



IT und KI.

Durch die Steigerung von Energieeffizienz und
Ressourcenmanagement Nachhaltigkeitsziele erreichen



18.09.2024

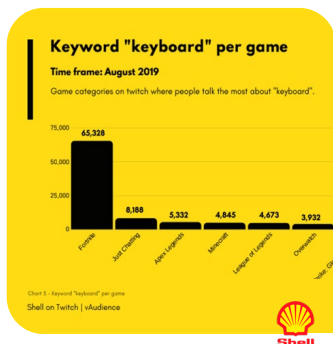
Forum Energie 2024



Dr. Toni Wagner

- 1977 in Bamberg geboren
- 1986 erster Programmierspaß mit dem C64
- 1997-2002: Studium Molekular-Biologie
- 2002-2007: PhD Signal-Quantification in Stem Cells
- 2006-2011: Group-Leader Signalquantifikation & Stammzellforschung Universität Würzburg
- 2010-2014: myLinkCloud (IT-Startup) Founder&CEO
- 2011-2016: Co-Founder & CTO meinUnterricht.de
- seit 2016: Founder & CEO vAudience GmbH
- seit 2016: KI-Projekte (mostly machine-learning)
- seit 2022: vA Fokus auf KI-Automation & Multi-Agenten-Systeme

Seit 2016 Beispielprojekte mit KI (Machine Learning)



TEXT (~2017-2019)

Nutzung von über 1Mrd Chat-Nachrichten pro Monat um Persona-, Sentiment und Themen-Analysen auf Basis für Kunden durchzuführen

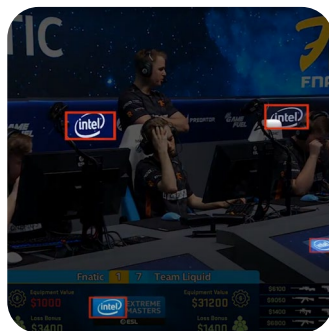
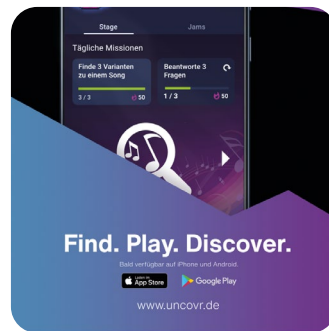


BILD (~2018-2019)

Quantifizierung der Reichweite und "Sichtbarkeit" von Objekten (z.B: Logos) in Live-Videos



AUDIO(2020-2021)

Konzeption und Umsetzung eines gamifizierten Labelling-Systems und Training eines Modells für Audio-Erkennung



MASCHINENBAU(2024)

Auswertung von Sensordaten in Fertigungsprozessen um Event-Vorhersage zu ermöglichen

vAudience Customer Journey

1



Erstgespräch

2



KI-Kurs

3



Workshop/
Prozess-
begleitung

4



Handlungs-
empfehlung

5



Produkt-
Umsetzung



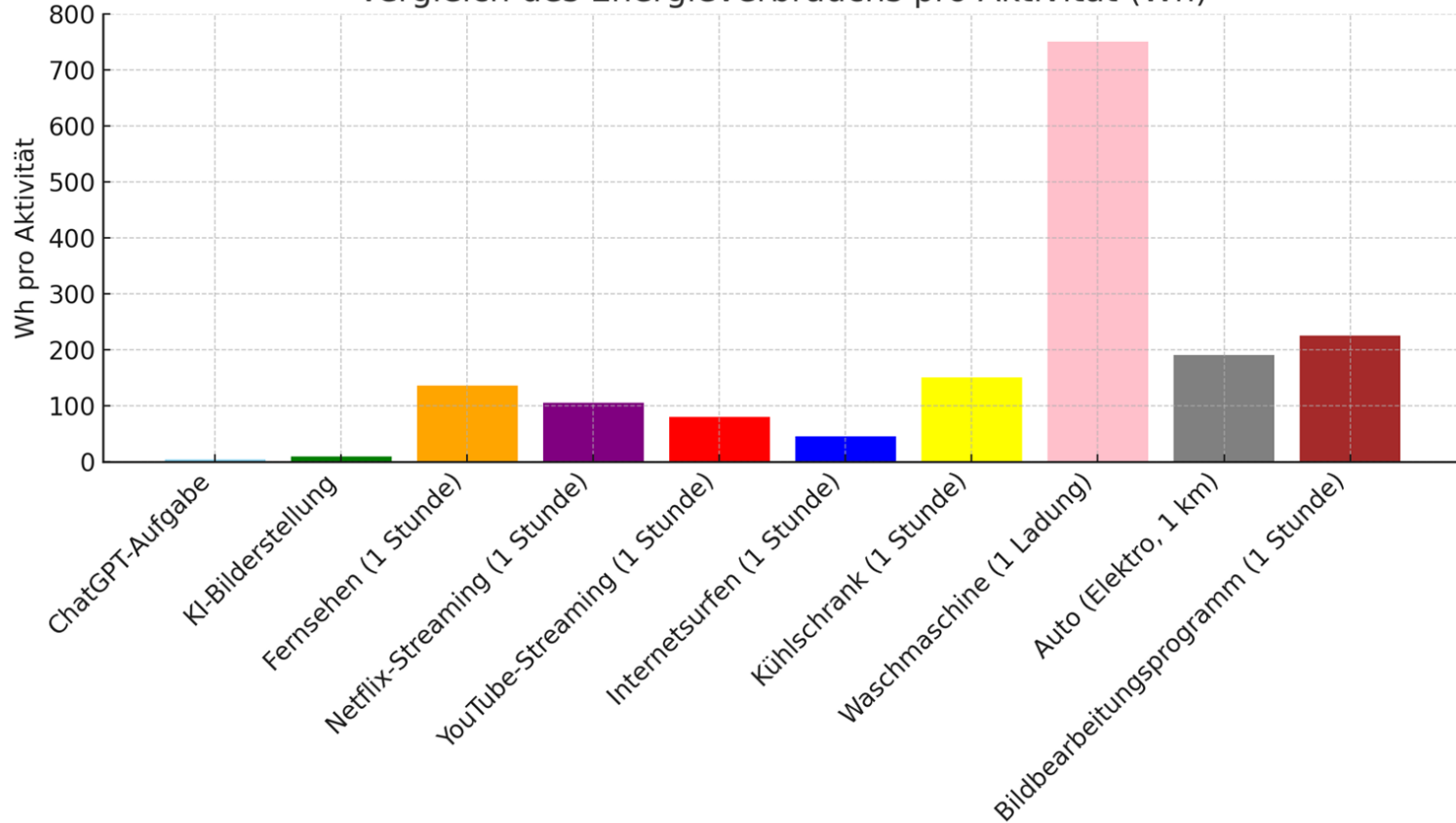
Intelligenz braucht Energie



Spezies	Energieverbrauch des Gehirns (% des Grundumsatzes)	Energieverbrauch des Gehirns (kWh/Tag)	Neuronen im Gehirn
Mensch	20-25%	~0.34	~86 Mrd
Ratte	3-5%	~0.0025	~200 Mio
Maus	3-5%	~0.0004	~71 Mio
Katze	5-10%	~0.015	~250 Mio
Hund	5-10%	~0.028	~530 Mio
Schimpanse	8-10%	~0.120	~28 Mrd
Delfin	5-15%	~0.245	~5.8 Mrd
Elefant	0.5-0.7%	~0.4	~257 Mrd

