates entering government, nonprofits, or industry will be well equipped to operate at the intersection of AI technology and public policy.

Complementing coursework, initiatives such as AI and Development further integrate real-world applications, exploring how AI can better serve low-income countries by building on existing digital infrastructure and promoting the development of more useful, robust, and socially aligned algorithms. Through this combination of research, education, and practice, SIPA is building a comprehensive model for educating the next generation of policymakers equipped to govern and deploy AI for global climate mitigation.

Source: Columbia SIPA

AI in Talent: Global Competition for Next-Gen

Countries increasingly use immigration, tax, and visa policies to attract AI and technology talent. These tools reduce friction and signal openness to globally mobile professionals. Singapore offers Tech.Pass and the Overseas Networks and Expertise Pass (ONE Pass), which allows senior technologists and founders to live and work flexibly across roles, with long-term residence and family sponsorship. The United Kingdom's Global Talent visa provides a similar route for AI and digital leaders, including fast-track settlement and no minimum salary requirement. Portugal's digital nomad and startup visas offer pathways from temporary residence to long-term settlement, linked to certified incubators and EU-supported networks.

> *AI will not eliminate jobs; instead, AI-enabled operating models will generate more employment to meet rising global energy needs.*
>
> **Hon. Warwick Smith AO**
> Former Federal Government Minister, Australia

Laura Nguyen, Partner at GenAI Fund, notes that many founders face stalling not due to technological failure, but due to challenges in accessing compute resources, obtaining clean data, or achieving customer adoption. Dubai's DIFC Innovation Hub brings many of these elements together in a single, integrated platform. As home to a cluster of technology companies across AI, fintech, and emerging sectors, DIFC offers tailored licences, direct access to regional and global markets, and a regulatory environment designed for fast-moving innovation. Its AI Licence is a flagship instrument that provides AI startups with a legal presence, co-working space, fast-track visa access, and access to the Ignyte platform for capital, mentorship, and partnerships. DIFC also anchors the Dubai AI Campus, the largest AI cluster in the Middle East, which combines research facilities, accelerator programs, and real-world testbeds across sectors ranging from telecommunications to space technology.

But visas and tax benefits mainly help people arrive, not stay. Leading countries now focus on integration and empowerment, especially for younger talent. Sashwat Pandey, Founder of Young Sapiens Network, admits that achieving meaningful youth influence, rather than just symbolic "youth-washing", requires concrete institutional steps. Youth must be treated as rights-holders in sustainability processes, not just as advocates. Instead of viewing young people only as employees or founders, many countries create "real seats" for them in government, public-sector AI projects, and national innovation agendas. Rao Wei, Deputy Secretary-General of Shanghai Climate Week, admitted that beyond a learning subject, AI is more of an empowering tool to promote more youth climate actions and leadership achievements. The UAE provides structured roles for young people in policy discussions through the Ministry of State for Artificial Intelligence, Youth Councils, and Future Councils. Public-sector AI deployments in smart government, energy systems, urban planning, and digital infrastructure are used as practical training environments where young people learn how technology operates within real institutional and regulatory constraints.

Education and early leadership platforms reinforce this pipeline. In Singapore and several European countries, AI education is linked to public problem-solving rather than technical training alone. Schools and universities support AI invention programs, applied research challenges, youth policy labs, Youth Delegate Programs, and model parliament and model United Nations platforms. These initiatives expose students early to how AI interacts with regulation, ethics, and public value.

Entrepreneurship policy reflects the same logic. In the United Kingdom, Portugal, and many other countries, regulatory sandboxes, public procurement pilots, and early-stage funding allow young founders to experiment without requiring long track records or senior credentials. These systems accept iteration and failure as part of learning. Rather than waiting for young people to become fully established, these countries allow them to build, test, and learn within the national innovation system. Ahmad Ali Alwan, Chief Executive Officer of Hub71, mentioned Hub71's mandate to attract startups and young people from around the world and build a diverse community that works together towards a shared purpose.

Immigration and tax policy function as enablers. Long-term advantage depends on whether countries give young people real roles, institutional platforms, and clear pathways to leadership. The countries that perform best are those that allow young talent not only to enter, but to stay, contribute, and shape public decisions in AI and sustainability.

Overall, the global competition for AI talent has become multi-dimensional. Successful jurisdictions no longer rely on a single policy lever, but combine flexible visas, attractive living and working conditions, targeted tax incentives, and credible innovation ecosystems. The lesson for policymakers is clear: attracting AI talent today means offering not just permission to stay, but a coherent environment in which individuals and small teams can build, experiment, and scale across borders.

CASE STUDY 9 | A New Model for AI Talent Development

Established on June 28, 2025, the Joint Academy on Future Humanity, co-founded by Renmin University of China and Westlake University, represents China's first high-level interdisciplinary platform dedicated to the study of "Future Humanity." From its inception, the Academy has been designed as a talent-first institution, centered on cultivating the next generation of AI researchers, thinkers, and innovators through a youth-driven, full-cycle development model.

At the idea formation stage, the Academy anchors talent development in long-horizon questions shaped by artificial intelligence. It has released the Top Ten Topics on Future Humanity, spanning themes such as human evolution, cognition, values, governance, civilization, and security in the AI era. Building on this framework, the Academy launched the Future Humanity Vision Collection Project, inviting young people worldwide to contribute forward-looking ideas, and is organizing the Global Conference on Future Humanity under the theme "AI and the Future of Humanity." These initiatives position young researchers not as passive learners, but as agenda-setters in global AI discourse.

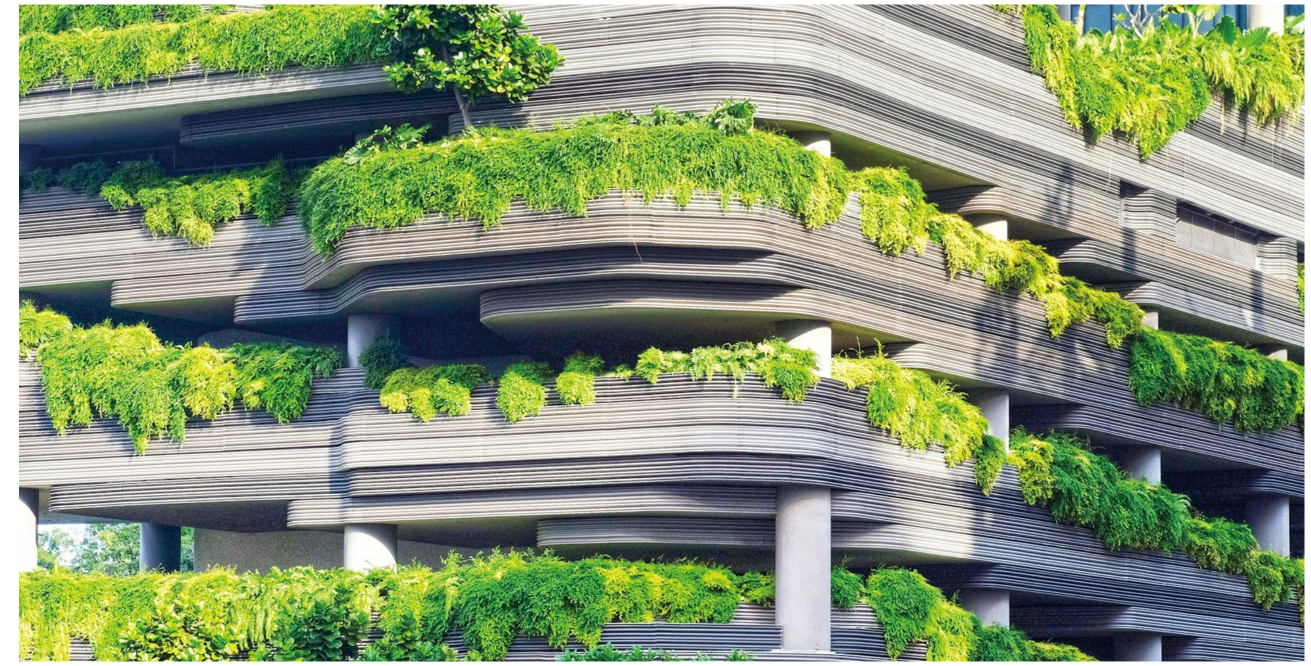
At the research and incubation stage, the Academy operates a project-based Young Researcher Program that selects outstanding scholars under the age of 35 and provides them with funding, compute resources, and institutional support to pursue frontier AI-related research aligned with the Ten Topics. To strengthen incentives and intellectual property protection, the Academy has developed a blockchain-based Future Humanity Research Platform, which assigns each research output a unique cryptographic identity. This system enables verifiable authorship, digital publishing, and international recognition, while lowering barriers for early-career researchers to participate in global knowledge production. The Academy is also preparing to launch *Future Humanity Studies*, the world's first English-language academic journal fully initiated and led by students, further reinforcing youth leadership in AI scholarship.

At the application and translation stage, the Academy supports the transformation of research into practice through the "Future Engine · Futurengent Smart Studio", which incubates AI applications across domains such as information retrieval, music, archaeology, and social platforms. Complementary platforms – including the "Future Dialogue Hall" and the "Voices of Tomorrow Youth Exchange Program" – extend talent development beyond academia into public engagement and global collaboration.

Together, these initiatives form an integrated pipeline for AI talent development, spanning idea generation, research incubation, and real-world application. The Academy's model – combining youth leadership, interdisciplinary inquiry, and technological infrastructure – offers a replicable approach to cultivating AI talent oriented toward long-term societal and civilizational challenges.

> *How can we preserve students' imagination? There is, in truth, no fixed paradigm to follow. What we can do is inspire them to gaze at the stars and dare to envision the seemingly impossible. The Academy aims to inspire young minds from around the world, inviting them to envision the future at the crossroads of science and the humanities. Here, bold and seemingly improbable ideas can evolve into transformative works capable of reshaping our world and steering the course of tomorrow, thereby advancing our era and pioneering future development.*
>
> **Dr. Shi Yigong**
> President, Westlake University

Source: The Joint Academy on Future Humanity



AI in Future: From Science to Art

Advancing AI does not mean everyone needs to become an AI engineer, nor does it mean AI can replace everything. As AI takes over computation, optimization, and repetitive work, the value of human contribution becomes more focused, not less. What matters most for a sustainable future are the capabilities AI cannot replace: creativity, ethical judgment, empathy, and the ability to create meaning.

