Globant

AI | Intelligent Energy

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SustAInability powered by tech

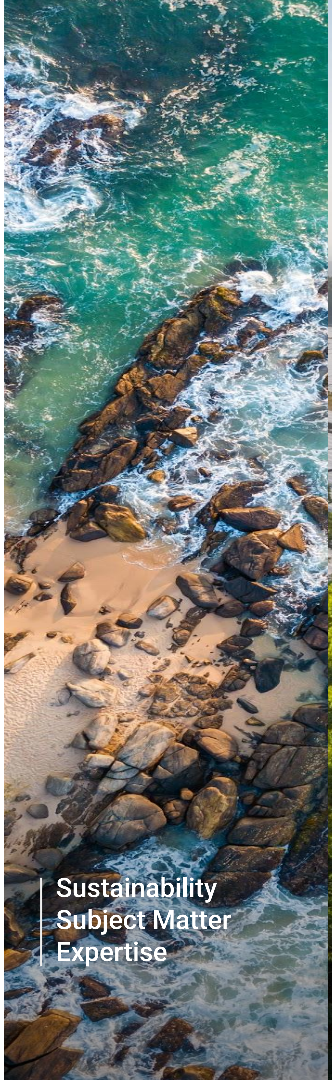
Sustainable Business Studio **Globant**

El **Sustainable Business Studio** de Globant opera en la intersección entre sostenibilidad, diseño e innovación, *powered by tech*.

Con + de 30 expertos en clima y ESG creamos conocimiento en sostenibilidad digital, experiencia y prácticas en todas las industria desde el diseño hasta el producto final - *sustainable by design*.

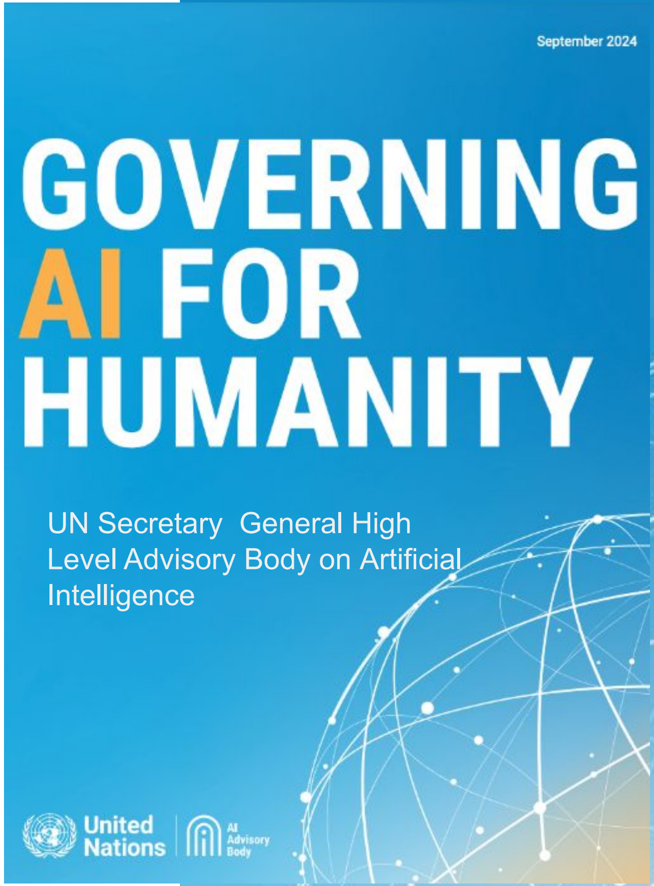
Nuestro enfoque creativo y orientado a soluciones tech+AI, desarrolla estrategias ESG, hojas de ruta y objetivos 2030 para todas organizaciones.

- ESG Transformation
- NetZero & decarbonization & strategies
- Emissions Calculator
- Sust. Mgmt Platforms
- Carbon Energy, Water and Waste
- Communities
- Financial Inclusion
- Tokenization of green assets
- Climate Finance & Financial Inclusion
- Sustainable AI
- Compensation Mechanisms



Relevant practices for **Responsible AI**

1. Consider guidelines of the **UN Secretary General High Level Advisory Body on Artificial Intelligence -** *September* 2024 report
2. As part of the **#justransitions**, human always first, with AI systems **#madebyhumans. Have the *digitaldivide* always present upfront in projects.**
3. Calculate AI energy consumption as main KPI of Green IT
4. Always georeference assets and systems on climate risk maps
5. Constant innovations and constant evolving landscape: **tiny AI - small nuclear**



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Infrastructure Modernization **New York** Climate Week 2024