Energieverbrauch im Alltag

Vergleich des Energieverbrauchs pro Aktivität (Wh)





KI braucht (mehr) Energie



Weltweiter Energieverbrauch

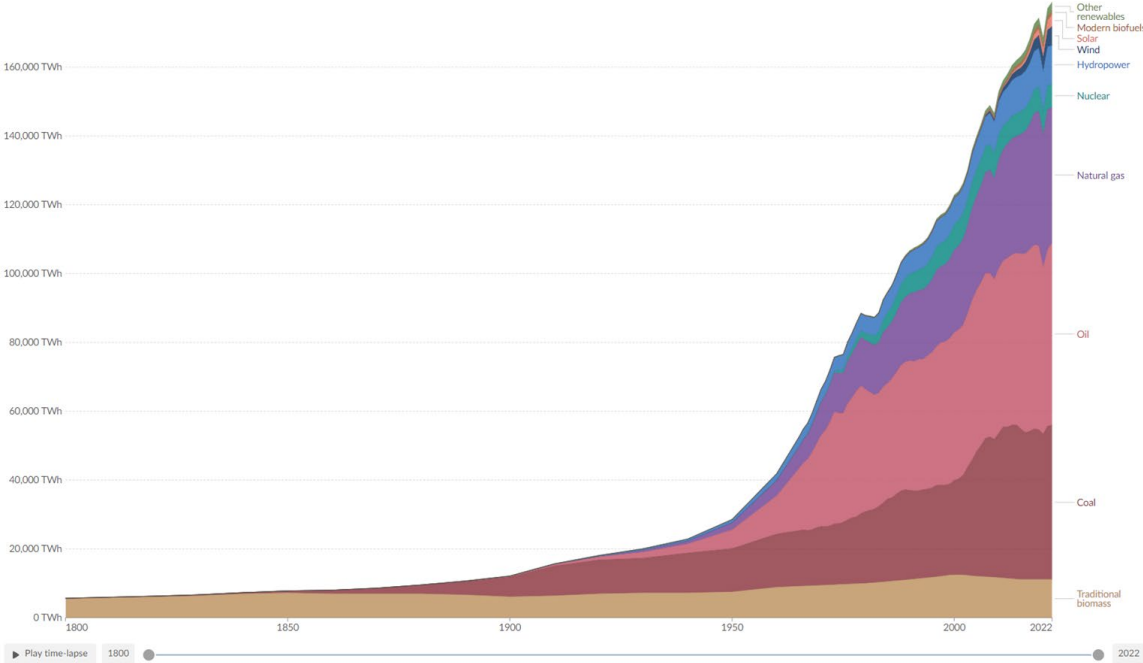
Global primary energy consumption by source

Primary energy is based on the substitution method and measured in terawatt-hours.

Table Chart

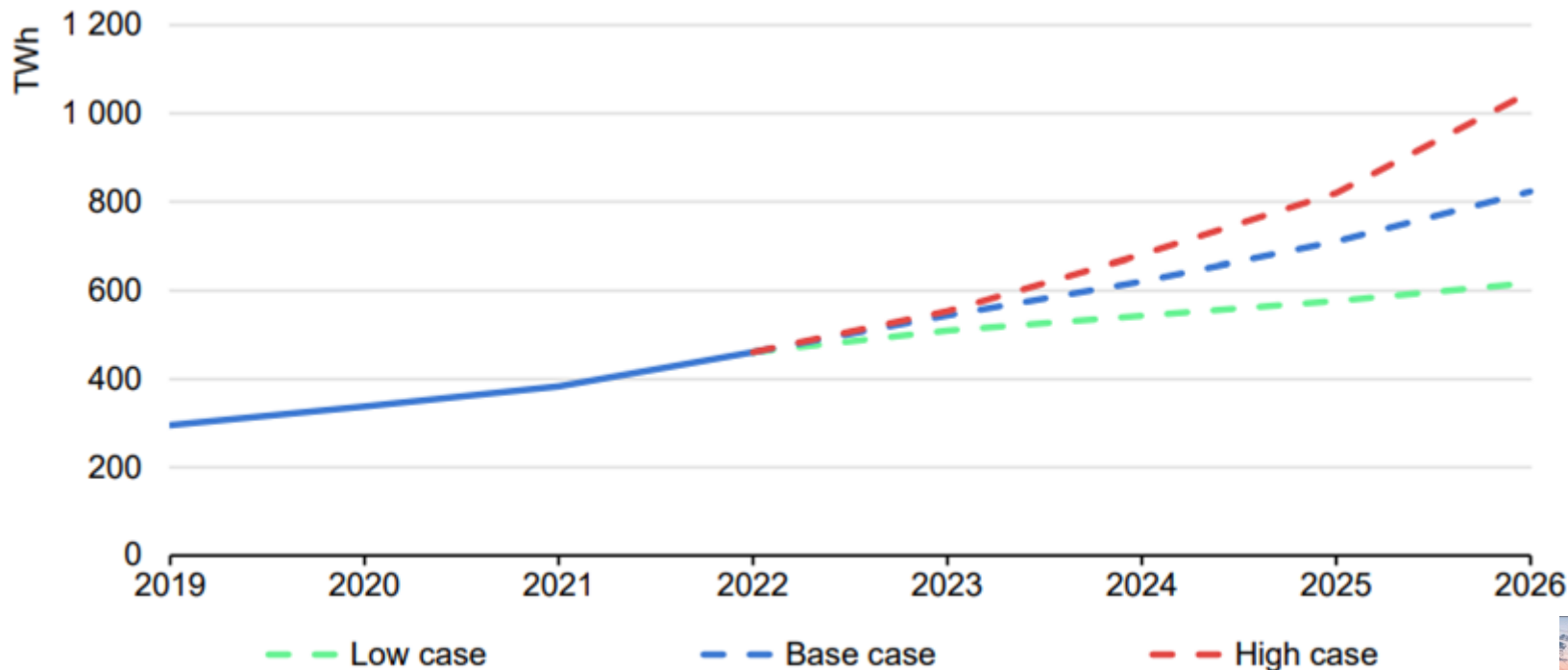
Our World in Data

Settings



Data source: Energy Institute - Statistical Review of World Energy (2023); Smil (2017) - [Learn more about this data](#)