> *Artificial intelligence is not our master, but a tool for humans to improve people's lives – happier, healthier, better educated, with more jobs and more fun.*
>
> **Erik Solheim**
> Former Under-Secretary-General, United Nations

AI's role is to improve efficiency, not to define human purpose. Automating routine tasks frees people to spend more time on design, education, storytelling, and social connection. A human-centered AI future is built on a clear division of labor: machines handle what can be optimized; humans remain responsible for intent, values, and direction.

Architecture and urban design illustrate this shift clearly. AI can process data-heavy analysis and technical constraints at speed, allowing creativity and human experience to move back to the center of design. As Ariane Dienstag, General Secretary of the Council on Tall Buildings and Urban Habitat (CTBUH) French Chapter, notes, AI compresses months of engineering work into hours, enabling professionals to focus more directly on environmental responsibility and human well-being.

As planning and design processes accelerate, the role of architects and planners becomes sharper rather than weaker. When measurable tasks are automated, human judgment shifts to what cannot be optimized: spatial quality, cultural context, and lived experience. In practice, AI reduces technical overhead and expands time for exploration, dialogue, and composition, supporting more diverse, human-centered outcomes rather than uniform or automated ones.

Open & Equitable AI for All

> *AI is not the desired result; it is the enabler. Developed thoughtfully, it can become shared infrastructure — scalable for institutions and transformative for people.*
>
> **H.E. Professor Dr. M. Iqbal Chaudhary**
> Coordinator-General, OIC-COMSTECH

Data Asset in the Open-Source Era

As AI systems rely increasingly on large volumes of data, openness brings both clear benefits and growing risks. Shared datasets can improve model quality and widen participation, but poorly governed data use can erode privacy, security, and public trust. Unlike software code, data is rarely neutral: it is contextual, often sensitive, and directly linked to people, communities, and critical infrastructure. As Alexandre Borde, Member of the CDM Registration and Issuance Team at the UNFCCC, notes, data was already an asset two centuries ago; what has changed in the AI era is its centrality, as advanced systems depend on large and diverse datasets, making access to information a decisive factor in who can innovate and participate.

Existing technical tools for data governance are insufficient to address the challenges posed by modern AI and large-scale data use. Commercial data governance platforms, while more comprehensive in functionality, tend to be expensive, lack standardized archetypes for diverse contexts, and require significant expertise and resources to implement, making them inaccessible for many public institutions and smaller organizations. Government-provided tools and frameworks often face another limitation: they are high-level and theoretical, lacking clear operational guidance and practical mechanisms for institutions to manage data governance effectively in real-world settings. AI systems further strain these weak frameworks by learning patterns without reproducing the data and by generating outputs that are legally distinct yet functionally equivalent to the original material. As a result, existing governance approaches fail to meaningfully constrain misuse or ensure equitable control over data in contexts where it matters most.

> *We call for and commit to supporting open innovation partnerships in AI and climate technology, to build fairer technology transfer and financing mechanisms and back AI-driven projects that bring clean energy, resilient agriculture, and green livelihoods to Global South communities. This support is not a one-way transfer of technology. It is a partnership that builds long-term local capacity and strengthens local innovation ecosystems.*
>
> **Tony Dong**
> Chief Representative, Sino-International Entrepreneurs Federation

In the Global South, the absence of well-designed open data-sharing frameworks creates a real risk that data, which could otherwise be used to address climate change and improve public welfare, becomes privatized by a small number of commercial actors. As Amandine Hardowar de Rosnay, Head of Sustainability & Inclusive Growth at Business Mauritius, has noted, this imbalance is particularly visible in developing and small-island contexts. Locally generated data is critical for climate risk analysis and sustainability planning, yet access to such data and the dissemination of resulting analyses are often structurally concentrated within a small set of institutions. In many small island states, governments are the primary – or sometimes the only – actors able to commission climate and coastal risk studies, which can unintentionally limit wider circulation of data and findings across researchers, practitioners, civil society, and the private sector. By contrast, in larger countries, climate and coastal science is produced by and for a much broader range of institutions, enabling parallel research efforts, stronger academic ecosystems, and more frequent publication in open scientific literature. While this concentration of data access and knowledge predates artificial intelligence, the rapid expansion of data-intensive AI systems risks reinforcing these asymmetries, further constraining countries' ability to derive broad-based value from their own data resources unless data governance and access are explicitly addressed.

These dynamics show that openness in the AI era cannot be unconditional. Cooperation remains necessary, but it must come with clear limits. As H.E. Corinne Lepage, former French Minister of the Environment & former Member of the European Parliament, emphasized "cooperate, yes; depend, no", stating open collaboration should strengthen shared capacity without locking countries into long-term dependence on external data, models, or infrastructure. This means moving beyond informal norms toward practical governance tools: clear usage rights, traceable data provenance, transparent disclosures of model training, and shared mechanisms to signal permitted uses across jurisdictions. The aim is not to reduce openness, but to make it sustainable, so data and AI systems can support innovation while preserving trust and strategic autonomy.

Equitable AI Access for the Global South

Zoe Zhang, Secretary General of Sino-International Entrepreneurs Federation, believes leading AI from China and around the world should serve as a fair bridge that empowers the Global South to tackle climate challenges. This means not only sharing technology, but also working together to build local innovation capacity, combining intelligent algorithms with local ecological knowledge to shape an inclusive, resilient, and sustainable future. As such, technology dividends should not be captured by a small group of countries. For the Global South, artificial intelligence must be shaped through inclusive cooperation that turns technological progress into shared development, not deeper fragmentation. The goal is not simple diffusion, but transformation – using AI to narrow the North-South gap and enable green, leapfrog growth. Seema A. Khan, Senior Advisor of OIC-COMSTECH, urges that over the next decade, we must construct AI systems that are interoperable, ethical, and equitable, so that governments and citizens alike can depend on them.

In practice, inclusivity depends on addressing structural constraints. Many developing countries face chronic shortages of computing power and network capacity. This makes adaptive approaches – such as lightweight models, distributed computing, and shared resource mechanisms – essential to closing the "compute divide." Regional cooperation plays a critical role. In parts of Africa, community-based data cooperatives are pooling agricultural and health data to support climate resilience while retaining local ownership. This results in a shortage of supporting capital. In the second quarter of 2024, African AI startups secured just $4 million across five deals, less than 1% of worldwide investment, with $23.2 billion raised globally.

According to Chantele Carrington, Chief Executive Officer of Invest Africa, AI-enabled systems can improve transparency, efficiency, and trust across global supply chains, particularly for emerging economies that remain underrepresented in AI investment. Inclusive AI development requires coordinated investment, institutional capacity, and alignment with how infrastructure is actually planned and delivered. For example, Shi Hao Zijdemans, Digital & Technology Specialist at Asian Infrastructure Investment Bank, explains that rather than a single "AI moment," AIIB's experience is that value can emerge whenever AI is embedded across the infrastructure lifecycle – from project design and risk assessment, to construction oversight, operations, and long-term maintenance. Applied this way, AI supports more reliable services, better asset performance, and more informed decision-making across all infrastructure sectors. When paired with open collaboration and trust-based governance frameworks, these technologies can meaningfully contribute to climate resilience, sustainable trade, and inclusive growth across the Global South.

> *We still need to work harder collectively to give access to regions where networking opportunities aren't available.*
>
> **Ahmad Al Ghardaqa**
> Lead Negotiator and Senior Legal Advisor, UAE National Negotiation Team

Equitable access to AI is now a practical issue, not a theory. Across parts of the Global South, local governments are already deploying AI in practical, resource-constrained settings, leveraging modest infrastructure, open data flows, and community participation to address mobility, disaster risk, public health, and environmental degradation. These experiences offer concrete insight into how inclusive AI can be designed from the ground up, ensuring that technological capability translates into everyday public value rather than remaining concentrated in a few institutions. [91]

CASE STUDY 10

Inclusive AI Deployment in the Philippines

Across several Philippine cities, artificial intelligence is being deployed not as an abstract "smart city" upgrade, but as public infrastructure designed around everyday needs – how people move, how they stay safe during disasters, how they protect their health, and how vulnerable groups are included rather than displaced.

In daily mobility, AI systems directly affect how residents experience the city. By combining traffic sensors, public transport data, and citizen reports, city governments are able to adjust traffic management in real time. For commuters in Pasig City, this means shorter travel times, safer intersections, and more predictable public transport. Importantly, residents are not passive data subjects: motorists and passengers actively report accidents and congestion through mobile platforms, ensuring that planning reflects lived experience, not just technical models.

AI is also used to enhance communities from clean energy adoption and climate risk resilience. In Quezon City, solar adoption is mapped across the city to identify potential destinations for upcoming solar installations. Also, the I-RISE UP system monitors flood levels and air quality, triggers disaster risk reduction efforts ahead of time, and nurtures climate change awareness.

In public health, AI helps communities act earlier, not later. In Cauayan City, Isabela, AI-supported monitoring identifies rising mosquito infestation before outbreaks spread, triggering sanitation alerts and community mobilization. Health officers remain in the loop, using AI as decision support rather than a substitute for human judgment. Across these cases, AI reduces uncertainty for people with limited time, income, and resilience. By converting data into timely, understandable action, these city-level deployments show how equitable AI in the Global South can improve daily life, strengthen trust in public institutions, and ensure that technological progress is felt first by those who need it most.

> *Digitalization means automating or digitizing existing services. AI, on the other hand, involves machine-driven analysis and decision-making without human input. Many cities, even globally, are still at the digitalization stage where true AI adoption remains rare.*
>
> **Michael Victor N. Alimurung**
> City Administrator, Quezon City

Source: Pasig City, Quezon City, and Cauayan City, Phillippine

Inclusive AI for Agricultural SMEs

> *We want to be a leader of AI adoption in West Africa. The first thing is to use this artificial intelligence to increase financial inclusion for our population by developing affordable AI-enhanced banking products working closely with our national bank and the foreign banks.*
>
> **H.E. Lalsaga Sayouba**
> Advisor to the President of Burkina Faso

Small and medium-sized enterprises (SMEs) in agriculture are among the most climate-exposed and economically fragile actors in the global economy. Acute physical risks – floods, droughts, heatwaves, and pest outbreaks – directly undermine yields and income, while transition policies such as fuel switching, electrification mandates, and tighter emission standards introduce additional compliance and capital pressures. As climate volatility intensifies, the central question is no longer whether AI can be applied to agriculture, but whether it can deliver tangible, distributable value to those least able to absorb climate and transition risks.