New Operational paradigm

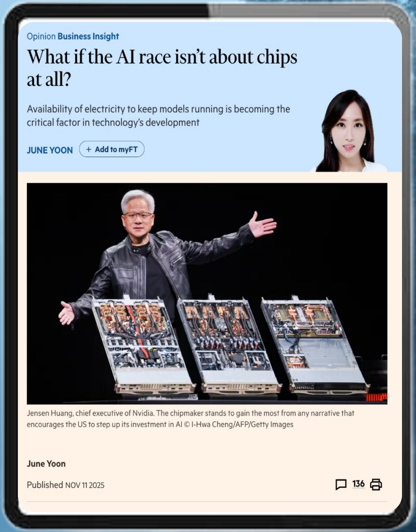
Energy in the ***prompt era***

AI + Real time data orchestration

The energy sector has entered a new operational paradigm — one defined not by infrastructure alone, but by intelligence.

The ***Prompt Era*** is characterized by systems that adapt, respond, and execute both on demand and within automated workflows. In this environment, the advantage lies in the ability to act cohesively, combining both AI and real-time data orchestration.

Utilities
NEWS


Opinion Business Insight

What if the AI race isn't about chips at all?

Availability of electricity to keep models running is becoming the critical factor in technology's development

JUNE YOON + Add to myFT

Jensen Huang, chief executive of Nvidia. The chipmaker stands to gain the most from any narrative that encourages the US to step up its investment in AI © I-Hwa Cheng/AFP/Getty Images

June Yoon

Published NOV 11 2025

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Even a 0.42 Wh short query, when scaled to 700M queries/day, aggregates to annual electricity comparable to ***35,000 U.S.*** homes, evaporative freshwater equal to the annual **drinking needs of 1.2M** people, and carbon emissions requiring a **Chicago-sized forest to offset**.

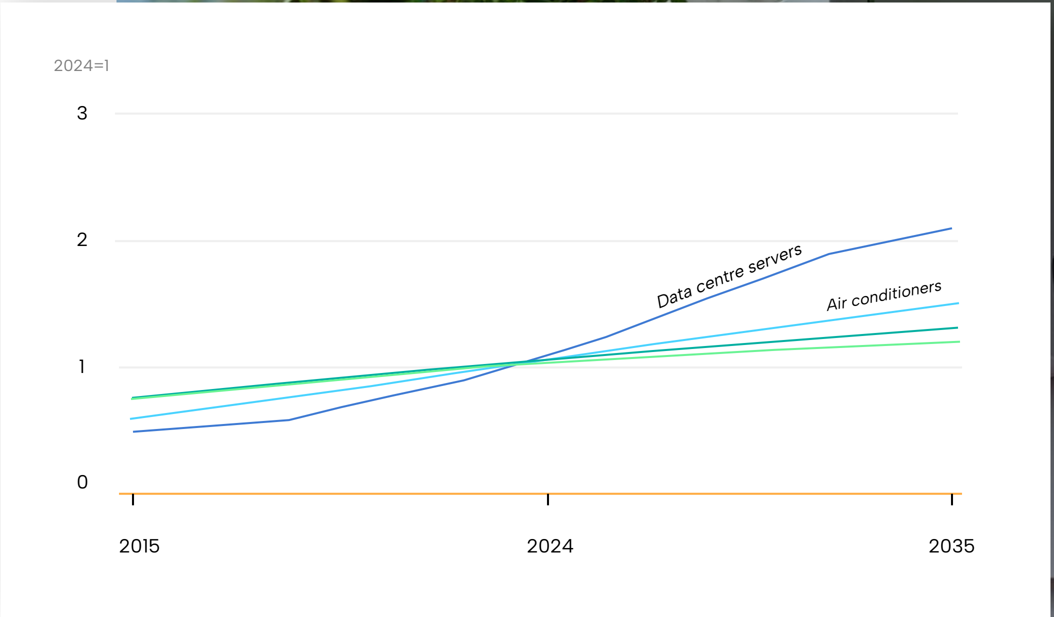
How Hungry is AI?