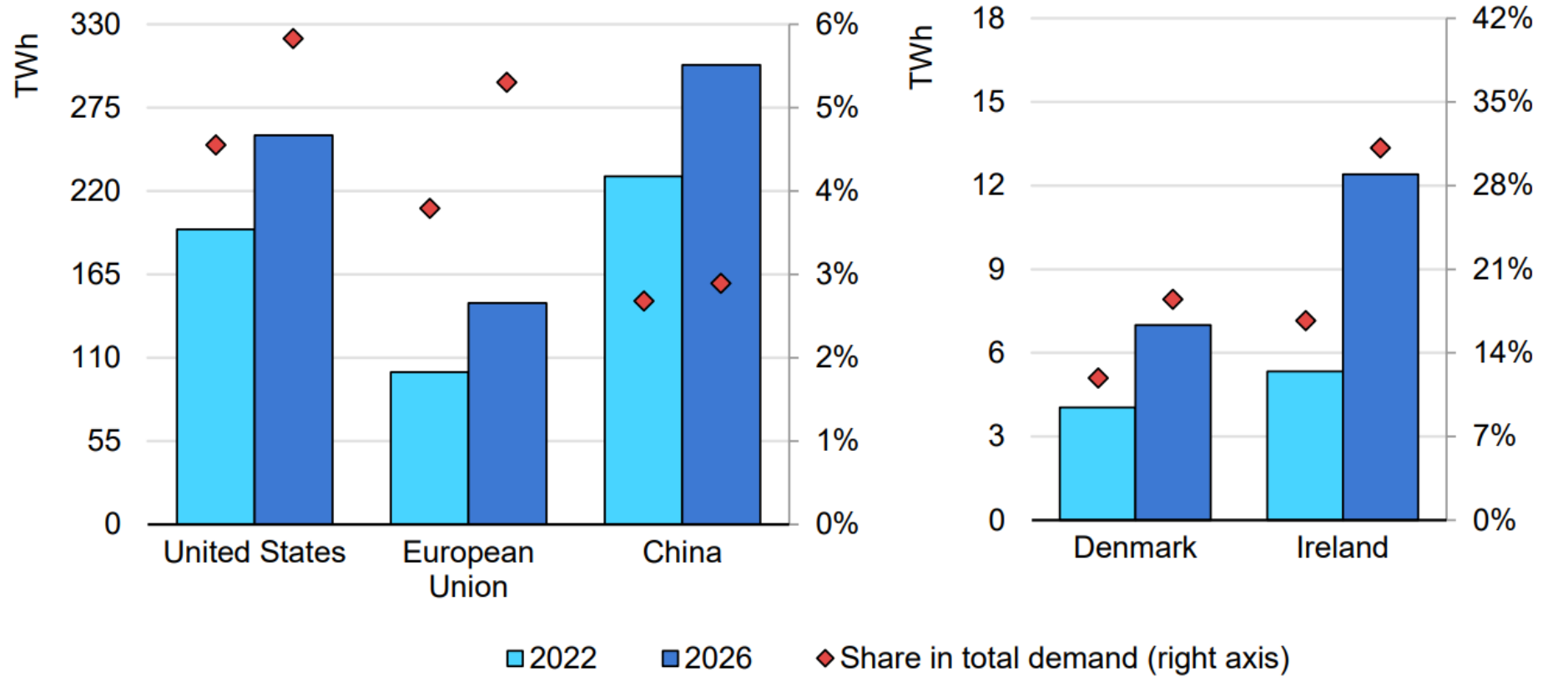
Weltweiter Energieverbrauch durch Datenzentren 2019-2026



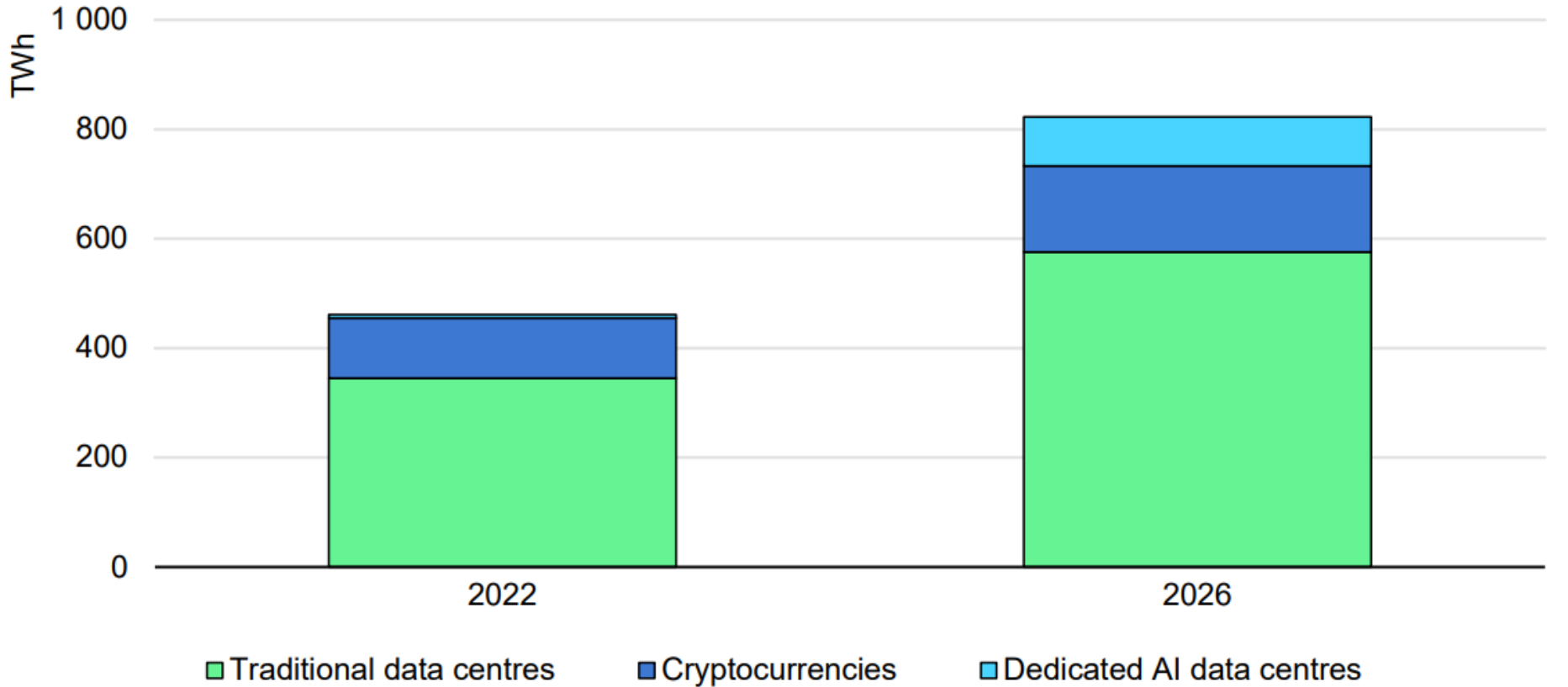
8Mrd. menschliche Gehirne brauchen etwa 1460TWh pro Jahr