Paradoxically, agriculture remains one of the least digitized and least AI-adopting sectors. The McKinsey Global Institute consistently identifies food and agriculture as lagging across all dimensions of digitization, reflecting fragmented land ownership, highly localized practices, limited rural connectivity, and persistent skills gaps. Yet this structural lag also signals latent potential. The global digital farming market was valued at approximately USD 24.9 billion in 2023 and is projected to grow at around 16.3% annually through 2030, as infrastructure constraints ease, upfront costs decline, and technical barriers gradually diminish.

In the near term, the most significant value of AI for agricultural SMEs lies not in abstract optimization but in risk anticipation, loss avoidance, and income stabilization. AI-enhanced weather and disaster forecasting already demonstrates measurable social and economic benefits. Systems such as Google Flood Hub combine machine-learning-based hydrological forecasting with inundation modelling to predict flood extent and depth up to seven days in advance. As of its latest update, the platform covers more than 80 countries and reaches roughly 460 million people, providing critical lead time for evacuation, crop protection, and emergency response, and materially reducing losses from extreme flooding.

Beyond early warning, AI increasingly supports decision-critical functions that directly affect resilience and profitability. By integrating satellite imagery, soil data, and localized weather forecasts, machine-learning models can identify water stress, nutrient deficiencies, and heat damage earlier than visual inspection, enabling timely intervention before irreversible yield loss. Precision input management further allows water, fertilizers, and pesticides to be applied more selectively, lowering costs while reducing runoff and soil degradation, an increasingly important advantage as input prices rise and environmental regulations tighten. Low-cost computer vision tools, often deployed via smartphones, help detect pests and diseases at early stages, narrowing response windows and reducing the need for blanket chemical spraying, which disproportionately burdens small producers. AI-driven market and price forecasting also helps SMEs decide when and where to sell, reducing exposure to price volatility and information asymmetries that remain a chronic source of income instability in fragmented local markets.

For agricultural SMEs, AI does not replace agronomic knowledge or local experience. Its primary function is to compress uncertainty into actionable signals – translating climate variability, market opacity, and policy complexity into decisions that can be made with limited capital, limited time, and limited technical capacity. In this sense, AI operates less as an efficiency multiplier for already industrialized agriculture and more as a risk-buffering infrastructure for producers operating at the margins of climate and economic resilience.

Governance of AI Risks

Every Transformation Was Once Feared

Capacity training for the private sector on new regulations and climate compliance is essential, with public-private dialogue important for addressing implementation gaps. International partners such as development banks should also offer tailored training aligned with national development levels rather than a one-size-fits-all model.

Dr. Kaewkamol Karen Pitakdumrongkit
Interim Secretary General,
PECC International Secretariat

Throughout modern history, every transformative technology has faced resistance before becoming an engine of social and economic progress. The steam engine was accused of destroying labor and destabilizing cities; electricity was feared for its safety risks and social disruption; railways were said to collapse space and time beyond human control; the internet was once viewed as a threat to sovereignty, morality, and social order. In each case, early anxieties were not unfounded, yet history shows that societies advanced not by rejecting these tools, but by learning how to govern, integrate, and adapt them. Artificial intelligence is following a similar path, raising legitimate concerns about employment, security, and inequality. But treating AI solely as a risk is a mistake that confuses uncertainty with danger, and disruption with decline. Like its predecessors, AI is a continuation of long-term technological evolution.

Current regulatory approaches reflect different historical experiences and institutional priorities. The United States has largely favored an innovation-first model, allowing AI development to proceed rapidly with limited ex ante regulation, on the assumption that market competition and post-hoc oversight will correct failures. Europe has taken a more precautionary approach, emphasizing rights, safety, and accountability through comprehensive frameworks such as the AI Act. China, meanwhile, has pursued a governance model focused on systemic stability, social impact, and alignment with national development objectives. Each approach responds to real risks and legitimate societal concerns.

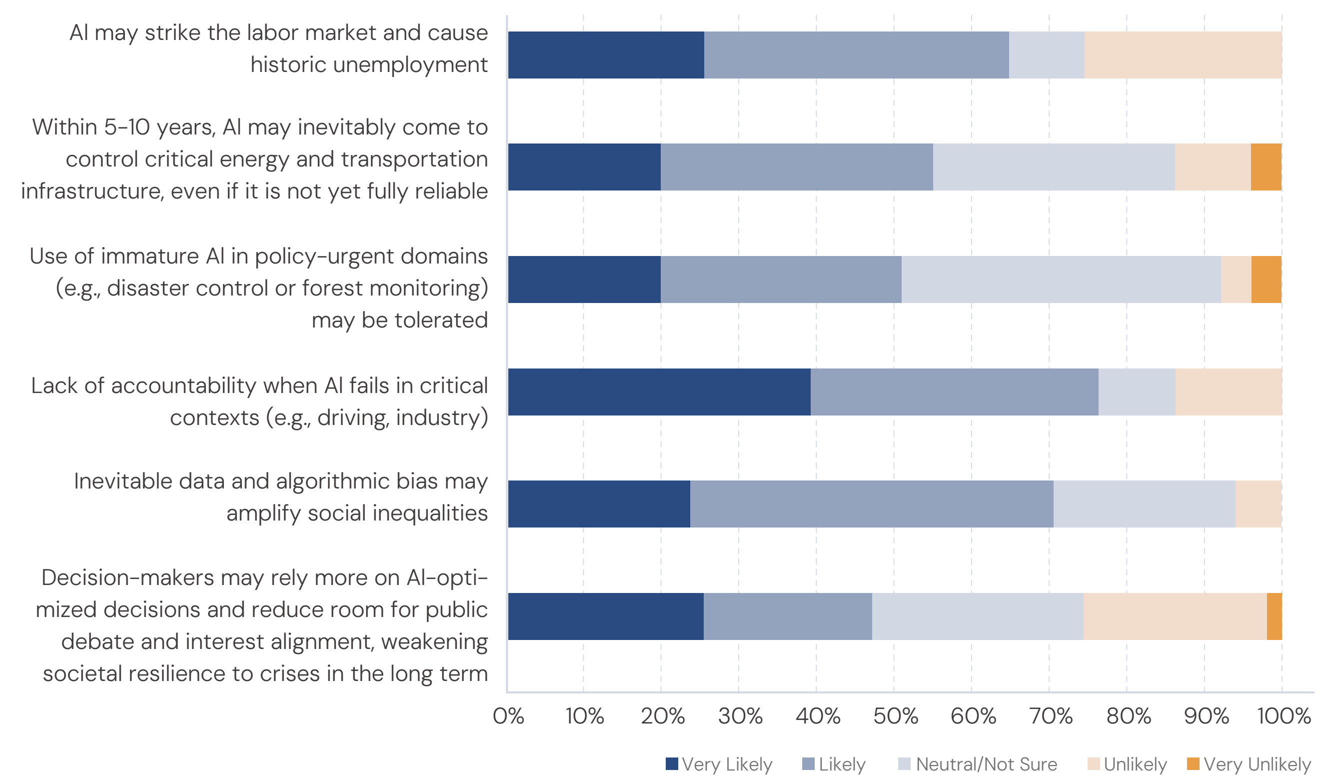
Crucially, governance should be understood not as resistance, but as the mechanism through which society learns to live with AI. Just as labor laws and safety standards enabled industrialization, AI governance should focus on mitigating risks and ensuring accountability while preserving space for experimentation. The goal is not to slow progress, but to channel it toward socially beneficial, economically inclusive, and sustainable outcomes. Embracing AI means recognizing and managing its risks, not being paralyzed by fear. Progress has always depended on moving beyond initial anxiety toward responsible adoption. The task of governance is not to stop this transformation, but to guide it, ensuring society moves forward.

Trust, Accountability, and Public Participation

Contributors of this report most often rate the following risks as “very likely” or “likely”: accountability gaps, algorithmic bias, and over-trust in AI decisions. This suggests a shared view that AI will be deployed in critical systems faster than governance can keep up. They expect AI to be used in energy, transport, and disaster management within the next 5 to 10 years, even if it is not fully reliable. This raises concern that systems will depend on AI too early, driven by urgency rather than readiness. Great concern about bias and labor displacement shows that many see AI’s social effects as broad, built-in consequences of widespread adoption. Worry about AI-driven decision-making dominating also points to risks of weaker public debate and reduced political accountability in long-term crisis governance.

Figure 4.4a **Most Concerned AI Risks**

Source: ClimateTech In Focus Responding Contributors



AI risk governance is often described through four connected themes: trust, transparency, fairness, and accountability. Imad Lahad, Global Chair of AI and Intelligence at APCO, emphasizes that trust and transparency are foundational. Trust cannot exist without transparency. Public trust holds the AI ecosystem together. Yukio Sakaguchi, President of the Clean Energy Research Lab, observes that AI is often promoted as a “miracle cure,” while the real constraints lie in infrastructure readiness and regulatory capacity.

Many AI systems still operate as black boxes, with opaque model designs, undisclosed data sources, and decision logic that the public cannot review or understand. This is especially concerning in climate mitigation and adaptation, where AI is increasingly used for infrastructure planning, land-use decisions, energy system design, and disaster response.

Ravenna Chen, Chief Executive Officer of Intrinsic SEA, points out that technology can cross borders easily, but trust and institutional recognition must be built intentionally. When designed responsibly, AI can strengthen public participation. AI-driven personalization, such as advice on mobility choices, household energy use, or agricultural practices, can turn millions of daily decisions into real emissions cuts. With open models, explainability tools, and user-friendly interfaces, people can see how their choices affect climate outcomes, thereby strengthening trust and civic engagement.

The risks are also serious. When AI outputs are presented as purely technical results without explanation, the ability to question decisions, or transparency, they can limit democratic discussion and scientific debate. This is most dangerous in climate decisions that affect livelihoods and social stability, such as hydropower development, coastal protection, land relocation, or food security. 47% of this report's contributing survey respondents agree that when communities are told that "the AI model has determined" an outcome, without access to assumptions, uncertainty, or trade-offs, public consent is replaced by top-down decision-making. This can shift power from public institutions to computational systems and exclude vulnerable groups whose lived experiences and local knowledge are poorly captured in the data.

Addressing this requires governance that builds transparency into AI systems from the start. Sonia Dunlop, Chief Executive Officer of the Global Solar Council, has noted that trust, cybersecurity, and policy coherence are essential conditions for safe deployment. This supports a risk-based regulatory approach where high-impact climate uses face stricter requirements for explainability, human oversight, and public accountability. Other measures include AI audits and certifications, public review or consultation for AI-backed policy decisions, and rules requiring that models used in public governance be auditable and understandable to non-experts. Transparency is not just a technical feature. It is required for legitimate, socially grounded climate governance.