Benchmarking Energy, H2O, and CO2 Footprint of LLM Inference

https://arxiv.org/pdf/2505.09598

Selected drivers of GDP growth **2015-2023**

Keep in **mind...** for later

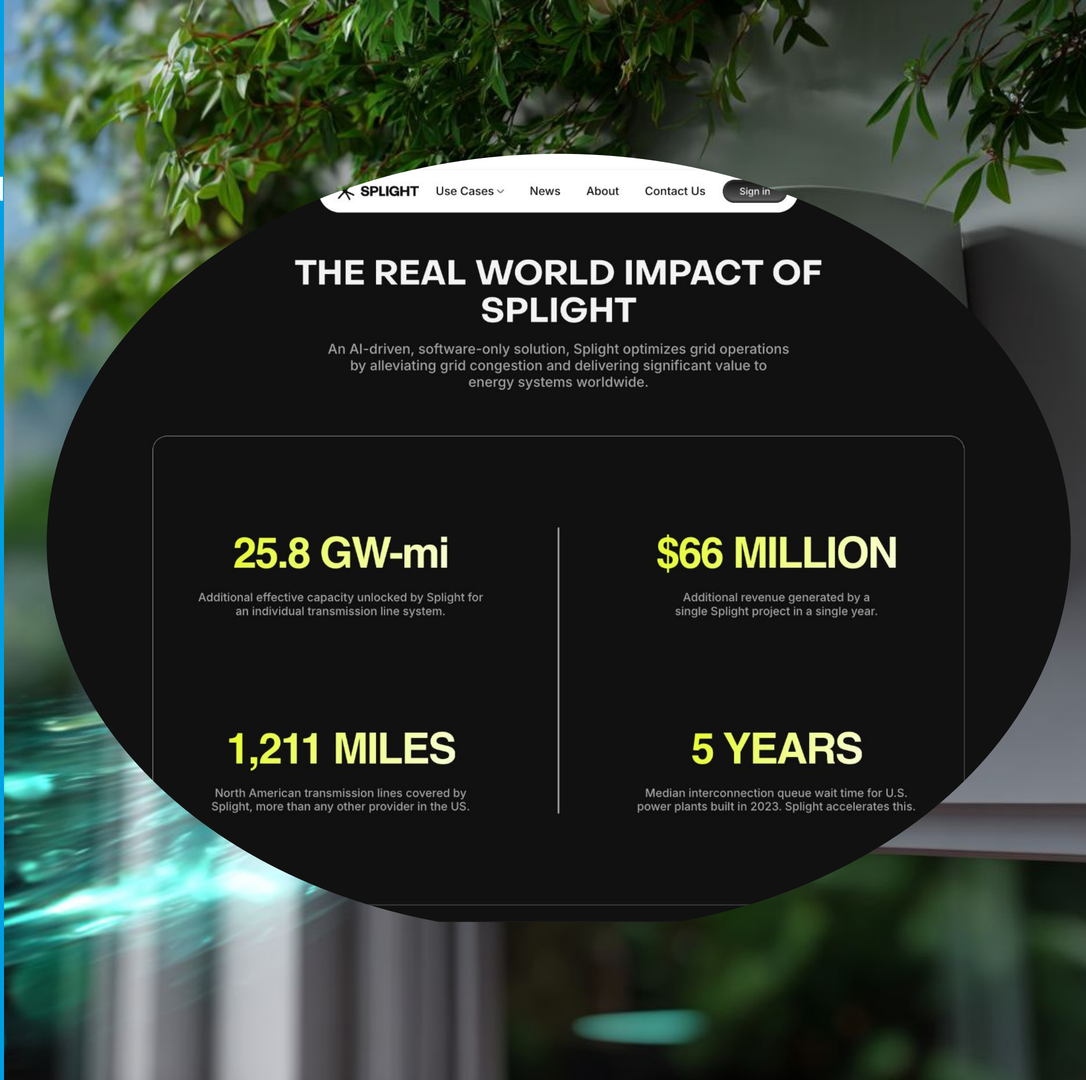


- Air conditioners
- Car fleet
- Data centre servers
- Plastic production

By using Splight technology to tackle contingencies in real-time, up to 2x extra transmission capacity is unlocked enabling terawatts of clean energy to be injected into the grid while simultaneously adding reliability.

The no-tradeoff solution is transformative for grid operations: Splight's tech is the key to prevent clean energy being wasted and facilitate the deployment and connection of renewable energy, DERs, and batteries at the pace needed and with the existing transmission infrastructure.

"Our technology is proven and commercially viable: we are solving grid congestion while adding reliability. It can be deployed fast enough to inject more than 3,000 GWs of clean energy within months. This round is a huge vote of confidence and will be used to expand our business globally," said Fernando Llaver, CEO of Splight.