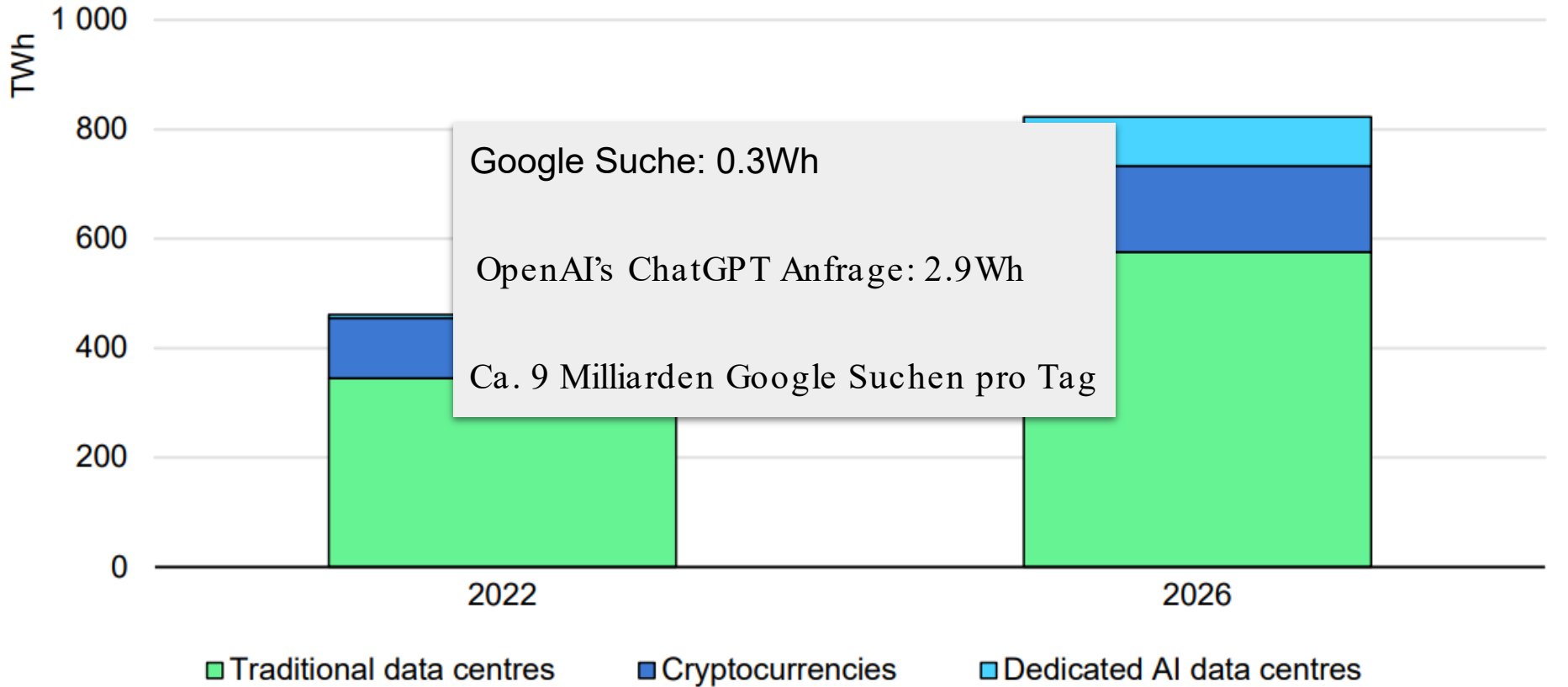
Estimated data centre electricity consumption and its share in total electricity demand in selected regions in 2022 and 2026




Estimated electricity demand from traditional data centres, dedicated AI data centres and cryptocurrencies, 2022 and 2026, base case




Estimated electricity demand from traditional data centres, dedicated AI data centres and cryptocurrencies, 2022 and 2026, base case





Energieverbrauch für KI-Training und Inferenz



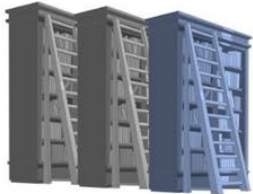
Das OpenAI GPT4 Modell

TRAININGS DATEN

für 13 Billionen* Tokens

650 km

lange Reihe von Bücherregalen



100.000 Tokens pro Buch
100 Bücher pro Regal
2 Regale pro Meter

RECHEN ZEIT

für 2,15 e25 FLOPs

7 Mio. Jahre

auf mittelgroßem Laptop (100 GFLOPs)



100 GLOPs pro Sekunde

MODELL GRÖSSE

für 1,8 Billionen* Parameter

30.000

fußballfeldgroße Excel-Tabellen



1x1 cm pro Excel-Zelle
100x60 m Feldgröße

Model-Training Kosten

Year	Model Name	Model Creators/Contributors	Training Cost (USD) Inflation-adjusted
2017	Transformer	Google	\$930
2018	BERT-Large	Google	\$3,288
2019	RoBERTa Large	Meta	\$160,018
2020	GPT-3 175B (davinci)	OpenAI	\$4,324,883
2021	Megatron-Turing NLG 530B	Microsoft/NVIDIA	\$6,405,653
2022	LaMDA	Google	\$1,319,586
2022	PaLM (540B)	Google	\$12,389,056
2023	GPT-4	OpenAI	\$78,352,034
2023	Llama 2 70B	Meta	\$3,931,897
2023	Gemini Ultra	Google	\$191,400,000

Model-Training Ausstoß

CO2 Equivalent Emissions (Tonnes) by Selected Machine Learning Models and Real Life Examples, 2022

Source: Luccioni et al., 2022; Strubell et al., 2019 | Chart: 2023 AI Index Report

