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Can AI grow green? Evidence of a *Kuznets curve* among AI, renewable energies and emissions

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A B S T R A C T

The relationship between artificial intelligence (AI) and the *green agenda* is one of the key current economic and social topics, driven by conflicting assumptions and evidence. On the one hand, AI use cases can drive energy savings, support renewable transition, and reduce emissions. However, its initial adoption significantly increases energy consumption, thereby deepening the challenges countries face to reach their environmental sustainability goals. This paper presents novel empirical evidence on AI development and its environmental implications in 23 middle and high-income countries, confirming that, initially, in the majority of countries AI increases energy consumption and CO2 emissions. However, we also show that these relationships are not linear, since, for high spending levels, AI has a positive impact on the environment in terms of emission reduction and higher reliance on renewable energies, a kind of *green AI Kuznets curve*. This reversal in the trend is achieved from $220-$580 AI market per capita, and therefore, as of today, only AI leading countries, such as Singapore and the US, are benefitting from this technological dividend. These results have clear policy implications, calling for a less fragmented global AI and energy governance given environmental externalities, national AI strategies with a solid energy pillar, and innovations in financing towards greener AI adoption, while achieving more transparency and standards for measuring and reporting its energy use.

1. Introduction

Artificial intelligence (AI) is driving radical changes in production and consumer welfare. Generative AI could add up to US$ 4.4 trillion to the global economy, a positive shock not just for productivity in the technology and telecommunications sectors, but also in finance, retail and the life sciences (McKinsey, 2023). These remarkable effects stem both from labor productivity and automation, and an acceleration of innovation in a scenario where AI, as a *general-purpose technology*, spreads across the economy (Baily et al., 2024). Many caveats in this assessment are in order though. First, AI's full potential remains untapped. Some authors argue that at least in the next decade AI impact will only involve automation of discrete tasks and some task complementarity, with modest impact on productivity, while others are more optimistic (for contrasting economic perspectives see Acemoglu, 2024 vs Baily et al., 2024; OECD, 2024 for a panoramic survey). Second, in the absence of a more integrated global governance – particularly involving low- and middle-income countries - and under the existing significant human capital and technology gaps across and within countries, AI development can reproduce and even amplify socioeconomic and environmental risks.

Focusing on these environmental risks, one of the most pressing issues raised by the AI boom is the significant resource consumption associated with AI innovation, from minerals and rare earth extraction for manufacturing its semiconductors and batteries, to water and energy required by data centers' operations in the training of large language models (LLMs) (Lebdioui et al., 2025).[1] Rn reporting on the

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[1] For instance, on metals, Ollion et al. (2024) examine the use and criticality of 25 metals in digital equipment in France, mapping their full value chain from extraction to end-of-life recycling. The report finds that recycling infrastructure is insufficient for many metals, limiting circularity. This calls for improving value chain transparency, developing sovereignty strategies for supply security, and promoting smarter demand and design.

In a rare and yet valuable exercise, Gupta et al. (2024) present a comprehensive dataset capturing hourly water consumption related to cooling systems and electricity generation across major U.S. cities and states. This work reveals significant temporal and spatial differences in water efficiency, enabling applications such as water-aware EV charging schedules, building load management, and geographically optimized data center operations to reduce water consumption and enhance sustainability. Extending our analysis to water and minerals are future steps of our research.

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extraordinary surge in energy demand from AI development and data centers' consumption of electricity and water, and their contribution to greenhouse effects and climate change appear regularly even in the general media (Crownhart, 2024; Mehta, 2024). Companies' environmental reports, in fact, confirm a significant increase in electricity and natural resource consumption, partially due to the AI boom. Greenhouse gas emissions from three top AI platform suppliers - Alphabet, Amazon and Microsoft - are up 62 percent from 2020, reaching 47 million metric tons alone in 2023 (ITU and WBA, 2024), which amounts to half of the total emissions of a country like Peru. Electricity use by these three companies has grown even faster, up 78 percent and standing at just over 100 TWh in 2023, similar to Colombia and Dominican Republic joint annual consumption. The latest projections from the International Energy Agency (IEA, 2025) show that data center electricity consumption is set to more than double to around 945 TWh by 2030, slightly more than Japan's total electricity consumption today.

Admittedly, a challenge for evaluating the relationship between AI, energy and nature is the lack of comparable comprehensive emissions data, as prominent model developers such as OpenAI, Google or Anthropic do not report emissions in training LLMs, a particularly high energy-consumption phase given that it involves numerous resource-intensive iterations (Stanford Institute for Human-Centered AI, 2024; ITU, 2024). Also, external reports show that currently, a single OpenAI's ChatGPT search consumes as much as ten Google searches (Lokwon, 2025). Partially, due to this lack of reliable data, the empirical academic research on the impact of AI on energy consumption and on the environment is still relatively thin and fragmented, lacking consistent measurement methodologies.

This paper aims to contribute towards filling this gap, providing empirical evidence on the relationship between AI investment, energy requirements, CO2 emissions and the energy transition towards renewables. For this purpose, we have built an original database covering 23 countries – including all AI-leaders worldwide, and tested these relations, with a focus on non-linearities to capture the potential effect of AI after it is widely adopted and consolidated. We find that AI initially has a negative impact on environmental indicators, but it turns positive once certain (high) spending threshold is crossed. We believe this to be the first contribution providing evidence on the inverted-U relationship between AI and emissions, and a U-shaped between AI-renewable energies - a kind of *green AI Kuznets curve* as the environmental impact of AI first worsens and then improves with AI progress[2] - covering such ample sample with all AI leaders (both users and producers).

In short, these are our main findings:

- Rising AI spending increases energy use.
- *Kuznets curve* found: AI impact on emissions and renewable energy adoption is non-linear across countries.
- Higher AI spending is linked to greener economic growth, as already seen in Singapore and the US.
- Mandates on AI energy use and carbon reporting standards, and conditioning public support on energy performance could help the *green AI agenda.*
- Innovation in financing green AI with *digital development bonds* and co-financing focused on low- and middle-income countries is key.

The paper is structured as follows. Section 2 reviews the literature and sets the main empirical hypotheses. Section 3 describes the data. Results and policy implications are reported in Section 4. Section 5 concludes and discusses limitations and potential research extensions of the paper.

[2] The *Kuznets curve* refers to the hypothesis proposed by the economist Simon Kuznets in the 1950s showing that as economies develop (measuring by income per capita), market forces first thrive inequality up, and then down.

2. Literature review and hypotheses

Despite the recent surge of AI as a *general-purpose technology*, empirical academic research on AI energy consumption is still relatively limited due to the lack of comprehensive comparable data. That said, emerging findings confirm a tension between AI development, resource use (specifically water and energy) and environmental sustainability.