Hold Hands, Not Build Fences

As climate change intensifies pressures on societies, economies, and ecosystems, many see artificial intelligence as a useful tool for climate action, but it also introduces new risks and governance challenges. AI can improve climate models, strengthen early warning systems, optimize energy and resource use, and support decisions across complex systems. Ravenna Chen, Chief Executive Officer of Intrinsic SEA, notes that AI can make climate efforts smarter and even more collective by enabling coordination across actors, sectors, and geographies that would otherwise be difficult to manage.

> *The greatest enabler for addressing any global challenge that we face, is to increase trust between us – that we are proposing solutions that benefit everyone, not just ourselves.*
>
> **Seema A. Khan**
> Senior Advisor, OIC-COMSTECH

AI is not a plug-and-play tool that works the same everywhere, and it brings real challenges, including data sovereignty and public infrastructure, safety risks in critical systems and disaster response, and equity concerns about who benefits and who pays the costs. These risks are why countries should cooperate instead of isolating themselves. Climate impacts cross borders, and the best way to improve data quality, reduce bias, strengthen accountability, and expand access is to share datasets, standards, tools, and operational lessons across countries. No single institution or country can do this alone. Imad Lahad, Global Chair of AI and Intelligence at APCO, highlights that no single body can solve the climate challenge or govern AI independently. With trusted collaboration and open, interoperable approaches across governments, the private sector, civil society, and international organizations, including shared commitments to interoperable data, common ethical standards, transparent governance, and resilient digital infrastructure, AI can become safer, fairer, and more useful, especially for climate finance, infrastructure planning, and disaster response.

Figure 4.4b **International Governance Initiatives on AI**

Owner	Name	Description
United Nations	UN High-level Advisory Body on AI	• Global institutional design for AI governance • Multilateral coordination and policy harmonization • Strong Global South representation
UNESCO	Recommendation on the Ethics of Artificial Intelligence	• Human rights and fundamental freedoms • Environmental and social sustainability
APEC	APEC AI Governance Framework	• Trade-enabling AI governance • Cross-border data flow compatibility • Digital economy trust
OECD	OECD AI Principles	• Human-centered and trustworthy AI • Transparency, robustness, and accountability
China	Global AI Governance Initiative (GAIGI)	• AI for Good, AI sovereignty, and peaceful use of AI • Inclusive digital development for the Global South • State-led governance and non-hegemonic rule-setting
European Union	EU AI Act	• Binding supranational AI regulation • Risk-based system classification and compliance • Extraterritorial effect across the EU market
Council of Europe	Framework Convention on Artificial Intelligence and Human Rights (CAI)	• Legally binding human-rights protection in AI implementation
G7	Hiroshima AI Process	• Generative AI safety coordination • Frontier model risk management
BRICS	BRICS AI Governance Track	• South-South AI cooperation • Data sovereignty and capacity building • Development-first AI governance
African Union	AI Continental Strategy (Draft)	• AI sovereignty for African states • Digital inclusion and skills development

Global AI rules are still taking shape. Regulation often trails new technology, but governments are moving to catch up. The European Union is advancing its AI Act, the United States has released the NIST AI Risk Management Framework, and China has issued interim measures for managing generative AI. In March 2024, the United Nations General Assembly adopted a resolution stressing the global need for "safe, secure, and trustworthy" AI. [103] Across the EU's risk-based approach and the more flexible, sector-specific frameworks in the UK, Asia, the Middle East, and other regions, one point is clear: AI governance is becoming a basic expectation.

Meanwhile, effective AI governance cannot rely on formal regulation alone. In practice, shared norms, mutual trust, and operational understanding are often shaped through continuous dialogue and collaboration beyond statutory frameworks. In the context of climate action, where uncertainty, speed, and cross-border coordination are the norm, governance is shaped not only by rules but also by the quality of dialogue and cooperation among those applying AI in practice.

CASE STUDY 11

Convening Without Borders in AI and Climate Innovation

Technology and innovation were central to London Climate Action Week (LCAW), underscoring the Capital's position as a global hub for clean tech and highlighting the rapidly growing role of AI in climate solutions. In 2025, LCAW's dedicated cleantech cluster was led by Undaunted, a UK and global hub for green entrepreneurship, London & Partners, Sustainable Ventures, and the Blue Earth Forum, which connects investors with high-growth, solutions-driven businesses. But the role of AI extended well beyond the cleantech cluster. Conversations about its impact, risks, and practical uses ran across the entire programme, spanning food systems, nature, energy, resilience, and green finance.

This year's LCAW featured events from world-leading tech giants such as Google, alongside start-ups developing emerging AI applications for climate tech and the financial institutions backing them. Barclays, for example, convened a discussion on AI's investment potential in the energy sector. Academia was also strongly represented, with the London School of Economics and Kingston University London hosting sessions on the social, economic, and governance dimensions of AI in climate action.

One highlight of the week was the 2025 Responsible AI Impact Awards, featuring speakers including BNP Paribas, the United Nations, and Deloitte, reflecting growing momentum behind ethical and accountable AI deployment.

Across the week, discussions explored the expanding role of AI data centres in supporting the clean energy transition; AI's potential to accelerate climate innovation and strengthen resilience and conservation efforts; the importance of robust technology governance; advances in climate-modelling tools; and practical applications ranging from energy-efficiency optimization to precision agriculture.

Together, these conversations demonstrated how deeply AI is shaping the next generation of climate solutions, and how London continues to convene the people and ideas driving that transformation.

> *Events like climate weeks can help define and coordinate mission-driven AI, ensuring that AI tools move from conceptual discussions toward practical use that supports local decision-makers and smaller actors.*
>
> **Nick Mabey**
> Chief Executive Officer, E3G

Source: London Climate Action Week

Contributors to this report identify that AI governance for climate uses should follow a few guiding principles:

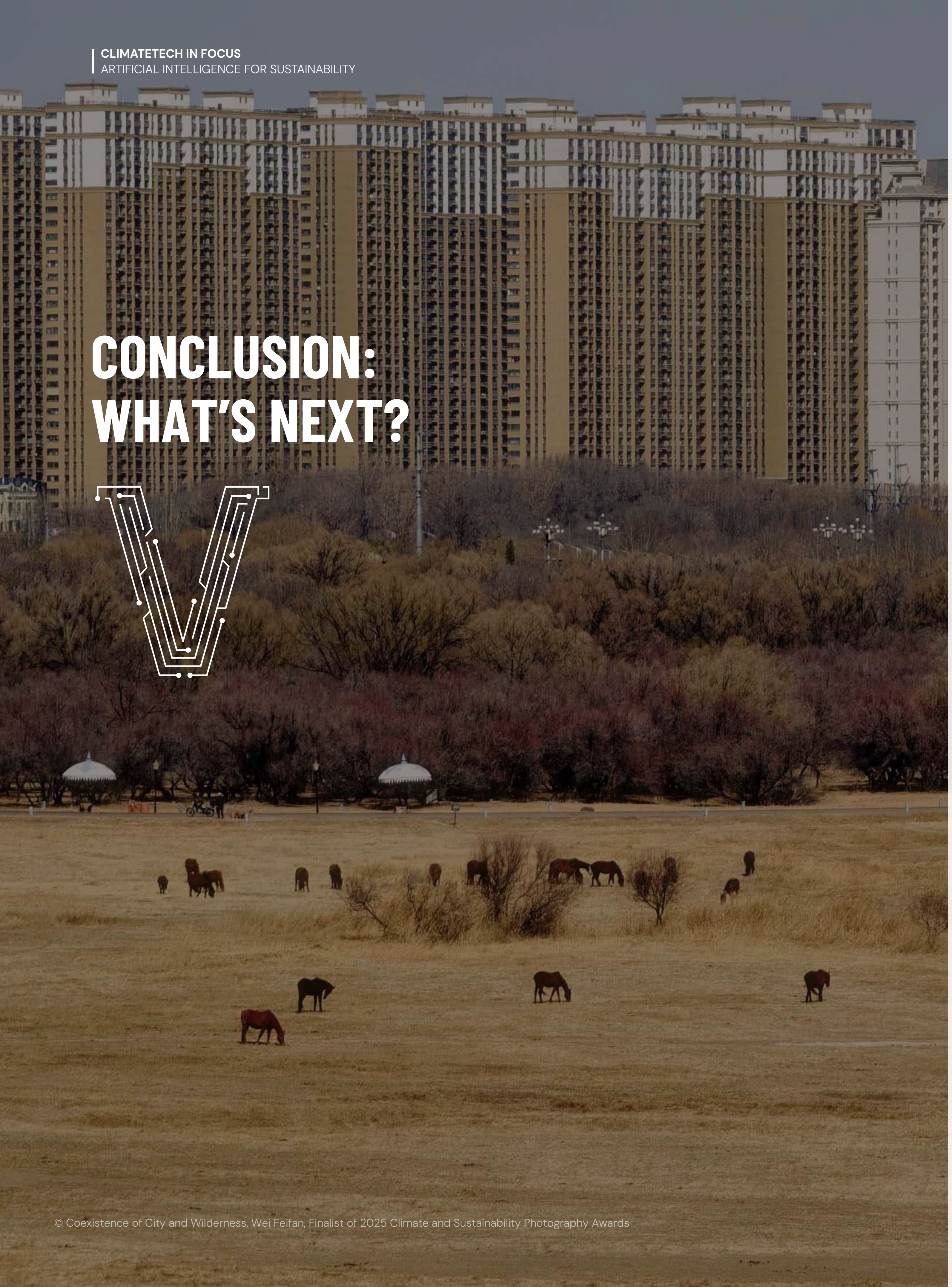
- Focus on proven public value, not just technical performance. Cross-border AI cooperation should be grounded on clear benefits for people and balanced against risk. For example, disaster warning systems can save lives quickly and deliver direct value relative to the risks they entail, making them a common priority for global AI use cases in the climate context.
- Start by sharing experience, not raw data. Data sharing is sensitive, but countries can still exchange scientific and operational lessons through open channels.
- Classify data and apply tiered access. Keep information open to improve verification and learning, such as data, benchmarks, and methods. Apply stronger controls when systems affect critical infrastructure or rights-sensitive decisions, such as dispatch, evacuation, credit, and insurance. There should always be a balanced choice between "open everything" and "build fences."
- Tolerate reasonable uncertainty and risk. AI models exhibit errors and bias, and the future development pathway of AI remains uncertain. Governance should not assume uncertainty and risk must be eliminated. With reasonable safeguards in place, some mistakes are acceptable, and systems should be designed to tolerate error.
- Treat people as AI's co-owners, not just users. Governments should prevent AI from harming society, but people also need the skills to use AI to protect themselves. Government oversight should have limits, rather than trying to control everything in the name of protection.