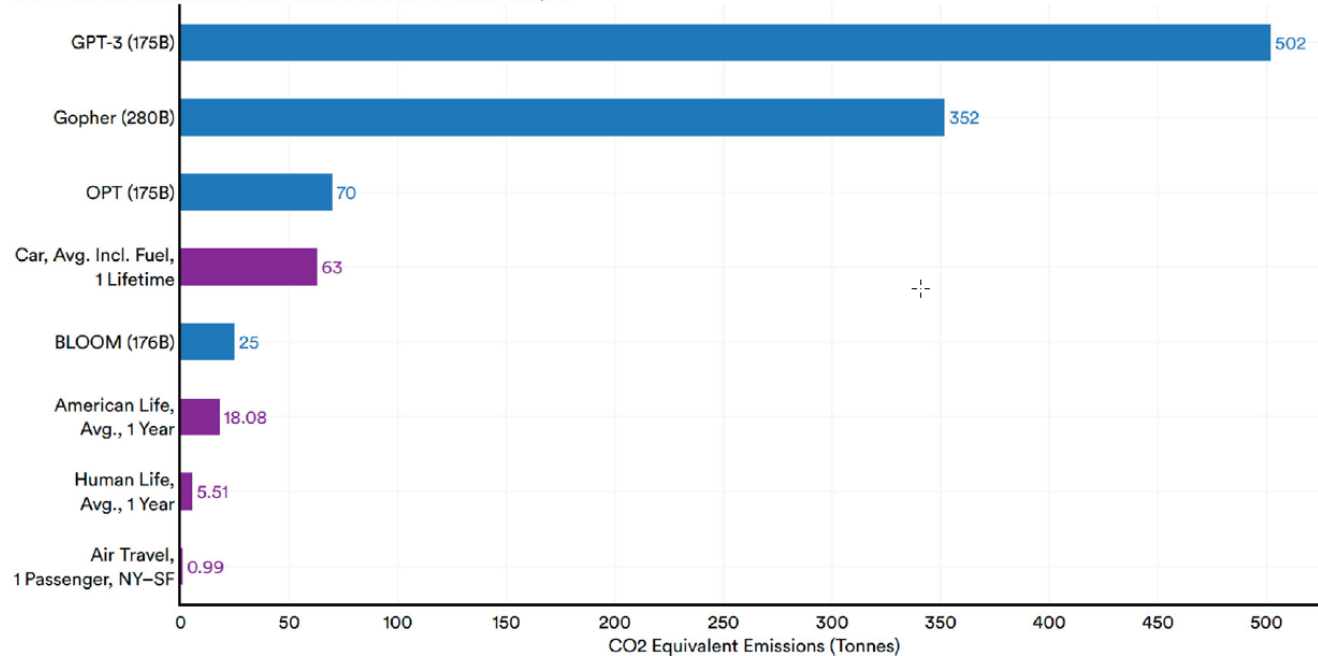


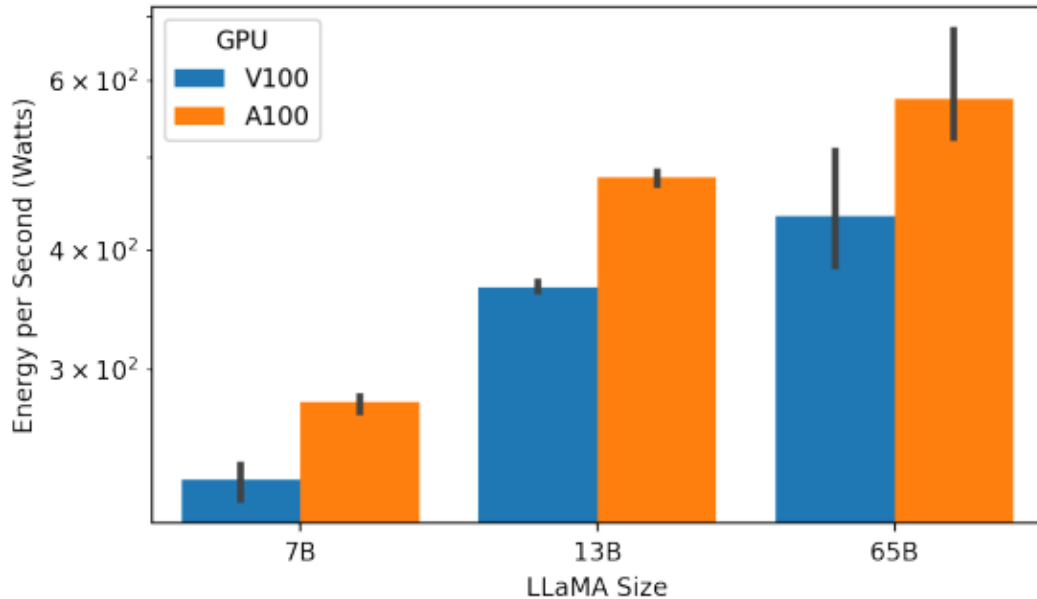
Fig. 1. CO2 equivalent emissions for training ML models (blue) and of real-life cases (violet). In brackets, the billions of parameters adjusted for each model.

From Words to Watts: Benchmarking the Energy Costs of Large Language Model Inference

Siddharth Samsi^{*§}, Dan Zhao[†], Joseph McDonald^{*}, Baolin Li[‡], Adam Michaleas^{*},
Michael Jones^{*}, William Bergeron^{*}, Jeremy Kepner^{*}, Devesh Tiwari[‡], Vijay Gadepally^{*}

^{*} MIT, [†] NYU, [‡] Northeastern University

LLaMA 7B/13B/65B - Inference Energy per Second (GSM8K)



A100 65B needs 600W/s, which is about 14,4 kWh per day.

Remember, your brain needs about 0,5 kWh per day!

Energy consumption for training of

- GPT-3 ~1287 MWh
- HF BLOOM ~433MWh

In 2023, OpenAI consumed about 564MWh per DAY for ChatGPT's ops



Kyle Corbitt ✓

@corbtt

Spoke to a Microsoft engineer on the GPT-6 training cluster project. He kvetched about the pain they're having provisioning infiniband-class links between GPUs in different regions.

Me: "why not just colocate the cluster in one region?"

Him: "Oh yeah we tried that first. We can't put more than 100K H100s in a single state without bringing down the power grid." 🤡

Last edited 11:38 PM · Mar 25, 2024 · **1.8M** Views

225

1.1K

5.9K

2K



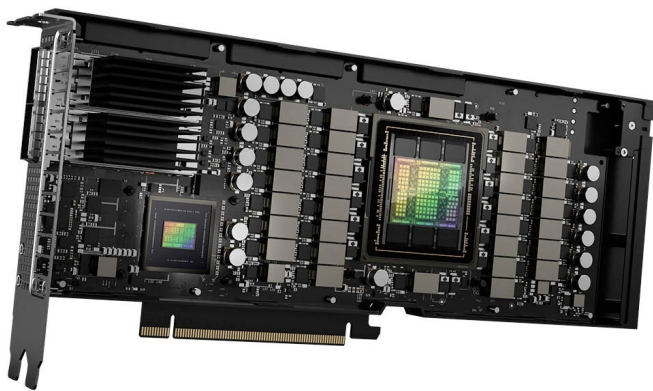
Post your reply

Reply



Kyle Corbitt ✓ @corbtt · Mar 26

All the AI haters in my replies don't realize what GPT-6+ will do for humanity's standard of living.



This is Nvidia's H100 GPU. It has a peak power consumption of ~700W. At a 61% annual utilization, it is equivalent to the power consumption of the average American household occupant (based on 2.51 people/household).