For starters, AI algorithms are energy-intensive, leading to increased CO2 emissions. A seminal study covering some of the most popular LLMs in 2022 showed that the training of BLOOM model – today seen as quite basic - demanded energy equivalent to 25 times that of flying one passenger round trip from New York to San Francisco (Stanford Institute for Human-Centered AI, 2023; Luccioni et al., 2024). Since then, model parameters have increased exponentially, requiring higher computation power. The recent emergence and extensive use of generative AI further increased energy demand and emissions. Even with lighter and efficient models like 2025 DeepSeek, AI energy demand is projected to increase as, according to the so-called *Jevons paradox,* as AI systems become more efficient and accessible, their usage and the resources they consume increase due to wider adoption and increased demand (e.g. Rosalsky, 2025).

On the positive side, AI applications are becoming a key component of the so-called *green agenda* (Fig. 1).[3] AI can optimize and potentially reduce energy consumption and CO2 emissions. Widespread adoption of existing AI applications could save around 8 EJ of industry energy demand by 2035, equivalent to more than the total energy demand of Mexico today, according to the IEA (2025). In agriculture, AI-driven precision farming reduces energy consumption while enhancing productivity, by employing sensors and advanced analytics to monitor soil, water and climate. AI and digital finance can also significantly enhance carbon productivity both locally and in neighboring cities (Sun et al., 2023). Similarly, AI implementation in manufacturing enhances resource efficiency through real-time shop-floor monitoring enabled by IoT and 5G networks (Tace et al., 2023).

In the energy sector AI can significantly improve efficiency through predictive analysis, optimizing real-time energy consumption and adjusting demand based on environmental and operational data, as seen in applications like smart grids and energy management systems. AI further enhances flexibility by forecasting supply and demand, optimizing production patterns based on historical data, environmental conditions and power plant capacities, thus minimizing energy waste (Rojek et al., 2023; Rozite et al., 2023; Serebryantseva, 2023; Şerban and Lytras, 2020).[4]

In addition, AI is launching initiatives to *"green itself"* such as advanced cooling technologies and dynamic workload management. Also, AI models increasingly rely on low-carbon energy grids and renewable resources. Salesforce trained its models in lower-carbon data centers, powered by electricity sources that emit nearly 70 percent less carbon than global average electricity. This resulted in 105 fewer tons of carbon dioxide equivalents than if data centers with global average carbon intensity were used for training models Leading tech companies have shown significant emission reductions by utilizing energy-efficient data centers and advanced cooling technologies. For instance, applying DeepMind's machine learning to Google data centers, reduced the amount of energy for cooling by up to 40 percent according to the company (Gamazaychikov, 2024; Walsh, 2024; Amazon Team, 2023; Intel, 2023; Evans and Gao, 2016).

Moreover, AI can speed up renewable energies' adoption, thereby

[3] This *AI and green agenda* framework is based on Lebdioui et al. (2025). We refer the interested readers to it, including the AI and biodiversity preservation angle not developed in this paper.

[4] An additional increasingly relevant dimension is that of AI and security, given energy growing geopolitical role and its advanced digitization (see for instance Lewis and Oxby, 2024). This is a natural extension of this research.

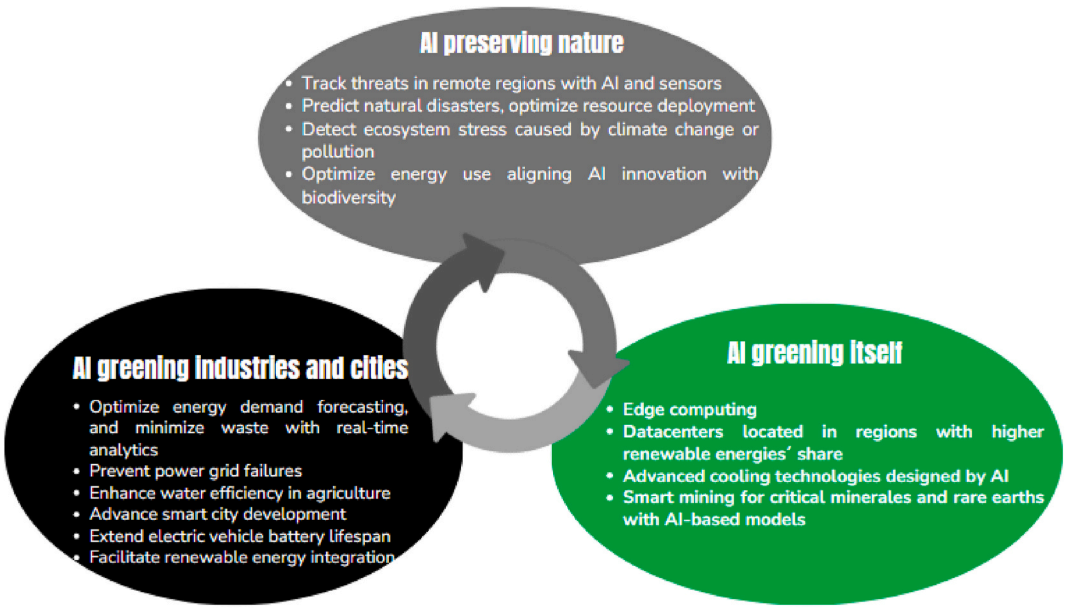

Fig. 1. AI and the green *agenda*. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)
Source: Lebdioui et al. (2025).

also reducing CO2 emissions. AI facilitates the integration of renewable energy sources by improving forecasts of the variability of solar or wind generation, thus balancing energy supply more effectively across the grid. Various AI-based approaches, including structured data management, data mining capabilities and machine learning techniques, support an ecosystem that enables smart energy grids (Rozite et al., 2023; Serebryantseva, 2023; Şerban and Lytras, 2020). AI can also support the transition to greener energy sources by optimizing mining processes for critical materials and improving the efficiency of renewable energy infrastructure. Finally, AI indirectly contributes to preserving nature by speeding up the process of securing renewable energy supply.

What is the actual net balance of all these countervailing AI-energy-environment effects? Illustratively, Delanoë et al. (2023) provided quite realistic estimations of the impact of three machine learning (ML) models for solar panels in Brazil, water pumping in Tunisia and electric vehicles in Sweden could have on CO2 emissions. Double digit reductions were erased by energy needs of the models unless these solutions were scaled up. Patterson et al. (2022) examined the carbon footprint of ML training, and projected that some good practices - model design, specialized hardware, cloud mechanization, and location choice - will make ML training carbon footprint plateau and then shrink this decade.