These realities explain why "holding hands" matters. The goal is not a borderless AI market. It is border-aware collaboration: open where openness supports truth and public value, and protected where protection safeguards rights, safety, and legitimacy.

In practice, strong international climate AI partnerships will look less like technology exports and more like shared infrastructure and shared assurance. That means trusted data, comparable evaluation, sustained capacity, and governance that can respond when issues arise. This is how climate AI can support collective action rather than create new divisions.

CONCLUSION: WHAT'S NEXT?

V



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> *We are carrying out a vast, frightening experiment of changing every ecological condition, all at once, at a pace that far outstrips Nature's ability to cope. As we work towards a zero-carbon future, we must work equally towards being Nature-positive.*

His Majesty King Charles III
King of the United Kingdom

For Governments, Regulators, and International Organizations

First, treat AI-enabled sustainability as a system-level challenge of decision delegation and institutional infrastructure: across energy, transportation, trade, and climate governance, impact depends on sustained deployment support, clear accountability, machine-interpretable rules, and data-verifiable enforcement rather than standalone technology promotion.

Second, align regulation, market design, and enforcement capacity with AI-enabled operational realities by scaling obligations with risk and impact, using tiered governance, sector-specific rules, and market mechanisms that support reliability, flexibility, transparency, and public legitimacy as automation accelerates decision speed.

Third, invest in long-term institutional capacity through talent ecosystems and data infrastructure: embedding AI into public services, infrastructure projects, and policy experimentation converts global talent into durable capability, while sensing systems, interoperable standards, and shared verification expand equitable participation, especially in the Global South.

Lastly, coordinate internationally through differentiated yet compatible pathways that respect sovereignty and asymmetries in data, computing, and institutional readiness, enabling cooperation without forcing uniform automation trajectories or dependencies.

For Enterprises, Platforms, and Infrastructure Operators

First, move sustainability from compliance toward operational intelligence by deploying AI where system value is highest – advisory and bounded orchestration roles in energy, manufacturing, logistics, and mobility that improve dispatch, optimization, maintenance, routing, and safety without displacing accountability.

Second, exercise awareness of the appropriate automation level for Governor, Orchestrator, Arbiter, Advisor, Interpreter, and Observer, based not only on problem definition and technological capabilities but also on risk tolerance and responsibility. Define ownership and operational metrics to complement workflows for use cases and enterprises and translate innovation into reliable outcomes.

Third, invest in data foundations, IT-OT integration, interpretability, and control architectures – supported by digital twins, simulation, and stress testing – so automation strengthens resilience, cybersecurity, and continuity as systems become more interconnected.

Lastly, embed AI end-to-end as a production capability rather than isolated pilots, allowing efficiency, decarbonization, safety, and workforce transformation to reinforce one another over time.

For SMEs, Startups, and Individuals

First, think slowly before moving swiftly. Take time to identify industry pain points. Maintain an agile, swift team focusing on minimally commercial viable products and scale the team in line with product growth.

Second, design AI products with data security, explainability, and regulatory compliance embedded from the outset, enabling smoother expansion across markets governed by different AI and data protection regimes.

Third, experiment rapidly while deliberately bounding risk, using AI to accelerate learning, deployment readiness, and market integration without amplifying downside exposure.

Lastly, recognize that human judgment, ethics, and responsibility remain central anchors in AI-enabled systems, defining boundaries, absorbing uncertainty, and sustaining social legitimacy.

For Financial Institutions, Investors, and Trade & Compliance Ecosystems

First, integrate AI and climate intelligence directly into core decision chains – credit, underwriting, provisioning, valuation, stress testing, certification, and market access – so sustainability shifts from disclosure and paperwork to auditable, decision-grade execution.

Second, treat climate and compliance intelligence as shared infrastructure by prioritizing transparency, uncertainty management, provenance, and governance over algorithmic novelty to ensure trust across finance, trade, and regulatory systems.

Third, apply multimodal AI – satellite, operational telemetry, laboratory data, and documents – to align claimed performance with observed reality, strengthening discipline, comparability, and confidence across global value chains.

Lastly, leverage AI and data transparency in innovative green loans/bonds and investment structures to direct capital to high-integrity Global South opportunities, such as credible carbon credit and renewable energy transition projects, thereby accelerating low-carbon growth.

For Education Institutions, NPOs, and Talent Ecosystems

First, shift from awareness-raising toward decision-literacy capability building, helping learners and institutions understand where AI should advise, orchestrate, or act – and where human judgment must remain primary.

Second, redesign education around systems literacy by teaching AI with sustainability, integrating governance, data quality, uncertainty, ethics, and interdisciplinary application rather than narrow tool proficiency.

Third, leverage youth leadership on real public challenges and provide meaningful seats, resources, and opportunities for youth in government and enterprise on AI for Sustainability.

Lastly, ensure inclusion is structural through sustained investment in access, local context, gender balance, and participation from the Global South, so AI capacity does not reflect inequality but opportunity.

Institutions

The United Nations University (UNU) is a global think tank and postgraduate teaching organization within the United Nations System. UNU engages in policy-relevant research, capacity development, and knowledge dissemination in furtherance of the purposes and principles of the United Nations. The work of the UNU contributes to solving pressing global problems that are the concern of the United Nations and its Member States.

Website: www.unu.edu

Pacific Economic Cooperation Council (PECC) is an independent, regional mechanism with 23 member countries and 2 institutional members that advances economic cooperation and market-driven integration. It has served as a regional forum for cooperation and policy coordination to promote economic development in the Asia-Pacific region since 1980. As APEC's only non-government official observer, PECC provides information and analytical support to APEC ministerial meetings and working groups in facilitating private sector participation in the formal process.

Website: www.pecc.org

Shanghai Climate Week (SHCW) is a global non-profit platform for governments, businesses, academic institutes, and social institutions to communicate & collaborate on climate actions under the support of the UN & Chinese governments. It aims at "China Action, Asia Voice, Global Standard," pushing social forces of engagement in China's commitment to carbon peaking and neutrality goals, amplifying Asia's voice for green transformation, enhancing international communication & collaboration in response to climate change, and participating in design & implementation of international standards.

Website: www.shanghaiclimateweek.org.cn

Presenting Partner

Sino-International Entrepreneurs Federation (SIEF) is a global, non-profit, non-partisan organization established in 2008 by Rt. Hon. Gordon Brown, Jean-Pierre Raffarin, Hon. John Howard, and H.E. Long Yongtu. It is incorporated in Zurich and headquartered in Beijing at the Prince Palace, serving as a trusted facilitator connecting leading business leaders across industries, continents, and cultures. Over the past decades, it has helped public- and private-sector leaders achieve their goals by advising on strategy, policy, and delivery.

Website: https://www.sief.org

Knowledge Partner

WeCarbon is a globally leading ClimateTech firm offering AI-powered sustainability solutions. Leveraging innovative technology and global thought leadership, it empowers industrial parks, testing & certification, shipping & logistics, and global trade to enhance operational efficiency, reduce carbon emissions, and accelerate green and AI transitions. Beyond technology, it also serves as a strategic bridge across continents, bringing world-class ClimateTech innovation, policy advisory, and sustainable infrastructure solutions to the Global South, enabling scalable climate and development outcomes.

Website: www.we-carbon.com

Supporting Organization

(Listed in alphabetical order)

Aon
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CHINT Group
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New Energy Nexus
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Light & Bright

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Author

William Wang
Chief Representative for Asia Pacific, Shanghai Climate Week & Chief Representative for Middle East & Africa, Sino-International Entrepreneurs Federation

Dr. Tshilidzi Marwala
Under-Secretary-General, United Nations & Rector, United Nations University

Antonio Basilio
Director, APEC Business Advisory Council & Chairman, Pacific Economic Cooperation Council Philippine National Committee

Remoca Shi
Deputy Secretary General, Shanghai Climate Week & Founder and Executive President, WeCarbon

Eric Ma
Founder and Chief Technology Officer, WeCarbon

Amber Sun
Business Manager for Middle East & Africa, Sino-International Entrepreneurs Federation

Debra Jiang
Engagement Manager for Middle East & Africa, Sino-International Entrepreneurs Federation

Contributor

(Listed in alphabetical order of last name)

The author team would like to thank the following experts from academia, industry, finance, public policy, and sustainability sectors who contributed their insights to this publication through content inputs and strategic guidance:

Mohammed Usman Abdul-Razaq
Senior Vice President, African Finance Cooperation

Lloyd Alexander Adducul
Chief Research Officer of the Foreign Service Institute, Philippines Department of Foreign Affairs

Ahmad Al Ghardaqa
Lead Negotiator and Senior Legal Advisor, UAE National Negotiation Team

Razann Al Ghussein
Office of Development Affairs, UAE Presidential Court

Nabil Al-Khowaiter
Former Chief Executive Officer, Aramco Ventures

H.R.H. Prince Khalid bin Saud bin Khalid Turki Al Saud
General Advisor, Saudi Arabia General Authority of Meteorology and Environmental Protection

Michael Victor N. Alimurung
City Administrator, Quezon City

Butti Almheiri
Co-lead Adaptation Negotiator, UAE Climate Change Special Envoy

Sameer Al Shethri
Vice President, National Industrial Development Center

Ahmad Ali Alwan
Chief Executive Officer, Hub71

Muhammad Mustafa Amjad
Program Director, Renewable First

Felix Ayque
Co-founder and Chief Executive Officer, Komunidad

Michael Baldock
Chief of Staff, United Nations University

Stephen Ball
Chairman, The Queen Elizabeth II Commonwealth Trust

Dr. Renee Barcellona
Associate Director of Cybersecurity, EY

Dr. Alexandre Borde
Member of the CDM Registration and Issuance Team, UNFCCC

Travis Bradford
Founder and President, Prometheus Institute for Sustainable Development

Chantele Carrington
Chief Executive Officer, Invest Africa

Eric Chan
Chief Public Mission Officer, Cyberport

Frankie Chang
Chief Executive Officer, Forbes China Group

H.E. Daniel Francisco Chapo
President, Mozambique

His Majesty King Charles III
King of the United Kingdom

H.E. Professor Dr. M. Iqbal Chaudhary
Coordinator-General, OIC-COMSTECH

Benny Chen
Member of Youth Council, Shanghai Climate Week

Ravenna Chen
Chief Executive Officer, Intrinsic SEA

Johnson Chng
Asia Chairman, VenCap

Dai Mingjiang
Manager, WeCarbon

Ariane Dienstag
General Secretary, Council on Tall Buildings and Urban Habitat (CTBUH) French Chapter