Nvidia's estimated sales of H100 GPUs is 1.5-2mil H100 GPUs in 2024.



Nachhaltigkeit & Herausforderungen durch KI



Herausforderungen für die IT -Nachhaltigkeit durch KI

Direkter **Anstieg des Energieverbrauchs** und der CO₂-Emissionen durch erhöhten Bedarf an Rechenleistung und Speicherkapazität für das Training und die Nutzung generativer KI-Modelle in Rechenzentren.

Indirekte Zunahme des Energieverbrauchs durch wachsende Nutzung und Verbreitung von KI-Anwendungen, die auf rechenintensiven generativen Modellen basieren.

Herausforderungen für die IT -Nachhaltigkeit durch KI

Erhöhter **Bedarf an seltenen Rohstoffen und Materialien** für die Produktion leistungsfähiger Hardware, die für generative KI benötigt wird, was indirekte Umweltauswirkungen mit sich bringt.

Herausforderungen für die IT -Nachhaltigkeit durch KI

Schwierigkeiten bei der Entwicklung und Umsetzung von **Standards und Regulierungen** für die nachhaltige Nutzung generativer KI aufgrund der rasanten technologischen Entwicklung.



Anti-electricity cartoon from ~1900



Nachhaltigkeitsziele durch KI erreichen



Grüne Künstliche Intelligenz

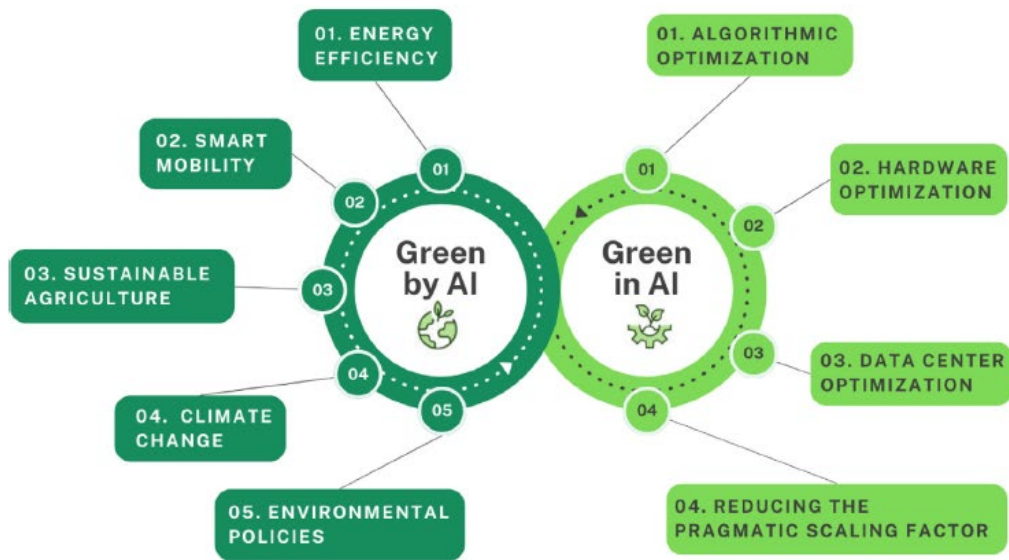


Fig. 3. Overview of green-in vs green-by algorithms.

Der Einfluss von Künstlicher Intelligenz

Every 1% increase in the level of AI development corresponds to 0.0025% increase in energy transition, a 0.0018% decrease in ecological footprint, and a 0.0013% decrease in carbon emissions.

In other words, AI has the strongest effect in promoting energy transition, followed by the reduction effect on ecological footprint, and then the impact of AI on carbon emissions.

Humanities & Social Sciences
Communications



ARTICLE



<https://doi.org/10.1057/s41599-024-03520-5>

OPEN

Ecological footprints, carbon emissions, and energy transitions: the impact of artificial intelligence (AI)

Qiang Wang^{1,2}, Yuanfan Li¹ & Rongrong Li²

Handlungsempfehlungen

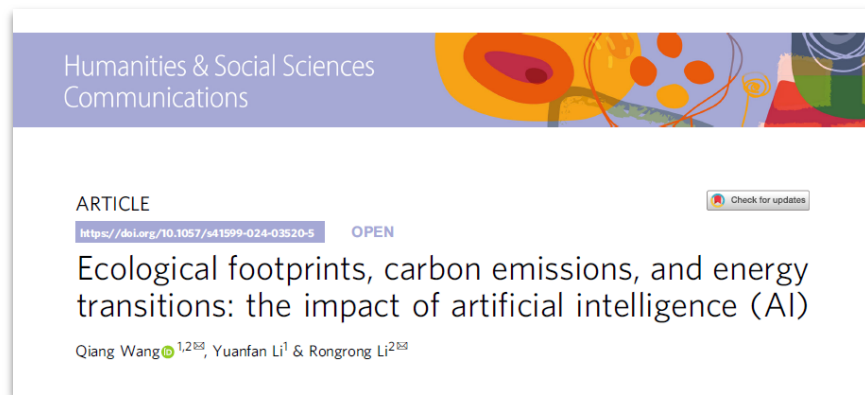
Countries should increase investment in AI R&D propose AI development strategies and establish long-term development mechanisms

Countries with high industrial proportions should make full use of the advantages of their own industrial systems to develop renewable energy with the help of AI

Trade openness plays an important role in exerting the positive effects of AI

Setting binding long-term goals for AI development is of great significance to all countries

A higher level of energy transition can help AI better reduce its environmental footprint



Humanities & Social Sciences
Communications

ARTICLE Check for updates

<https://doi.org/10.1057/s41599-024-03520-5> OPEN

Ecological footprints, carbon emissions, and energy transitions: the impact of artificial intelligence (AI)