Therefore, the net effect remains an empirical question, which is the natural field of empirical cross-country studies. Econometric analyses show that AI spending correlates positively with renewable energy adoption and reduced CO2 emissions, although its potential savings effect on total energy consumption is less clear. However, the former positive patterns are more apparent in high-income and AI-leading countries, suggesting the existence of a non–linear pattern linking energy consumption and AI spending (and/or per capita income). These results are robust to various ways to measure AI, from AI investment, the number of AI software projects or AI companies, to the number of industrial robots or the number of AI technology patents. Granularity on the different impacts by industries is mostly limited to China, where the positive effects in energy- and tech-intensive industries stand out.

Most research literature has focused so far on sustainable energy transition, consistently finding positive effects on greater adoption of renewable energy sources. Yin et al. (2023) analyze the impact of the number of AI software projects (released in the GitHub platform) on the share of renewable energy as percent of total energy consumption for a sample of 62 economies covering the period 2011–2020. Authors find a positive effect of AI software development on the sustainable energy transition in the following year, as it facilitates measuring and reporting consumption. Yang et al. (2024) confirm these results for a global sample of 44 countries from 2000 to 2022, estimating a positive effect of AI patents index on the share of renewable energy. Related to it, Chun and Hwang (2024) show that for 139 countries between 1990 and 2019, those that are proficient in both green and AI technology patents – especially when AI is integrated in green technologies - show greater capability in developing and sustaining green technological advancements. Finally, Rasheed et al. (2024) confirms this positive effect also on energy supply, based on the positive interaction of AI patents on renewable energy production in 22 leading robotics and innovative countries, from 1991 to 2020.

Interestingly, and compatible with the non-linear hypothesis, Zhao et al. (2024) for China find that AI adoption (again, measured by the number of robots) increase the share of renewable energies in total energy in the long term. However, in the short and medium term, AI negatively impacts renewable energies share in the matrix due to considerable challenges in integrating AI into its sector (cost and complexity), and the faster adoption in traditional energy sectors such as coal.

Regarding the impact on energy productivity (identified as energy efficiency EI, that is the lowest energy consumption required to achieve output), Hossin et al. (2023) show for 12 Middle East and North Africa (MENA) countries between 2000 and 2021 that the impact of AI (measured as applications to register industrial designs) is significant but weak. Katz and Jung (2024) showed that energy consumed by cloud computing and the information technology industry in general is more economically productive (higher value per unit of energy) than other sectors. Deepening on industrial sectors in China, Liu et al. (2022) and Li et al. (2023) provide evidence that AI contributes to the reduction of EI, especially in labor-intensive sectors (e.g., textiles and paper) and technology-intensive sectors (e.g., industrial machinery and transportation equipment) using industrial robot adoption from 2006 to 2016. For a sample of Chinese manufacturing listed enterprises during the period of 2011–2019, Zhang and Zeng (2024) show that incorporating an additional unit of industrial robots per hundred workers leads to an approximate 2.5 percent reduction in enterprise EI by advancing technological innovation and digital transformation.

As results might vary regionally, Liu et al. (2025) focus on 41 cities in Chinese major tech and innovation hub Yangtze River Delta 2006–2020, confirming that the digital economy (broader than AI) significantly improves energy efficiency through mechanisms such as industrial structure upgrading, enhanced transaction efficiency, and green innovation, while environmental regulations and regional resource endowment moderate this effect. By states in the US, regions that have high deployment of cloud computing data centers and accelerate the migration to an IT-intensive economy benefitted from high energy productivity, measured as gross value added per unit of energy consumed (MWh).

In terms of the impact of AI on emissions, the evidence is mixed. For a sample of 14 East Asian and Pacific countries from 2000 to 2023, Shah et al. (2024) obtained contrasting results regarding the impact of AI (measured by AI research publications) on CO2 emissions. Doran et al. (2024) showed inconclusive results on the impact of AI (measured by industrial robots, AI companies, and total and private AI investments in USD) on GHG emissions in 44 European countries during the period 2012-22. While the deployment of industrial robots and investment in AI technologies may have a significant impact on GHG emissions, and large companies exhibit higher investment levels potentially contributing to reduced emissions, authors claim the relationship between private investment in AI and GHG emissions requires further scrutiny. In a similar line, Zhong et al. (2023) studied the diverse impacts of AI (number of intelligent robots installed) on carbon emissions in 66 countries from 1993 to 2019 and found carbon reduction effects mainly in high-carbon emission and high-income countries.

Finally, Wang et al. (2024a) analyzed 67 countries between 1993 and 2019 and showed that AI (proxied by the stock of industrial robots) significantly reduced carbon emissions, and promoted renewable energies share. Furthermore, the environmental benefits of AI were more pronounced at higher levels of AI development. Wang et al. (2024b) added to a similar sample of countries the role of trade openness, indicating that when trade openness crosses a certain threshold, AI has a significant negative impact on carbon emissions, and a positive impact of AI on energy transition. These last two papers - the studies closest to ours - suggested a non-linear effect between AI and environmental development, as Lee and Yan (2024) and Zhao et al. (2024). These authors showed that the density of robots (as a proxy of AI) and the share of clean energy consumption in total energy consumption display a U-shaped relationship based on data covering Chinese provinces from 2016 to 2019.

Drawing on this literature, the main thesis of this paper is that AI will play a transformative role in creating sustainable and greener economic development. While AI has in the combined increased energy consumption worldwide, it will also reduce the environmental footprint of economic growth and will speed up renewable energies' adoption. For that purpose, we will test the empirical relationship between AI and energy consumption, AI and energy productivity, AI and CO2 emissions, and AI and the share of renewable energies. We will check where there are potential non-linear relationships, as AI adoption might initially have negative environmental effects, more than compensated when it reaches widespread adoption across the economy (particularly in the energy sector and energy-intensive ones like agriculture, tech, finance and mobility). This opens a key global policy area since certain levels of AI spending might not be affordable to or even available in low- and middle-income economies.

In sum, we contribute to the literature by first testing the complete set of AI effects on energy, sustainability and development as proposed by the economic and policy literature: energy requirements, energy productivity, emissions and renewable energy adoption. Second, we believe the AI market (measured as the acquisition of software and applications, hardware and business services to provide AI capabilities) is the most appropriate indicator to measure AI usage intensity compared to others used in the research literature (who rely on quantitative indicators such as the number of AI projects, AI publications, number of IP applications, or the number of industrial robots, number of AI companies). Third, our sample covers most AI-leading countries starting in 2019 through 2023, allowing to contrast the non-linearity – as suggested due to scaling, trade openness, or industrial structure in the literature - in all these relationships from certain income and AI investment levels.

3. Dataset and descriptive analysis

We built a panel for 23 countries covering the period 2019–2023 of data on the AI market. The countries included in the panel represent 78 percent of the global GDP in 2024 according to the data reported by the International Monetary Fund (IMF), and practically all main AI users and producers worldwide (Table 1).