Tony Dong
Chief Representative, Sino-International Entrepreneurs Federation

Sonia Dunlop
Chief Executive Officer, Global Solar Council

Rt. Hon. Dr. Ekperikpe Ekpo
Honourable Minister of State, Petroleum Resources (Gas), Nigeria

John Carlo Fatallo
Management Information Systems Office, Pasig City

Hon. Karim Fatehi OBE
Chief Executive Officer, London Chamber of Commerce and Industry

Dr. Lamya Fawwaz
Executive Director, Masdar

Amb. Francisco Noel R. Fernandez
Director General of Foreign Service Institute, Philippine Department of Foreign Affairs

Lisa Fischer
Associate Director of Energy Transition, E3G

Kristian Flyvholm
Chair & Chief Executive Officer, Institute of Sovereign Investors

Dr. Fu Xiaolan
Founding Director, Technology and Management Centre for Development

Don Jaime Gaisano
Staffer, ABAC Philippines

Dr. Hosni Ghedira
Senior Advisor, ai71

Alyssa Gonzaga
Program Officer, APEC Business Advisory Council International Secretariat

Gu Hao
Head of Sustainability, CHINT Group

Floriane Gusciglio
General Delegate, ParisTech

Estelle Han
Initiating Founder, Global Artificial Intelligence for Sustainable Development Alliance (GAISD)

Abdelrhman Hatem
Founder, Electrify

Alice Ho
Chief Youth Officer, Global Alliance of Universities on Climate

Jason Ho
President, Macao Technology General Association

Hu Jianjun
Vice President, Siemens China

Huang Jingbo
Director of the United Nations University Institute in Macau

H.E. Jin Liqun
President and Chair of the Board of Directors, Asian Infrastructure Investment Bank

Sergey Kanavskiy
Executive Secretary, Shanghai Cooperation Organization Business Council

Alejandro Diego Luis Giles R. Katigbak
Chief Risk Officer, PHINMA Corporation

Hon. Matt Kean
Chair of Climate Change Authority, Australia

Seema A. Khan
Senior Advisor, OIC-COMSTECH

Mohammed Abdul Mujeeb Khan
Project Manager, Clean Rivers

Dr. Mohamed Bashir Kharrubi
Board Member, Abu Dhabi Investment Group

Rembrandt Koppelaar
Lead for Global & EU DPP Regulations Observatory, CIRPASS-2

Alexander Kormishin
Chairperson, BRICS Youth Energy Agency

Imad Lahad
Global Chair of AI and Intelligence, APCO

H.E. Corinne Lepage
Former French Minister of the Environment & Former Member of the European Parliament

Li Yuxin
Consultant, WeCarbon

Dr. Li Zheng
President of the Institute of Climate Change and Sustainable Development, Tsinghua University

Liao Shuanghui
Chairman, Shanghai Jinsinan Institute of Finance

Dr. Tyne Lin
Chief Product Officer, Annto Logistics under Midea Group

Liu Qing
President, National Innovation Center par Excellence

Karla Mikhaela P. Lomibao
Program Officer, APEC Business Advisory Council International Secretariat

Tomy Lorsch
Founder and Chief Executive Officer, ComplexChaos

Dr. Lu Gang
Co-founder, BEYOND Expo

Guillermo M. Luz
Chairman, Liveable Cities Philippines

Dr. Lü Xuedu
Former Deputy Director-General, China's National Climate Center

Nick Mabey
Chief Executive Officer, E3G

Dr. Shahid Mahmud
Senior Advisor, OIC-COMSTECH

Bernice Mendoza
Management Information Systems Office, Pasig City

Ivan Mozharov
Co-founder and Managing Partner, Offset8 Capital

Nan Junyu
Board Director and Vice President, CHINT Electric

Laura Nguyen
Partner, GenAI Fund

Ajay Bhushan Pandey
Vice President of Investment Solutions, Asian Infrastructure Investment Bank

Sashwat Pandey
Founder, Young Sapiens Network

Alexander Peng
Vice President, Shanghai Humanoid Robot Innovation Incubator

Peng Peng
Secretary General, China New Energy Investment and Finance Alliance

Peng Yucheng
Chief Executive Officer, Midas Innovation Group

Dr. Kaewkamol Karen Pitakdumrongkit
Interim Secretary General, PECC International Secretariat

Rao Wei
Deputy Secretary-General, Shanghai Climate Week

Jennifer Richards
Chief Executive Officer, Asia Pacific, Aon

Amandine Hardowar de Rosnay
Head of Sustainability & Inclusive Growth, Business Mauritius

Yukio Sakaguchi
President, Clean Energy Research Lab

Dr. David Sandalow
Co-Director of the Energy and Environment Concentration, School of International and Public Affairs at Columbia University

Jonathan E. Savoir
Chief Executive Officer, Quincus

H.E. Lalsaga Sayouba
Advisor to the President of Burkina Faso

Dr. Shi Yigong
President, Westlake University

Dr. Robert Slone
Senior Vice President and Chief Scientist and Innovation Officer, UL Solutions

Isaac Smith
Managing Director, Clarendon Capital

Hon. Warwick Smith AO
Former Federal Government Minister, Australia

Erik Solheim
Former Under-Secretary-General, United Nations

Froland Tajale
Lead Staffer, ABAC Philippines

Dr. Yan Tao
Head of Business & Ecological Development,
Siemens China (SiTANJI)

Frank Wouters
Chairman, MENA Hydrogen Alliance

Helen Wang
Treasury Department, Asian Infrastructure Investment Bank

Jeffrey Wang
GCA Supplier Operations Manager, Maersk

Nick Wang
President, Chindata

Dr. Wang Xin
Director, CGN Europe Industrial Innovation Company

Xiao Jie
General Manager, New Energy Nexus China

Xu Jieping
Chief Executive Officer, Plug and Play China

Dr. Xu Li
Chairman and Chief Executive Officer, SenseTime

Yuki Yamada
School of International and Public Affairs, Columbia University

Yang Ming
Board Secretary, TusStar

Yin Zheng
Executive Vice President of China and East Asia operations, Schneider Electric

Zhang Han
Head of Sustainability, Plug and Play China

Zhang Junyi
Chief Financial Officer, Sense Auto

Zhang Yang
Managing Partner, Cibola Partners & Partner, WeCarbon

Zhang Yueni
Consultant, WeCarbon

Zoe Zhang
Secretary General, Sino-International Entrepreneurs Federation

Lucia Zhao
Senior Associate, Clinton Health Access Initiative

Zhou Yiping
Founding Director, United Nations Office for South-South Cooperation

Shi Hao Zijdemans
Digital & Technology Specialist, Asian Infrastructure Investment Bank

Bibliography

1. Arora, N., Chakraborty, I., & Nishimura, Y. (2024). AI–Human Hybrids for Marketing Research: Leveraging Large Language Models (LLMs) as Collaborators. *Journal of Marketing,* 89, 43 - 70. https://doi.org/10.1177/00222429241276529.

2. Zhao, J., Wen, T., & Cheong, K. (2025). Can Large Language Models Be Trusted as Evolutionary Optimizers for Network-Structured Combinatorial Problems?. *IEEE Transactions on Network Science and Engineering*. https://doi.org/10.1109/tnse.2025.3592367.

3. Wu, X., Wu, S., Wu, J., Feng, L., & Tan, K. (2024). Evolutionary Computation in the Era of Large Language Model: Survey and Roadmap. *IEEE Transactions on Evolutionary Computation,* 29, 534-554. https://doi.org/10.1109/TEVC.2024.3506731.

4. Guang, J., Chao, J., Zong, T., Siya, C., Cui, C., & Jun, F. (2024). Data Redundancy Elimination and Noise Processing via Large Language Model Prompt Engineering. *2024 10th International Conference on Big Data and Information Analytics (BigDIA),* 818-825. https://doi.org/10.1109/BigDIA63733.2024.10808217.

5. Zhao, H., Chen, H., Yang, F., Liu, N., Deng, H., Cai, H., Wang, S., Yin, D., & Du, M. (2023). Explainability for Large Language Models: A Survey. *ACM Transactions on Intelligent Systems and Technology,* 15, 1 - 38. https://doi.org/10.1145/3639372.

6. Raiaan, M., Mukta, M., Fatema, K., Fahad, N., Sakib, S., Mim, M., Ahmad, J., Ali, M., & Azam, S. (2024). A Review on Large Language Models: Architectures, Applications, Taxonomies, Open Issues and Challenges. *IEEE Access,* 12, 26839-26874. https://doi.org/10.1109/ACCESS.2024.3365742.

7. Kumar, P. (2024). Large language models (LLMs): survey, technical frameworks, and future challenges. *Artif. Intell. Rev.,* 57, 260. https://doi.org/10.1007/s10462-024-10888-y.

8. Yamin, M., Hashmi, E., Ullah, M., & Katt, B. (2024). Applications of LLMs for Generating Cyber Security Exercise Scenarios. *IEEE Access,* 12, 143806-143822. https://doi.org/10.1109/ACCESS.2024.3468914.

9. Thirunavukarasu, A., Ting, D., Elangovan, K., Gutierrez, L., Tan, T., & Ting, D. (2023). Large language models in medicine. *Nature Medicine,* 29, 1930-1940. https://doi.org/10.1038/s41591-023-02448-8.

10. Yang, J., Jin, H., Tang, R., Han, X., Feng, Q., Jiang, H., Yin, B., & Hu, X. (2023). Harnessing the Power of LLMs in Practice: A Survey on ChatGPT and Beyond. *ACM Transactions on Knowledge Discovery from Data,* 18, 1 - 32. https://doi.org/10.1145/3649506.

11. Luccioni, A. S., Viguier, S., & Ligozat, A.-L. (2022, November). ChatGPT training estimated to emit 502 metric tonnes of carbon. *AIAAIC Repository*. https://ww-w.aiaaic.org/aiaaic-repository/ai-algorith-mic-and-automation-incidents/chatgpt-training-emits-502-metric-tons-of-carbon

12. IEA (2025), Global data centre electricity consumption, by equipment, Base Case, *2020-2030, IEA,* Paris https://www.iea.org/data-and-statistics/charts/global-da-ta-centre-electricity-consumption-by-equipment-base-case-2020-2030, Licence: CC BY 4.0

13. Chien, A., Lin, L., Nguyen, H., Rao, V., Sharma, T., & Wijayawardana, R. (2023). Reducing the Carbon Impact of Generative AI Inference (today and in 2035). *Proceedings of the 2nd Workshop on Sustainable Computer Systems*. https://doi.org/10.1145/3604930.3605705.