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Globant | Georgetown University McDonough School of Business

Reducing Energy Consumption and GHG Emissions in **AI Computing**

Guidelines for Greener AI Software Development and Computation

July 2023

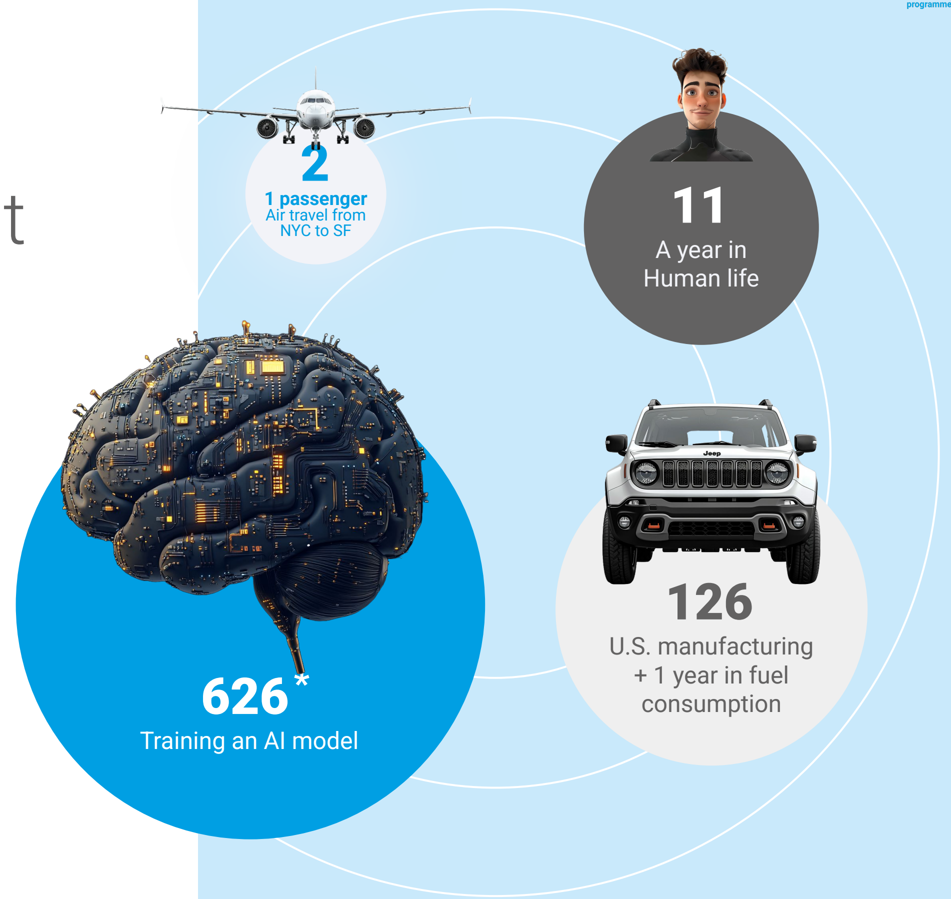
Georgetown MBA Team: Curran O'Connell, Sami Majumder, Stephen Golden, Anish Das, Erik DeVolder, Amit Soni

Project Context

AI Produces Significant **GHG Emissions**

“One algorithm that lets a robot manipulate a Rubik's Cube used as much energy as **3 nuclear plants** produce in an hour.”