We define five dependent variables. First, we focus on energy required by end users (*energy consumption* hereafter) considering the total MW/h by country per year, measured by the quantity supplied from either local or foreign production.[6] Next, we include energy productivity, measured as the ratio GDP/Energy supplied (i.e. $ of output per MW/h). Third, we also consider dependent variables linked to emissions. For this purpose, we calculated the GDP/CO2 ratio (production per carbon dioxide emissions, measured as billion dollars per Mt) per country, and on overall emissions *per capita* (Mt of carbon dioxide emissions per person). Finally, we introduced the share of the total energy that is sourced from renewable sources (hydro, geothermal, solar, wind, or biofuels). Energy variables come from the IEA dataset, emissions from the World Bank (WB) dataset, and GDP from the IMF (Table 2).

AI is defined as spending per person in AI, and it covers generative and non-generative AI comprising different technology groups, such as hardware (IaaS, server, and storage), AI applications, AI application development and deployment, AI platforms, and AI system infrastructures. Data on AI demand was compiled and validated from various sources including IDC, Gartner and Statista. Two important caveats are in order regarding our AI market definition. First, it basically captures AI use (that can potentially improve environmental outcomes), but not fully training, which is energy and capital intensive and is less transparent. Second, it may not be properly capturing the whole environmental impact associated with its use if the data centers are located in other countries. In this case, a part of the AI carbon footprint can be hidden from these statistics, outsourced to other countries and thus being complex to properly account for it. Both points may make our AI variable to underestimate the environmental impact associated with AI, thus being necessary to analyze the results with due caution. [7] We

[5] *Total energy supply* (TES) includes all the energy produced in or imported to a country, excluding the amount exported or stored. It represents all the energy required to supply end users in the country. Some of these energy sources are used directly while most are transformed into fuels or electricity for final consumption.

[6] Only covering hardware, Schneider et al. (2025) show how challenging measuring AI emissions is. AI hardware generates greenhouse gas emissions through several key channels over its life cycle. First, there are significant embodied emissions stemming from the extraction of raw materials, manufacturing of chips and memory, the assembly of servers, and transport to data centers. Second, operational emissions arise from the electricity consumed during model development, training, serving (inference), and the overheads of powering and cooling machines in data centers. The choice of energy source and procurement of carbon-free electricity can impact these operational emissions. Additionally, though smaller, emissions also stem from constructing the data centers and from recycling. Of these, operational electricity use is typically the largest channel, accounting for 70–90 % of lifetime emissions, while manufacturing generally represents less than 25 %.

Similarly, focusing on services using AI, Berthelot et al. (2024) propose a methodology to assess the full environmental impact of cloud-hosted digital services by distributing both embodied and operational footprints of hosting infrastructure across multiple heterogeneous services based on resource usage. It incorporates data from a real-world case study with Picasoft, analyzing diverse services' impacts in categories like carbon emissions, resource depletion, and energy use, while also considering network and user terminal footprints. The study highlights again challenges in allocation and measurement.

Table 1
Countries covered.

Argentina	Germany	Peru
Australia	Hong Kong[a]	Singapore
Brazil	India	South Africa
Canada	Israel	Spain
Chile	Italy	Turkey
China	Japan	United Kingdom
Colombia	Korea	United States
France	Mexico	

[a] We treat Hong Kong separately from People's Republic of China as it is usually considered a different entity in most statistical sources.

considered other alternative AI measurement variables. AI patenting was discarded as it may not necessarily be a good measure of usage intensity, as it focuses only on firms that produce AI-related innovations, not on the ones that use them. Second, AI penetration values (either among the entire population or by businesses) would surely capture the use level, but data was not available for all the period nor the all the countries included in the dataset. Also, correlation tests show a strong link between both penetration measures and our choice of AI market per capita.[8]

As for control variables, we include, as is usual in empirical literature, different indicators that can potentially explain energy and environmental patterns. First, we consider government spending (as a share of the GDP) as the public sector can potentially play a crucial role through actions of public interest involving significant energy consumption, such as buildings, transport, and public lighting (De Moraes e Soares et al., 2024). In addition, increased public sector investment in energy transition may yield positive environmental outcomes. Second, we include openness (measured in terms of trade by GDP). As argued by Osei-Assibey Bonsu and Wang (2022), a link exists between openness and energy use, as international trade can be associated with increased economic activity, or eventually to potential variations in the composition of the national output. Third, we consider the weight of the manufacturing sector in the economy, as the sectoral structure is an important driver in this field in past research (Atalla and Bean, 2017; Sineviciene et al., 2017; Chang and Hu, 2010). Industrial activity can be associated with larger energy requirements than most service sectors. Education is also considered, as improved educational levels may change the energy consumption habits of people (Mahmood, 2020). Finally, we also include GDP per capita as a measure of development and standard of living, as several authors identified it as relevant to explain energy efficiency metrics (Atalla and Bean, 2017; Sineviciene et al., 2017; Song and Zheng, 2012; Jimenez and Mercado, 2014; Chang and Hu, 2010). All these control variables come from WB databases.[9]

Preliminary evidence, based on the hypotheses described in Section 2, suggests a global increase in energy requirements due to the growth in AI spending. Additionally, a non-linearity pattern seems to emerge in the relationship between AI spending and energy requirements per capita, energy productivity and CO2 emissions, and to a lesser extent, the share of renewable energy. In all of these cases, the visual evidence points to an initial negative effect from AI spending on the environment, which beyond a certain level of AI spending per capita turns out to be a positive one, reducing emissions (Fig. 2).

4. Results and policy implications

This section reports on the econometric results on the relationship between the AI market and energy and environmental performance for the sample of 23 countries, from 2019 to 2023. All estimates incorporate country and year fixed effects.[10]

4.1. AI and energy requirements

The first issue we address is whether AI increases energy consumption, or, conversely, if it is able to reduce it by stimulating efficiency gains. Initially, we present estimates that include the AI market regressor in levels and then introduce it in both levels and squares to account for potential non-linearities (Table 3).

The positive link between the AI market and energy supply per capita is clear. This result is verified when using Ordinary Least Squares (OLS) in column (i) and also in column (ii) using Instrumental Variables (IV) to account for potential endogeneity in the link between AI and energy supplied.[11] This evidence is consistent with results reported in the case of energy productivity in columns (iii) and (iv). As energy consumption increases, the output per energy decreases.

Given non-linearities are a possibility, we replicate the estimations for both energy outcomes introducing AI in both levels and squares, in order to check potential non-linearities (columns (v) and (vi) in Table 3),[12].[13] Overall, we do not find evidence of non-linearities in the relationship between the AI market, Energy pc and GDP/Energy, as the squared AI regressor is never significant. As for the remaining controls, the sectoral structure of the economy is relevant, as the larger manufacturing sector becomes, the more energy intensive the overall economy is. The opposite effects seem to arise from GDP per capita, from where we can conclude that its increase is related to less energy requirements and its more efficient use.