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Developing target

Survey of **113** technologies

Results

AI

UNIV
WORK

for
S



Data



ELSEVIER



Energy Reports

Volume 8, November 2022, Pages 1602-1633



Research paper

Universal workflow of artificial intelligence for energy saving

Da-sheng Lee ^a  , Yan-Tang Chen ^a, Shih-Lung Chao ^b

Workable

35%

Building
energy c
savin



energy
saving



power



%
tory peak
ver
uction



Developing target

AI

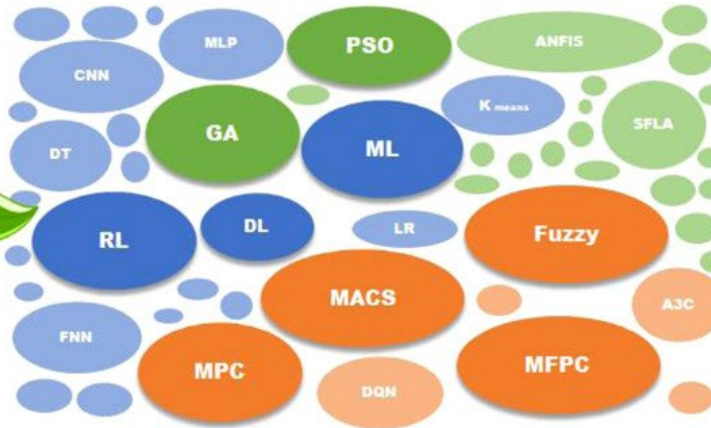


UNIVERSAL
WORKFLOW

for Energy
Saving



Survey of **113** technologies



Results



Workable method to assist the use of AI in **6** fields

35%
Building
energy cost
saving



25% HVAC
energy
saving



50%
artificial
lighting
energy
saving



Up to 70%
communication
power saving



**Grid energy
supplied with
the largest
renewable
energy up to
30% peak
power**



30%
factory peak
power
reduction



Sustainable Development Goals der UN





13.1 Strengthen resilience and adaptive capacity to climate-related hazards and natural disasters in all countries

13.2 Integrate climate change measures into national policies, strategies and planning

13.3 Improve education, awareness-raising and human and institutional capacity on climate change mitigation, adaptation, impact reduction and early warning

13.A Implement the commitment undertaken by developed-country parties to the United Nations Framework Convention on Climate Change to a goal of mobilizing jointly \$100 billion annually by 2020 from all sources to address the needs of developing countries in the context of meaningful mitigation actions and transparency on implementation and fully operationalize the Green Climate Fund through its capitalization as soon as possible

13.B Promote mechanisms for raising capacity for effective climate change-related planning and management in least developed countries and small island developing States, including focusing on women, youth and local and marginalized communities

*Acknowledging that the United Nations Framework Convention on Climate Change is the primary international, intergovernmental forum for negotiating the global response to climate change.



14.1 By 2025, prevent and significantly reduce marine pollution of all kinds, in particular from land-based activities, including marine debris and nutrient pollution

14.2 By 2020, sustainably manage and protect marine and coastal ecosystems to avoid significant adverse impacts, including by strengthening their resilience, and take action for their restoration in order to achieve healthy and productive oceans

14.3 Minimize and address the impacts of ocean acidification, including through enhanced scientific cooperation at all levels

14.4 By 2020, effectively regulate harvesting and end overfishing, illegal, unreported and unregulated fishing and destructive fishing practices and implement science-based management plans, in order to restore fish stocks in the shortest time feasible, at least to levels that can produce maximum sustainable yield as determined by their biological characteristics

14.5 By 2020, conserve at least 10 per cent of coastal and marine areas, consistent with national and international law and based on the best available scientific information

14.6 By 2020, prohibit certain forms of fisheries subsidies which contribute to overcapacity and overfishing, eliminate subsidies that contribute to illegal, unreported and unregulated fishing and refrain from introducing new such subsidies, recognizing that appropriate and effective special and differential treatment for developing and least developed countries should be an integral part of the World Trade Organization fisheries subsidies negotiation

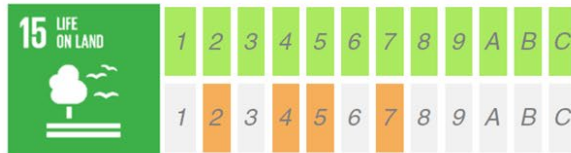
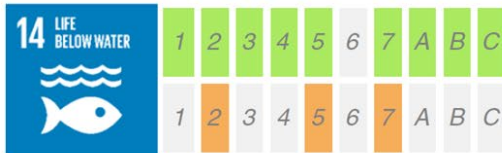
14.7 By 2030, increase the economic benefits to Small Island developing States and least developed countries from the sustainable use of marine resources, including through sustainable management of fisheries, aquaculture and tourism

14.A Increase scientific knowledge, develop research capacity and transfer marine technology, taking into account the Intergovernmental Oceanographic Commission Criteria and Guidelines on the Transfer of Marine Technology, in order to improve ocean health and to enhance the contribution of marine biodiversity to the development of developing countries, in particular small island developing States and least developed countries

14.B Provide access for small-scale artisanal fishers to marine resources and markets

Sustainable Development Goals der UN

Environment



PERSPECTIVE

<https://doi.org/10.1038/s41467-019-14108-y>

OPEN

The role of artificial intelligence in achieving the Sustainable Development Goals

Ricardo Vinuesa^{1*}, Hossein Azizpour², Iolanda Leite², Madeline Balaam³, Virginia Dignum⁴, Sami Domisch⁵, Anna Felländer⁶, Simone Daniela Langhans^{7,8}, Max Tegmark⁹ & Francesco Fusco Nerini^{10*}

Sustainable Development Goals der UN

Analyzing largescale interconnected databases to develop joint actions aimed at preserving the environment.

AI advances will support the understanding of climate change and the modeling of its possible impacts.

AI will support low-carbon energy systems with high integration of renewable energy and energy efficiency.

Algorithms for automatic identification of possible oil spills.

Neural networks and objective oriented techniques can be used to improve the classification of vegetation cover types based on satellite images.



nature
COMMUNICATIONS

PERSPECTIVE

<https://doi.org/10.1038/s41467-019-14108-y> OPEN

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Beispiele im Bereich Energieeffizienz-Optimierung