14. Bouza, L., Bugeau, A., & Lannelongue, L. (2023). How to estimate carbon footprint when training deep learning models? A guide and review. *Environmental Research Communications,* 5. https://doi.org/10.1088/2515-7620/acf81b.

15. Singla, A., Sukharevsky, A., Yee, L., Chui, M., & Hall, B. (2025, November 5). The state of AI: How organizations are rewiring to capture value. *McKinsey*. https://ww-w.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai

16. Fayza, F., Demirkiran, C., Rao, S. P., Bunandar, D., Gupta, U., & Joshi, A. (2025). Photonics for sustainable AI. *Communications Physics,* 8, Article 403.

17. Hinton, G., Vinyals, O., & Dean, J. (2015). Distilling the knowledge in a neural network. *University of Toronto*.

18. Sze, V., Chen, Y.-H., Yang, T.-J., & Emer, J. S. (2017). Efficient processing of deep neural networks: A tutorial and survey. *Proceedings of the IEEE, 105*(12), 2295–2329. https://doi.org/10.1109/JPROC.2017.2761740

19. Patterson, D., Gonzalez, J., Le, Q. V., Liang, C., Munguia, L.-M., Rothchild, D., ... Dean, J. (2021). Carbon emissions and large neural network training. *Joule, 5*(2), 1–13. https://doi.org/10.1016/j.joule.2021.02.001

20. Bello, S. F., Wada, I. U., Ige, O. B., Chianumba, E. C., & Adebayo, S. A. (2024). AI-driven predictive maintenance and optimization of renewable energy systems for enhanced operational efficiency and longevity. *International Journal of Science and Research Archive, 13*(1), 2823–2837.

21. Suci, A., Amini, R., Asri, A., & Martin, N. (2025). Artificial Intelligence in Renewable Energy: A Review of Predictive Maintenance and Energy Optimization. *Journal of Clean Technology*. https://doi.org/10.15294/joct.v2i1.27729.

22. Algburi, S., Abed Al Kareem, S. S., Sapaev, I. B., Mukhitdinov, O., Hassan, Q., Khalaf, D. H., & Jabbar, F. I. (2025). The role of artificial intelligence in accelerating renewable energy adoption for global energy transformation. *Unconventional Resources*. https://doi.org/10.1016/j.uncres.2025.100229.

23. Matias, Y., & Brandt, K. (2023). Accelerating climate action with AI. *Google*. https://blog.google/outreach-initiatives/sustainability/re-port-ai-sustainability-google-cop28/

24. Shehabi, A., et al. (2016). *United States data center energy usage report* (Report No. LBNL-1005775). Lawrence Berkeley National Laboratory. https://eta.lbl.gov/-publications/united-states-data-center-energy

25. Synergy Research Group. (2024). Hyperscale operators and colocation continue to drive huge changes in data center capacity trends. *Synergy Research*. https://www.srgresearch.com/articles/hyperscale-opera-tors-and-colocation-continue-to-drive-huge-changes-in-data-center-capacity-trends

26. Donnellan, D., et al. (2023). Uptime Institute global data center survey results 2023. *Uptime Institute*. https://uptimeinstitute.com/resources/research-and-re-ports/uptime-institute-global-data-center-survey-results-2023

27. Yin, Y., & Yang, Y. (2025). Sustainable Transition of the Global Semiconductor Industry: Challenges, Strategies, and Future Directions. *Sustainability*. https://doi.org/10.3390/su17073160.

28. Aruffo, C. (2025). *Dii Editorial Q3 2025: Data centers and common user infrastructure: Two pathways from vision to bankable reality*. Dii Desert Energy. https://dii-desertenergy.org/data-centers-and-common-user-in-frastructure-two-pathways-from-vision-to-bankable-reality/

29. Synergy Research Group, "Synergy identifies the world's top 20 locations for hyperscale data centers (62% of global capacity in just 20 metro markets)."

30. XDI, *2025 Global Data Centre Physical Climate Risk and Adaptation Report* — analysis of nearly 9,000 data centers' exposure to flooding, wildfires, extreme weather and climate-induced hazards.

31. International Energy Agency. (2024). *Electricity 2024: Analysis and forecast to 2026*. Paris: IEA.

32. BloombergNEF. (2023). Corporate clean energy buying reaches new highs: Power purchase agreements and data center demand. *Bloomberg Finance L.P*.

33. Opeyemi Amure, T. (2025). The cloud computing risk for the economy that many don' t see coming. *Investopedia*. https://www.investopedia.com/cloud-comput-ing-risk-for-the-economy-11777456

34. Griffiths, C. (2025). The latest cloud computing statistics. *AAG IT Support*. https://aag-it.com/the-latest-cloud-computing-statistics

35. Shetty, M. (2025). Concentration of AI capabilities poses systemic risks: NPCI chairman. *The Times of India.* https://timesofindia.indiatimes.com/business/in-dia-business/concentration-of-ai-capabilities-poses-systemic-risks-npci-chairman/articleshow/124375101.cms

36. Mukewa, Z. (2025). Frontier AI and the return of systemic infrastructure risk. *Medium*. https://medium.com/@zackfolio/frontier-ai-and-the-re-turn-of-systemic-infrastructure-risk-fc001622819d

37. National Telecommunications and Information Administration. (2024). Risks and benefits of dual-use foundation models with widely available model weights. U.S. Department of Commerce.https://www.ntia.gov/programs-and-initiatives/artifi-cial-intelligence/open-model-weights-report/risks-benefits-of-dual-use-foundation-models-with-widely-available-model-weights

38. Wiaterek, J., Perlo, J., & Nur Adan, S. (2025). AI safety and security can enable innovation in Global Majority countries. *The Brookings Institution*. https://www.brookings.edu/articles/ai-safety-and-securi-ty-can-enable-innovation-in-global-majority-countries

40. Milmo, D., & Wearden, G. (2025). Amazon Web Services outage shows internet users 'at mercy' of too few providers, experts say. *The Guardian*. https://www.-theguardian.com/technology/2025/oct/20/ama-zon-web-services-aws-outage-hits-dozens-websites-apps

41. Caroline. (2025). Cloud outage resilience: Here's how to safeguard your business. *Digital Craftsmen*. https://www.digitalcraftsmen.com/insights/cloud-outage-busi-ness-continuity-resilience

42. Covenco. (2025). Managing Business Risk in a World Built on Hyperscale Cloud. *Covenco.* https://covenco.com/insights/blog/managing-hyper-scale-cloud-outage-risk

43. Principle. (2025). When the cloud crashes: Why centralized data centers are becoming a critical vulnerability in the AI era. *Medium.* https://medium.com/@ReginaldBSimpsonII/when-the-cloud-crash-es-why-centralized-data-centers-are-becoming-a-critical-vulnerability-in-the-c88defbe2e5e

44. Amoah, M., Bazilian, M. D., Matisek, J. F., & Schweiker, K. (2025, November 11). Data centers at risk: The fragile core of American power. *Foreign Policy Research Institute.* https://www.fpri.org/article/2025/11/data-centers-at-risk-the-fragile-core-of-american-power

45. Esparza, M., Li, B., Ma, J., & Mostafavi, A. (2025). AI Meets Natural Hazard Risk: A Nationwide Vulnerability Assessment of Data Centers to Natural Hazards and Power Outages. *International Journal of Disaster Risk Reduction*, 105583.

46. Hayes II, D. (2025). Disaster-proofing: The role of data infrastructure in natural disaster management. *Forbes Business Council.* https://www.forbes.com/councils/forbesbusinesscouncil/2025/02/24/disaster-proofing-the-role-of-data-infrastructure-in-natural-disaster-management

47. Marrinan, C. (2025). Data center boom risks health of already vulnerable communities. *TechPolicy.Press.* https://www.techpolicy.press/data-center-boom-risks-health-of-already-vulnerable-communities

48. Hale, C. (2025). Swiss government urges people to ditch Microsoft 365 and others due to lack of proper encryption. *TechRadar Pro.* https://www.techradar.com/pro/security/swiss-government-urges-people-to-ditch-microsoft-365-and-others-due-to-lack-of-proper-encryption

49. Wiaterek, J., Perlo, J., & Nur Adan, S. (2025). AI safety and security can enable innovation in Global Majority countries. *The Brookings Institution.* https://www.brookings.edu/articles/ai-safety-and-security-can-enable-innovation-in-global-majority-countries

50. O'Flaherty, K. (2025). The unseen risks of cloud storage for businesses. *ITPro.* https://www.itpro.com/cloud/cloud-security/the-unseen-risks-of-cloud-storage-for-businesses

51. Cybersecurity Insiders. (2025). *2025 Cloud Security Report.* https://www.cybersecurity-insiders.com/state-of-cloud-security-report-2025

52. National Telecommunications and Information Administration. (2024). Competition, innovation, and research. In Risks and benefits of dual-use foundation models with widely available model weights (U.S. Department of Commerce). https://www.ntia.gov/programs-and-initiatives/artificial-intelligence/open-model-weights-report/risks-benefits-of-dual-use-foundation-models-with-widely-available-model-weights/competition-innovation-research

53. Onwusinkwue, S., Osasona, F., Ahmad, I. A. I., Anyanwu, A. C., Dawodu, S. O., Obi, O. C., & Hamdan, A. (2024). Artificial intelligence (AI) in renewable energy: A review of predictive maintenance and energy optimization. *World Journal of Advanced Research and Reviews, 21*(1), 2487-2499.

54. Ejiyi, C. J., Cai, D., Thomas, D., Obiora, S., Osei-Mensah, E., Acen, C., ... & Bamisile, O. O. (2025). Comprehensive review of artificial intelligence applications in renewable energy systems: Current implementations and emerging trends. *Journal of Big Data, 12*(1), 169.

55. Ukoba, K., Olatunji, K. O., Adeoye, E., Jen, T. C., & Madyira, D. M. (2024). Optimizing renewable energy systems through artificial intelligence: Review and future prospects. *Energy & Environment, 35*(7), 3833-3879.

56. Bi, K., Xie, L., Zhang, H., Chen, X., Gu, X., & Tian, Q. (2023). Accurate medium-range global weather forecasting with 3D neural networks. *Nature*, 619, 533–538.

57. Kurth, T., Subramanian, S., Harrington, P., Pathak, J., Mardani, M., Hall, D., ... & Anandkumar, A. (2023, June). Fourcastnet: Accelerating global high-resolution weather forecasting using adaptive fourier neural operators. *In Proceedings of the platform for advanced scientific computing conference* (pp. 1-11).