In sum, we conclude that AI has effectively generated an increase in energy requirements, verified both in per capita terms and in terms of output.

4.2. AI and CO2 emissions

Next, we estimate the drivers of emissions measured as the ratios GDP/CO2 and CO2 per capita.[14] The main hypothesis is that AI can contribute to reducing emissions and/or increasing the output per emission. Results for both OLS and IV methodologies are presented in Table 4.

Our results confirm, in line with the previous findings of AI driving

[7] This correlation analysis but is available for all the readers upon request to the authors. We thank an anonymous referee for highlighting this point.

[8] We considered including further variables as controls, such as the degree of urbanization, geographic conditions, or local endowments of natural resources and energy sources. However, these indicators show limited variance over time, especially given the short period of our panel, so their effects are likely to be absorbed by the country-level fixed effects.

[9] Country fixed effects reflect unobservable aspects related to cultural, idiosyncratic, or institutional reasons, if they are invariant over time. The addition of fixed effects per year, on the other hand, allows us to contemplate exogenous technological growth, as well as absorb any cyclical shocks that affect all economies. All estimates include robust standard errors.

[10] In the IV estimation, we use as instruments for AI spending the number of academic publications per capita on AI related topics by local universities with a temporal lag (published papers for periods 2000–2004 and 2005–2009). These instruments come from the *OECD AI Policy Observatory*. The tests conducted for the IV verify the suitability of the instruments, as under identification is rejected, the instruments are not weak, and the Hansen test of overidentification does not reject the null hypothesis of exogeneity. The significance of the endogeneity C-test indicator rejecting the null hypothesis provides support to the need of making this estimation through IV.

[11] See the seminal paper of Aghion et al. (2005) that addressed the non-linear link between competition and innovation.

[12] These estimations had to be conducted only through OLS with fixed effects, due to the unavailability of a sound instrument for the squared AI regressor. Note however that all previous IV estimations supported previous OLS findings.

[13] In this last case, the dependent variable is introduced in logs, due to better fit models.

Table 2
Variables definitions.

Group	Variable	Description	Mean	Std. Dev.	Source
Dependent variables	Energy pc	Total energy supply per capita (in MW/h).	34.119	22.635	IEA
	GDP/Energy	Production per unit of energy (dollars per MW/h)	900.867	616.525	IEA/IMF
	GDP/CO2	Production per carbon dioxide emissions (billion dollars per Mt)	4.771	2.706	IMF/WB
	LCO2 pc	Logarithm of carbon dioxide emissions per capita (Mt)	−12.109	0.650	WB
	Renewable share	Energy generated from hydro, geothermal, solar, wind, or biofuels (as % of total energy consumed)	15.023	10.584	IEA
Independent variable: AI	AI market per capita	AI market per inhabitant (in dollars)	52.850	89.234	Multiple sources
Control variables	Government spending	General government final consumption (% of GDP)	17.306	4.014	WB
	Openness	Trade (% of GDP)	80.671	84.684	WB
	Industry	Manufacturing, value added (% of GDP)	13.984	6.208	WB
	Education	Gross enrolment ratio, tertiary (%)	74.602	24.188	WB
	GDPpc	GDP per capita (in dollars)	31490.74	22639.88	IMF

Source: Authors

an increase in energy consumption, that AI also reduces the output per emission (column (i)) and increases overall CO2 per capita (column (iii)). These results are further verified when conducting the estimations through instrumental variable by controlling for endogeneity (using the same instruments as before for AI market per capita), in columns (ii) and (iv).[15]

However, the link between AI and the emissions-related variables may be non-linear. For that purpose, in columns (v) and (vi) we re-estimate the models for output per emission and CO2 per capita introducing the AI regressor both in levels and squares. Results are now clear in pointing out that the link between AI and emission-related outcomes is non-linear, as in both cases the AI regressor is significant both in levels and in squares. Moreover, we find that in the initial adoption phase AI results in negative environmental effects, but once a certain threshold in AI usage is reached, the effect turns positive. This is evident from the positive coefficient associated with the squared AI regressor in the GDP/CO2 estimation (for high values of AI spending, the technology drives an increase in output per emissions), as well as due to the negative squared coefficient in the CO2 estimate, meaning that for high values of AI spending, there is a reduction in emissions.

As for the control variables, again it is verified that higher GDP er capita is associated with lower emissions per person, or higher output per emission. There is also some evidence on the relevance of government spending, trade openness and human capital for improving the environmental outcomes related to emissions.

We then explore further these quantitative results to estimate the thresholds where AI market per capita has these positive environmental effects worldwide. For that goal, we use the coefficients estimated in Table 4 (including the constant term), to get the respective functions linking emission outcomes with AI[16]:

$$GDP / CO2 = 6.4741 - 0.03397^{*}(AI\,pc) + 0.00003^{*}(AI\,pc)^{2}$$

$$CO2\,pc = e^{\left[-12.37230+0.00437^{*}(AI\,pc)-0.00001^{*}(AI\,pc)^{2}\right]}$$

where the CO2 pc has a different functional form as it has been unlogged by applying the exponential function (see Fig. 3, for different AI pc levels). In the case of the output per emissions, the AI spending threshold after the technology starts yielding positive environmental outcomes is close to US$ 570 per capita. This is a quite high AI spending level, as currently only Singapore is close to it. As for the CO2 per capita estimation, the threshold is lower; AI spending per capita from US$ 220 contributes to reduce emissions. To date, only the United States and Singapore exhibit these spending figures. Overall, AI does not contribute to reducing CO2 emissions initially, but it does so beyond certain high thresholds of AI spending.

A potential explanation of this pattern could exist in the AI spending pattern. At lower levels of development, most spending of AI is dedicated to LLM training and foundational model development 2. Over time, as spending increases, two effects might be at work: AI is adopted in processes that result in growing energy efficiency, and AI use becomes less energy intensive since the increase in spending reflects a shifting mix from development to usage. Unfortunately, data is not available so far to test these different hypotheses.[17]

4.3. AI and renewable energies

We finally test whether AI accelerates energy transition toward renewable sources. Results are presented in Table 5 for both OLS and IV approaches. The estimations that introduce the AI regressors in levels indicate a negative coefficient associated with the spending in this technology. This effect is verified through both OLS and IV regressions presented in columns (i) and (ii), respectively (although the non-significant result for the endogeneity test suggests no need to use the IV approach in this case).

When testing non-linearities, both coefficients for AI in levels and squares are statistically significant, and their signs suggest that initially AI reduces the share of renewables, but after a certain threshold the effect is reversed and turns positive (column (iii)). A possibility may be related to AI-driven efficiency gains in fossil-heavy grids, while its implementation is more costly and complex in the renewable energy sector (as shown by Zhao et al. (2024) for China). Alternatively, it may be that AI optimization does not necessarily prioritize renewable energy expansion unless explicitly guided by policy incentives. Again, data does not allow us to disentangle these hypotheses.[18]

Finally, GDP per capita is a relevant control, being in all cases significant to explain larger share of renewable energy. To a lesser extent, some evidence arises regarding the role of government spending and education.