Präzise Bedarfsvorhersagen

KI kann eine Vielzahl verschiedener Kennzahlen in Vorhersagen einbeziehen

- Historischer Bedarf
- Wetter
- Auslastung

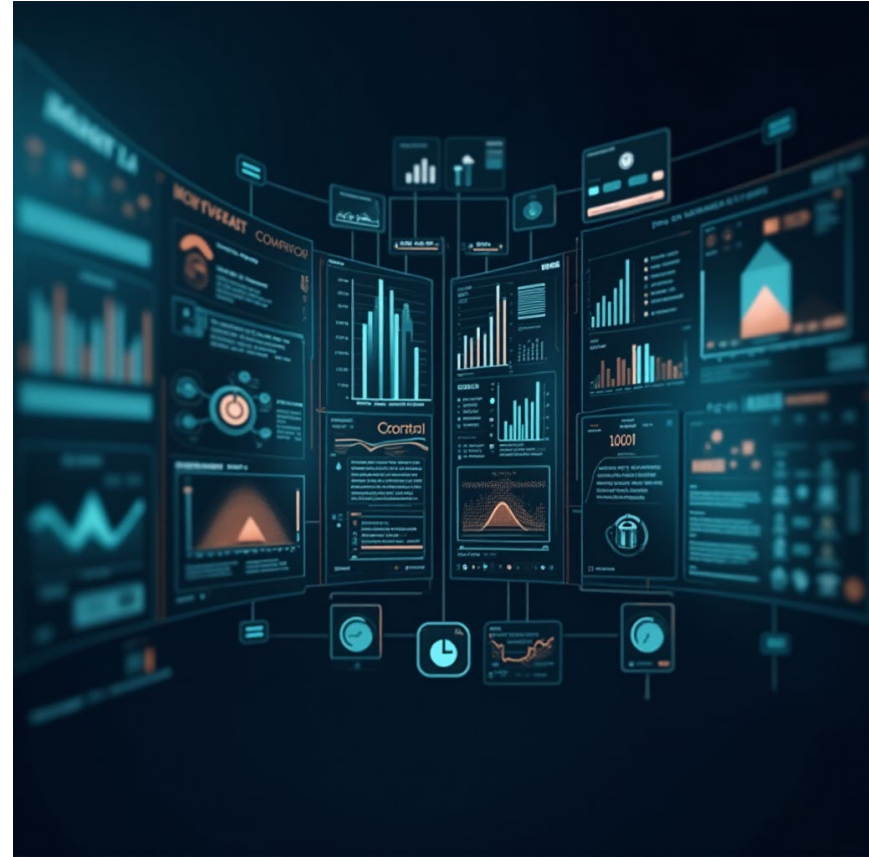


Echtzeit Monitoring und Kontrolle

Ermöglicht Reaktion auf sich ändernde Gegebenheiten.

- Auslastung
- Wetter
- Preis

Erhöht Effizienz und hilft dabei, mit Stoßzeiten besser umzugehen.



Erneuerbare Energien einbinden

KI kann erneuerbare Energiegewinnung vorhersagen und deren Verwendung maximieren.

“Demand Response Programs”, wodurch Verbraucher ihren Bedarf an Angebot-Nachfrage-Signale anpassen können.



Datensicherheit

Verbrauchsdaten können sehr sensitiv sein.

Robuste Cybersecurity ist essentiell, aber auch anspruchsvoll.



Regulierungen

Verstehen, Anwenden und Einhalten von Regulierungen/Vorschriften fügt ein weiteres Level an Komplexität hinzu.



Neue Kompetenzen

Implementierung und Verwendung von KI Lösungen bedarf spezielles Wissen in Bereichen

- KI Algorithmus
- Datenanalyse
- Energiesysteme

Integration in existierende Systeme kann komplex werden.




Heute im Einsatz

IMPACT

DeepMind AI Reduces Google Data Centre Cooling Bill by 40%

20 JULY 2016
Richard Evans, Jim Gao

Share



SIEMENS


HVAC Optimization



Did you know that by boosting your HVAC efficiency you can generate energy savings and improve your operations? We can optimize your chilled water and air distribution to allow systems to respond more effectively to demand, and to deliver energy where and when it's needed – all without

The Microsoft Cloud

Home / Sustainability / Sustainable by design: Innovating for energy efficiency in AI, part 1



Thought leadership 4 minutes
September 12, 2024

Sustainable by design: Innovating for energy efficiency in AI, part 1


By Mark Russinovich, CTO, Deputy CISO and Technical Fellow, Microsoft Azure

SHARE


TAGS

AI

Learn more about how we're making progress towards our sustainability commitments through the Sustainable by design blog series, starting with [Sustainable by design: Advancing the sustainability of AI](#)

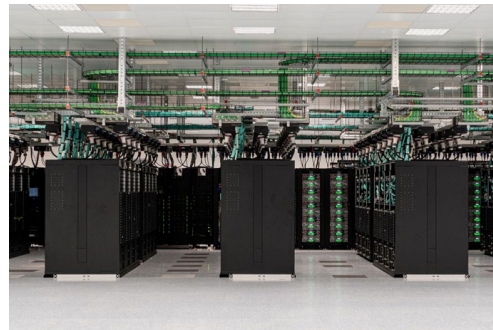
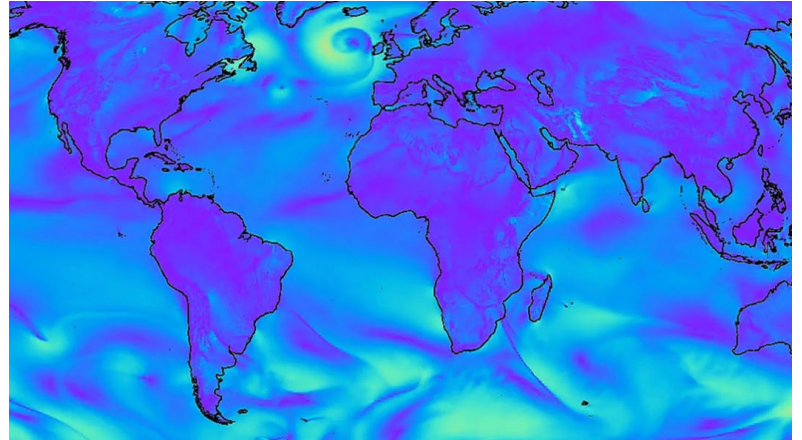


Entdeckung ungeahnter Möglichkeiten durch KI



GraphCast

- schlägt die aktuell besten aktiven Modelle in über 99% aller Wetter-Variablen in über 90% aller getesteten (1.300) Regionen
- läuft auf Standard-PC und generiert die Vorhersagen innerhalb weniger Sekunden



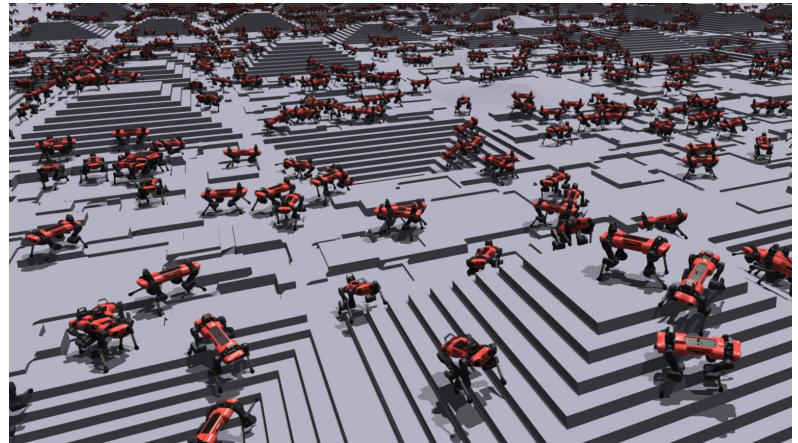
GNoME

- identifiziert > 2,2 Millionen neue Kristallstrukturen
- 380.000 als stabile neue Materialien vorhergesagt
- faszinierenden Eigenschaften, die neue Technologien ermöglichen werden
- >70% erfolgreich bestätigt
- Entspricht etwa 800 Jahre Materialforschung



NVIDIA Isaac Sim

- trainiert Roboter virtuell
- spart sehr viel Zeit und Geld
- entdeckt aktiv neue Ansätze





Fragen? Panik? Diskussion?





DANKE!

Wir hoffen, es war spannend!

Quellen

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