58. Estrada, F., Tol, R. S. J., & Botzen, W. (2025). Economic consequences of spatial variation and temporal variability of climate change. *Ann NY Acad Sci.*, 1547, 170–182. https://doi.org/10.1111/nyas.15335

59. Huawei Cloud. (2023). Pangu-Weather from Huawei Cloud outperforms NWP methods in terms of accuracy for medium-range forecast. *Huawei Cloud.* https://www.huaweicloud.com/intl/en-us/about/blogs/20230707.html

60. Gambhir, A. (2019). A review of criticisms of Integrated Assessment Models. *Energies*, 12(9), 1747.

61. Bruno, J. H., Jervis, D., Varon, D. J., & Jacob, D. J. (2024). U-Plume: automated algorithm for plume detection and source quantification by satellite point-source imagers. *Atmospheric Measurement Techniques, 17*, 2625–2636. https://doi.org/10.5194/amt-17-2625-2024

62. Rouet-Leduc, B., Kerdreux, T., Tuel, A., & Hulbert, C. (2024). Automatic detection of methane emissions in multispectral satellite data using deep learning. *Nature Communications.* Advance online publication. https://doi.org/10.1038/s41467-024-47754-y

63. Vaughan, A., Mateo-García, G., Gómez-Chova, L., Růžička, V., Guanter, L., & Irakulis-Loitxate, I. (2024). CH4Net: a deep learning model for monitoring methane super-emitters with Sentinel-2 imagery. *Atmospheric Measurement Techniques, 17*, 2583–2593. https://doi.org/10.5194/amt-17-2583-2024

64. Global Forest Watch. (2024). Integrated deforestation alerts. https://www.globalforestwatch.org/blog/data-and-tools/integrated-deforestation-alerts/

65. Global Forest Watch. (2021). Higher resolution alerts offer more detailed picture of forest loss: GLAD-S2 alerts provide enhanced monitoring of deforestation. https://www.globalforestwatch.org/blog/data-and-tools/glad-s2-offers-high-resolution-deforestation-alerts/

66. Zuo, J., Li, Z., Xu, W., Zuo, J., & Rong, Z. (2025). Automated Detection of Methane Leaks by Combining Infrared Imaging and a Gas-Faster Region-Based Convolutional Neural Network Technique. *Sensors,* 25(18), 5714. https://doi.org/10.3390/s25185714

67. Andersson, T. R., Hosking, J. S., Pérez-Ortiz, M., Paige, B., Elliott, A., Russell, C., ... & Shuckburgh, E. (2021). Seasonal Arctic sea ice forecasting with probabilistic deep learning. *Nature communications, 12*(1), 5124.

68. The Alan Turing Institute & British Antarctic Survey. (2022, December). *IceNet: Faster, more accurate sea ice forecasting with a new AI-based tool (ASG briefing paper). The Alan Turing Institute.* https://www.turing.ac.uk/sites/default/files/2023-05/asgbriefing_icenet_final.pdf

69. Andersson, T., & Hosking, J. (2021). Dataset record for IceNet sea-ice probability forecasts (SIP), 6-month lead time, 25 km resolution [Data set]. *NERC EDS UK Polar Data Centre.* http://www.antarctica.ac.uk/dms/metadata.php?id=GB/NERC/BAS/PDC/01526

70. Google Research. How we are using AI for reliable flood forecasting at a global scale (Flood Hub).

71. Google Research. (n.d.). Flood forecasting: AI for information & alerts. *Google.* https://sites.research.google/floodforecasting

72. IEA. (2024). Maintaining a stable electricity grid in the energy transition. https://iea.blob.core.windows.net/assets/cd1-eac26-6a3e-415a-94fd-3afda4d4ac42/IEA-maintaining-a-stable-electricity-grid-in-the-energy-transition-Jan2024.pdf

73. European Wind Energy Association. (2009). The economics of wind energy. *EWEA.* https://www.ewea.org/fileadmin/files/library/publications/reports/Economics_of_Wind_Energy.pdf

74. The Brattle Group. (2018, May 3). Defining reliability for a new grid: Maintaining reliability and resilience through competitive markets. *The Brattle Group.* https://www.brattle.com/insights-events/publications/defining-reliability-for-a-new-grid-maintaining-reliability-and-resilience-through-competitive-markets.

75. United Nations Environment Programme Finance Initiative. (2025). Bridging climate and credit risk: Current approaches and emerging trends for climate-related credit risk assessment methodologies — insights from a global survey (pp. ix). *UNEP FI.* https://www.unepfi.org/wordpress/wp-content/uploads/2025/07/Bridging-Climate-and-Credit-Risk.pdf

76. European Central Bank. (2025, July 11). Banks have made good progress in managing climate and environmental risks [Blog post]. *ECB.* https://www.ecb.europa.eu/press/blog/date/2025/html/ecb.blog20250711~f5c6a0259f.en.html

77. United Nations Environment Programme Finance Initiative. (2025). Bridging climate and credit risk: Current approaches and emerging trends for climate-related credit risk assessment methodologies — insights from a global survey (pp. ix). *UNEP FI.* https://www.unepfi.org/wordpress/wp-content/uploads/2025/07/Bridging-Climate-and-Credit-Risk.pdf

78. World Bank. (2022). Digital monitoring, reporting, and verification systems and their application in future carbon markets. *World Bank.* http://hdl.handle.net/10986/37622

79. W3C. (2022). Verifiable Credentials Data Model v1.1. *World Wide Web Consortium.* https://www.w3.org/TR/vc-data-model/

80. Kothari, S. (2025). Leveraging natural language processing for automated regulatory compliance in financial reporting. *Global Journal of Engineering and Technology Advances, 23*(3), 91–99. https://doi.org/10.30574/gjeta.2025.23.3.0187

81. Baviskar, D., Ahirrao, S., Potdar, V., & Kotecha, K. (2021). Efficient automated processing of the unstructured documents using artificial intelligence: A systematic literature review and future directions. *IEEE Access,* 9, 72894–72936. https://doi.org/10.1109/ACCESS.2021.3072900

82. McKinsey & Company. (2025). Corporate start-up partnerships satisfaction rates and success factors. *McKinsey Report on Corporate-Startup Collaboration.* https://www.mckinsey.com/capabilities/strategy-and-corporate-finance/our-insights/collaborations-between-corporates-and-start-ups

83. International Telecommunication Union. (2025). AI for Climate Action Innovation Factory: Challenge structure and outcomes. *AI for Good, International Telecommunication Union.* https://aiforgood.itu.int/about-us/ai-for-climate-action-innovation-factory

84. OpenAI. (2024). Introducing the GPT Store. Retrieved from https://openai.com/index/introducing-the-gpt-store/

85. Patel, N. (2025). OpenAI launches ChatGPT App Directory and Apps SDK. *The Verge.* https://www.theverge.com/news/847067/openai-app-store-directory-sdk-chatgpt

86. Wikipedia. (2025). Model Context Protocol. Retrieved from https://en.wikipedia.org/wiki/Model_Context_Protocol

87. Shell. (2023). Shell.ai Hackathon for Sustainable and Affordable Energy. https://www.shell.com/energy-and-innovation/digitalisation/shell-ai-hackathon.html

88. Enel. (2024). Open innovation and challenges. https://www.enel.com/company/innovation/open-innovation

89. Elewit. (2023). Innovation challenges and data-driven solutions. https://www.elewit.si/challenges

90. GEN-I. (2023). GEN-I trading and analytics challenges. https://gen-i.eu/careers/challenges

91. Organisation for Economic Co-operation and Development. (n.d.). Official development financing (ODF) receipts dataset [Data set]. *OECD Data Explorer.* Retrieved December 20, 2025, from https://data-explorer.oecd.org/vis?lc=en&df[ds]=DisseminateFinalDMZ&df[id]=DSD_DAC2%40DF_RECPTS&df[ag]=OECD.DCD.FSD&df[vs]=1.0

92. United Nations Framework Convention on Climate Change (UNFCCC) Technology Executive Committee, 2024. Artificial Intelligence for Climate Action: Opportunities, Challenges, and Risks. [online] Available at: https://unfccc.int/ttclear/misc_/StaticFiles/gnwoerk_static/tn_meetings/43ef8d5f37e6484ca634479e3b74a3a8/3ee3862a08c84afe971c29f2687a45f1.pdf.

93. Bills, T. S., & Ji, K. (2025). Wildfire recovery and resilience strategies for resource-constrained and vulnerable communities. *UCLA Institute of Transportation Studies.* https://www.its.ucla.edu/publication/wildfire-recovery-and-resilience-strategies-for-resource-constrained-and-vulnerable-communities.

94. Jalal, A., Mohsenian-Rad, H. and Aliprantis, D.C., 2023. Privacy Preservation in Smart Meters: Current Status, Challenges, and Future Directions. *Sensors,* 23(7), p.3456. Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10098615/.

95. Stockholm Resilience Centre, 2024. AI could create a perfect storm of climate misinformation. [online] Available at: https://www.stockholmresilience.org/publications/publications/2024-10-21-ai-could-create-a-perfect-storm-of-climate-misinformation.html

96. Friedrich, A., Asquith, N. et al.(2024). Applications of generative artificial intelligence to influence climate decisions. *Nature Human Behaviour.* Available at: https://www.nature.com/articles/s44168-024-00202-5

97. PRISM Sustainability Directory. (2025). Transparency for AI driven climate policy making. https://prism.sustainability-directory.com/scenario/transparency-for-ai-driven-climate-policy-making/

98. International Energy Agency. (2025). Energy and AI. *International Energy Agency.* https://www.iea.org/reports/energy-and-ai

99. Bouza, L., Bugeau, A., & Lannelongue, L. (2023). How to estimate carbon footprint when training deep learning models? A guide and review. *Environmental Research Communications,* 5. https://doi.org/10.1088/2515-7620/acf81b.

100. Environmental and Energy Study Institute. (2025). Data centers and water consumption. https://www.eesi.org/articles/view/data-centers-and-water-consumption

101. Wang, P., Zhang, LY., Tzachor, A. et al. E-waste challenges of generative artificial intelligence. *Nat Comput Sci* 4, 818–823 (2024). https://doi.org/10.1038/s43588-024-00712-6

102. *United Nations. (2024a).* General Assembly adopts landmark resolution on artificial intelligence. *UN News.* Retrieved July 21, 2024, Available at https://news.un.org/en/story/2024/03/1147831

103. Sothy, E. (2025) The hidden costs of artificial intelligence, *The Varsity*, 5 October. Retrieved from https://thevarsity.ca/2025/10/05/the-hidden-costs-of-artificial-intelligence/

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