[14] While the instruments again behave as expected, in this case there is less clarity on the need to treat AI as endogenous, as the C-test only rejects the null hypothesis of exogeneity in the estimation of GDP/CO2.

[15] Building an equation using the coefficients estimated requires assigning a certain value to the control variables that also form part of that equation. We use the sample averages in the values of the controls.

[16] See Budaragina et al. (2024) for a view on the potential variance that exists between the so-called Global North/South.

[17] Additionally, we conducted estimates for non-renewable energy sources. The results indicate that AI spending conducts to higher share of non-renewables in general, and of coal in particular. In the estimation the same $ 580 dollars threshold of AI demand is the point from where the share of non-renewable energy starts to diminish. These results are available upon request.

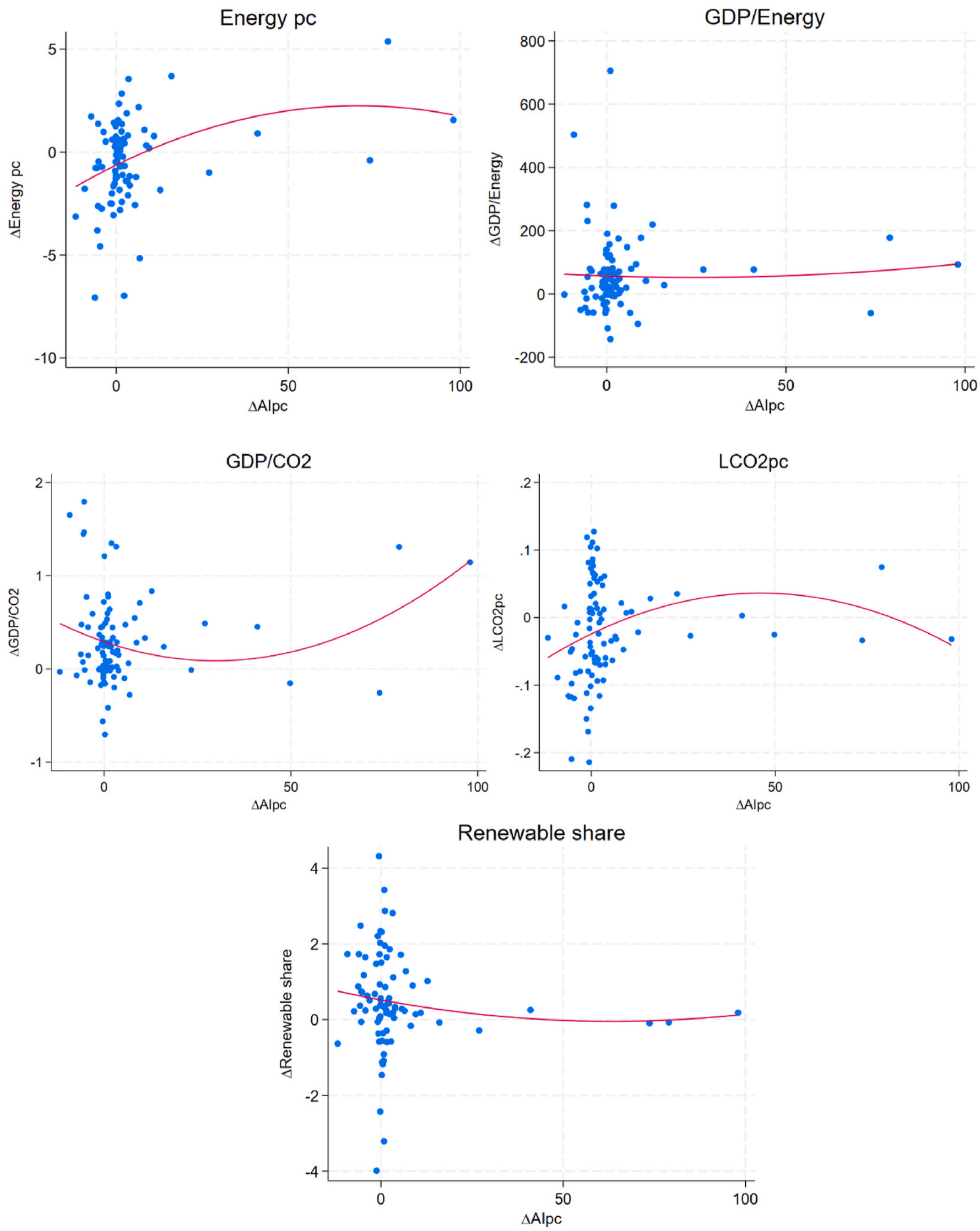

Fig. 2. Per capita AI spending (USD) **and key energy and environmental indicators**.
Source: Authors based on data from Statista, Gartner, IDC, IEA, WB and IMF

Taking the coefficients estimated in Table 5, and substituting for the sample average values of the variables, we obtain the respective functions linking renewable share with AI:

$$Renewable\ share = 18.621 - 0.05775 * (AI\ pc) + 0.00005 * (AI\ pc)^2$$

The estimated function is plotted in Fig. 4, for different AI market per capita levels. The share of renewable energy falls for initial AI spending levels and starts yielding a positive outcome from US$ 580 per population (in line with GDP/CO2 results). As mentioned before, only Singapore was close to this level in 2023.

4.4. Policy implications

Overall, these results highlight the need for strategic vision and solid institutions to drive AI with a view of its energy implications, both at the global and the national level. Indeed, at the global level there is technically some degree of governance, notably led by UN bodies, G20 and the OECD. However, it seems fragmented and divided, with a limited role for low- and middle-income countries. This occurs despite the fact that most natural resources – from rare earths, critical minerals and water – needed for batteries, semiconductors and data centers functioning are located in low- and middle-income countries.[19]

[18] See Sirimanne and Fu (2025) for a focus on financial incentives to drive AI towards improving education, health and environmental sustainability, and Mazzucato and Ramos (2022) focus on its governance (regulation, institutions and skills).

Table 3
AI market as driver of energy consumption and energy productivity.