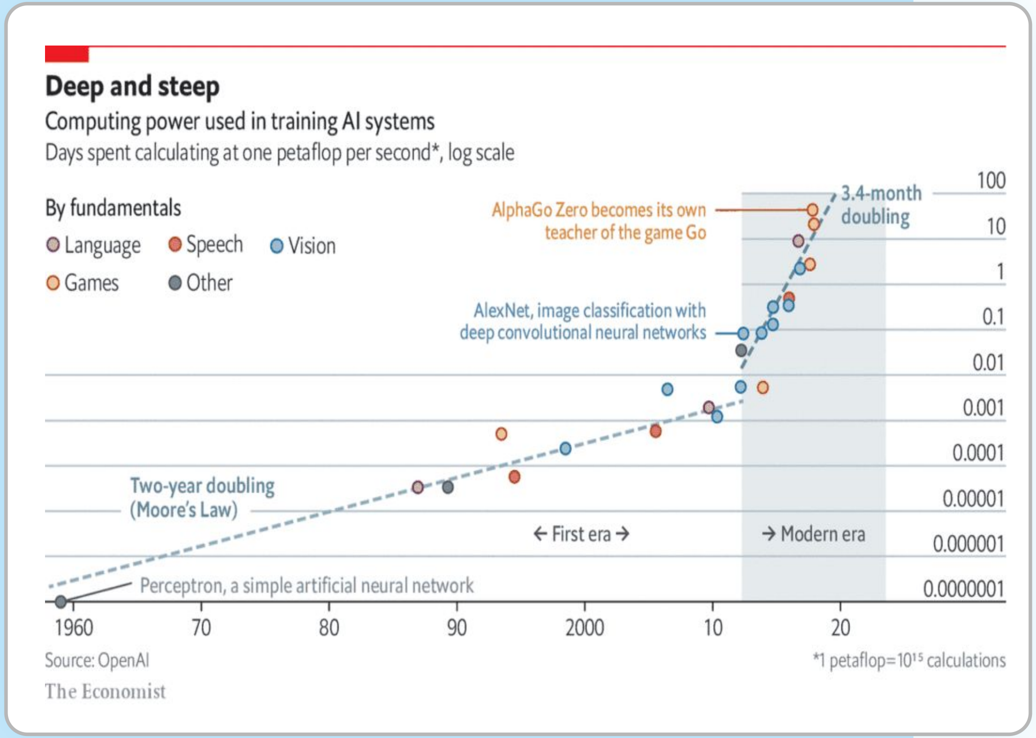
- Wired Magazine



*CO_2 emission benchmark 000s lbs

Project Context

This is a **Growing** Problem



The **computing power** required to train a cutting-edge model **doubles every few months**, and larger models are more costly, environmentally and economically, to train and operate.

At this rate, **training costs could exceed $1 billion USD by 2026,** and that represents just 10% of a model's lifetime energy consumption.

Overview of the AI Lifecycle

AI Lifecycle and **Model** Development

1. **Problem Identification**
2. **Data Collection and Preparation**
3. **Model Building**
4. **Model Testing and Training**
5. **Model Deployment**

Recommendations Roadmap

Applying **Our Strategies** for Each Phase

Issues	Recommendations	Applications
Identify key issues to consider at each stage of the AI lifecycle, each of which has implications for the energy consumption of the AI model	**Apply high-level strategies** to each stage and share tactical recommendations to reduce energy consumption at each stage of the AI lifecycle	**Present examples** that illustrate the impact of particular energy efficiency tactics

Synthesized best practices for energy efficiency across the AI lifecycle:

1. Problem Identification & Scoping

- **Evaluate Non-AI Alternatives:** assess if a simple rules-based solution can achieve the goal instead of a ML solution to avoid unnecessary energy use.
- **Incorporate Green KPIs:** include energy efficiency and GHG emissions as key metrics for evaluating model performance alongside traditional metrics
- **Benchmark Accuracy Needs:** determine the required level of accuracy by benchmarking against human performance; avoid over-engineering, as higher accuracy often requires exponentially more energy.

2. Data Collection and Preparation

- **Reduce Data Volume:** utilize data sampling to work with smaller subsets rather than processing entire raw datasets
- **Lower Precision:** decrease the precision of the dataset to reduce its size and computational load.
- **Simplify Input Data:** employ techniques like data quantization and dimensionality reduction.
- **Pre-process Upfront:** clean and normalize data upfront to prevent wasted computations during the training phase. Modifications on pre-processed datasets can drastically reduce energy consumption.

3. Model Building

- **Simplify Architecture:** use *shallow* model architectures (e.g., logistic regression) for simpler tasks instead of complex deep learning models
- **Prune Models:** remove unnecessary neurons - *pruning* - to reduce model complexity and parameter counts.
- **Leverage Pre-existing Models:** use Transfer Learning to adapt pre-trained networks, minimizing the need for training from scratch.
- **Automate Design:** use Neural Architecture Search to determine the optimal, most efficient architecture.
- **Use AI-as-a-Service:** Implement AI-as-a-Service (AIaaS) solutions, which can lower costs and energy requirements compared to custom in-house solutions.

4. Model Training and Testing

- **Stop Early:** implement *early stopping* to halt training once improvements in validation accuracy become negligible
- **Distill Knowledge:** create compact *student* models trained by larger *teacher* models to reduce computational requirements
- **Schedule Smartly:**
    - **Night Testing:** run testing activities at night to take advantage of lower carbon intensity.
    - **Pause and Resume:** pause workloads during periods of high grid carbon intensity and resume when the grid is cleaner.
    - **Flexible Start:** utilize a 24-hour flexible start time parameter to align processing with green energy availability.
- **Optimize Learning Rate:** schedule learning rate decay to speed up model convergence.

5. Model Deployment

- **Optimize Infrastructure:** use serverless computing to reduce energy consumption from idle servers.
- **Select Specialized Hardware:** consider using optimized Application-Specific Integrated Circuits (ASICs) for lower power consumption compared to general processors.
- **Parallelize Processing:** optimize the allocation of processor cores; while parallelization can reduce runtime, it must be balanced carefully as it does not always lead to lower emissions.
- **Leverage Cloud APIs:** use APIs from major cloud providers, which often offer more energy-efficient platforms than in-house deployments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