Dep. variable:	(i) Energy pc	(ii) Energy pc	(iii) GDP/Energy	(iv) GDP/Energy	(v) Energy pc	(vi) GDP/Energy
AI market pc	0.04542***	0.09461***	−2.75782**	−4.53012***	0.08719*	−5.99490
	[0.01025]	[0.02724]	[1.01138]	[1.57681]	[0.04855]	[5.00957]
AI market pc squared					0.00417	−0.00005
					[0.00006]	[0.00530]
Gov. Spending	−0.40241	−0.33222	5.74815	3.51524	−0.45793*	10.05124
	[0.27000]	[0.23629]	[15.36017]	[18.40531]	[0.25700]	[14.39154]
Openness	−0.03428	−0.11425*	0.38094	3.18048	−0.05449	1.94719
	[0.05907]	[0.05875]	[3.27556]	[3.32461]	[0.05705]	[3.72558]
Industry	0.35765	0.51683**	−36.16131*	−41.90103**	0.34507	−35.18644*
	[0.28263]	[0.25738]	[19.96805]	[19.44716]	[0.28689]	[19.75336]
education	0.06531	0.04012	18.55466	19.78314***	0.06189	18.81979
	[0.09751]	[0.06469]	[11.08666]	[6.86961]	[0.09372]	[11.01367]
GDP pc	−0.00013	−0.00046***	0.03219***	0.04366***	−0.00015	0.03381***
	[0.00010]	[0.00014]	[0.00853]	[0.00861]	[0.00010]	[0.01034]
Under-id test		7.490**		7.490**		
Weak-id test		12.731$^{(\gamma)}$		12.731$^{(\gamma)}$		
Over-id test		0.148		0.299		
Endogeneity test		7.479***		3.700*		
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	97	91	97	91	97	97
R-squared	0.5170	0.4511	0.7376	0.7126	0.5236	0.7436
Method	OLS	IV-LIML	OLS	IV-LIML	OLS	OLS

Note: ***p < 1, **p<5 %, *p<10 %. Robust standard errors in brackets. $^{(\gamma)}$ Stock-Yogo weak ID test critical values: 10 % maximal LIML size 8.68.
Source: Authors

Table 4
AI spending as driver of emissions and output per emission.

Dep. variable:	(i) GDP/CO2	(ii) GDP/CO2	(iii) LCO2 pc	(iv) LCO2 pc	(v) GDP/CO2	(vi) LCO2 pc
AI market pc	−0.00564**	−0.01493**	0.00046**	0.00163*	−0.03397**	0.00437***
	[0.00223]	[0.00750]	[0.00019]	[0.00089]	[0.01376]	[0.00090]
AI market pc squared					0.00003**	−0.00001***
					[0.00002]	[0.00000]
Gov. Spending	0.03424	0.00609	−0.02743***	−0.02473***	0.07634	−0.03323***
	[0.04971]	[0.06736]	[0.00779]	[0.00919]	[0.04636]	[0.00797]
Openness	0.00197	0.00228	−0.00414*	−0.00407*	0.02014*	−0.00665***
	[0.00725]	[0.01676]	[0.00208]	[0.00244]	[0.01095]	[0.00168]
Industry	−0.04526	−0.12642	0.00287	0.01389	−0.0333	0.00122
	[0.06045]	[0.09684]	[0.01133]	[0.01371]	[0.05741]	[0.01057]
Education	0.03178	0.03932**	0.00167	0.00093	0.03661*	0.00101
	[0.02413]	[0.01798]	[0.00293]	[0.00226]	[0.01852]	[0.00242]
GDP pc	0.00014***	0.00020***	−0.00001**	−0.00002**	0.00017***	−0.00001***
	[0.00003]	[0.00004]	[0.00000]	[0.00001]	[0.00003]	[0.00000]
Under-id test		5.379*		5.379*		
Weak-id test		6.330$^{(\gamma)}$		6.330$^{(\gamma)}$		
Over-id test		0.048		0.074		
Endogeneity test		5.227**		2.626		
Country FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	103	97	103	97	103	103
R-squared	0.8116	0.7174	0.4932	0.3613	0.8352	0.5384
Method	OLS	IV-LIML	OLS	IV-LIML	OLS	OLS

Note: ***p < 1, **p<5 %, *p<10 %. Robust standard errors in brackets. $^{(\gamma)}$ Stock-Yogo weak ID test critical values: 10 % maximal LIML size 8.68.
Source: Authors'

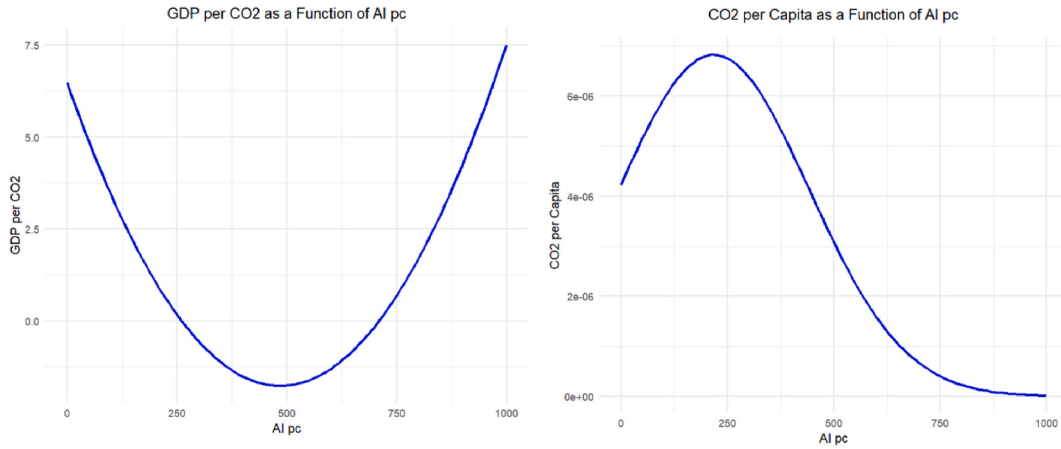

Fig. 3. Estimated relationship between AI spending and CO2 emissions.
Source: Authors' own elaboration

Table 5
AI spending as driver of energy transition towards renewable energies.

Dep. variable:	(i) Renewable share	(ii) Renewable share	(iii) Renewable share
AI market pc	−0.02131***	−0.02621*	−0.05775**
	[0.00586]	[0.01543]	[0.02323]
AI market pc squared			0.00005*
			[0.00003]
Gov. Spending	0.38328	0.38031*	0.43173*
	[0.22552]	[0.21247]	[0.21099]
Openness	0.04060	0.04089	0.05824
	[0.05080]	[0.05834]	[0.04952]
Industry	−0.04545	−0.09888	−0.03447
	[0.17227]	[0.19360]	[0.17553]
Education	0.09371	0.09812**	0.0967
	[0.06050]	[0.04085]	[0.05805]
GDP pc	0.00019***	0.00022*	0.00020***
	[0.00007]	[0.00012]	[0.00007]
Under-id test		7.490**	
Weak-id test		12.731$^{(\gamma)}$	
Over-id test		0.133	
Endogeneity test		0.364	
Country FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	97	91	97
R-squared	0.5659	0.5654	0.5750
Method	OLS	IV-LIML	OLS

Note: ***p < 1, **p<5 %, *p<10 %. Robust standard errors in brackets. $^{(\gamma)}$ Stock-Yogo weak ID test critical values: 10 % maximal LIML size 8.68.
Source: Authors' own elaboration

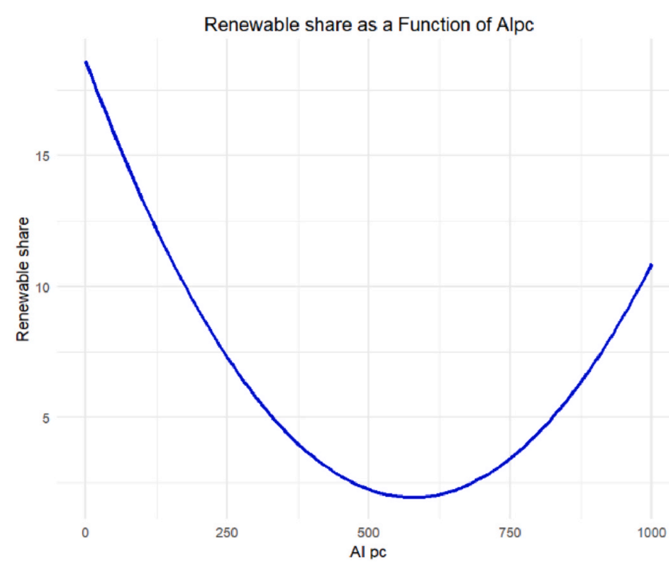

Fig. 4. Estimated relationship between AI spending and renewable energies.
Source: Authors' own elaboration

The AI and energy agenda also requires national strategies, adapted to technological maturity and fiscal space. Using our AI market thresholds, a policy sequencing framework could start at early phases (e.g. <US$100 per capita of AI spending) focusing on establishing basic AI governance for energy-intensive sectors, launching low-emissions regulatory pilots, and supporting foundational R&D for local energy-AI startups. In a mid-phase (US$100 – $US300 per capita of AI spending) governments should accelerate domestic deployment of AI for energy system planning, foster sectoral innovation hubs, and embed green AI standards into public procurement frameworks. In an advanced-phase (>US$ 300 per capita of AI spending) countries could position national AI ecosystems as global leaders by scaling AI-driven clean energy innovation, exporting sustainable AI technologies, and embedding AI into long-term climate and industrial strategies.[20] In all stages, energy-rich countries could attract AI investment – i.e. smart data and computing centers run on renewable energies -, within productive development policies (Lebdioui et al., 2025).

From an institutional standpoint, the enactment of national strategies addressing AI development while considering their energy implications raises the need for policy coherence. Notwithstanding the connectivity between the technology development strategy and its energy implications, it is common to observe governments implementing policies from agencies acting in an uncoordinated manner. It is critical that, in the same way as implementation of the sustainable development goals, governments need to coordinate AI development national strategies with energy sustainability objectives (Renda, 2021). At the sub-national level, the consideration of AI development strategies in light of their energy implications might require addressing spatial requirements. Startups focused on the implementation of AI in enterprises are generally located in urban areas although they rely on computing power resident in data centers that could be located in areas where energy is

[19] We owe and thank Riad Meddeb, Director of the Sustainable Energy Hub at UNDP, for suggesting this point.

less expensive. Interestingly enough, the *Eastern Data, Western Computing* project implemented in China is focused on optimizing the use of computing power by providing businesses located in the east of the country with processing capacity located in the western geographies, where factors of production, such as energy, are less expensive (Zhang et al., 2024).

On the financial incentives front, achieving environmental benefits from AI is heavily dependent on quite high investments as shown by our estimates, posing major inclusivity and equity challenges. This requires urgent action in the policy and finance environments if we are to accelerate towards an optimistic scenario. Conditioning public AI R&D support (e.g., tax incentives, procurement contracts, cloud service subsidies) on energy performance and emissions disclosure standards and establishing public-private co-financing instruments targeting AI for energy access and distributed renewables. As an example, *digital development bonds*, an innovative financial instrument designed to fund digital infrastructure and technology projects, modeled after green and social bonds, could channel capital into green AI infrastructures and applications (Balmaseda et al., 2025).

Finally, transparency and standardization of measuring and reporting AI energy use should be enhanced, to help shifting capital markets toward prioritizing low-emission, inclusive AI ecosystems. This could be done using mandatory carbon disclosures for AI development and data centers, or more market friendly instruments as enriched ESG frameworks and voluntary disclosures (e.g. AI score launched by Salesforce, Hugging Face, Cohere, and Carnegie Mellon University; or the individual initiative by the Mistral with Carbone 4 and the French ecological transition agency ADEME).

In short, to effectively harness AI for sustainable development, industrial policy must play a leading role in strengthening global AI and energy governance to coordinate climate strategies. Governments could mandate transparent AI energy use and carbon reporting standards, ensuring consistent and reliable data to inform decision-making.[21] Public support for AI R&D must be conditioned on meeting robust energy performance and emissions criteria, driving innovation toward greener technologies. Enhancing ESG frameworks and encouraging voluntary disclosure can further promote the emergence of low-emission AI ecosystems across industries. Finally, innovative financing mechanisms such as *digital development bonds* and targeted co-financing should be prioritized to mobilize investment in green AI solutions, especially within low- and middle-income countries, ensuring inclusive and scalable progress.[22]

5. Conclusions and further research

AI global boom is currently putting pressure on the environment worldwide, given its intensive use of natural resources, minerals, water and energy. The pace and depth of this impact has made the relationship between AI and the *green agenda* one of the economic, social and political key global topics.

By focusing on energy and environmental goals, AI can favor renewable energy transition and reduce emissions. While so far AI demand is significantly driving energy requirements and the CO2 footprint of countries and companies, this trend could shift over time and depicting significant variance across countries.

This paper presented novel empirical evidence on AI and its relationship with environmental indicators, based on an original database covering 23 AI-using and AI-producing countries. Our results confirm AI demand is driving significantly higher energy consumption in all countries. Also, due to this energy consumption, and the non-significant effect on renewable energies at lower spending levels, AI spending initially increases CO2 emissions. However, this does not necessarily imply that AI spending cannot foster the transition to sustainable energy. In fact, our empirical analysis also confirms the existence of certain non-linear relationships.

The positive effect on the environment in terms of emission reduction and higher reliance on renewable energies emerges beyond an AI market threshold; $580 per capita spending for renewable energy share; $570 for output per emissions and $220 in the case of CO2 per capita. This can be understood as a 'green AI' version of the *Kuznets curve* for AI progress, as AI markets first worsen the environmental footprint, and then improve it. Based on these thresholds, some countries would be already benefiting from this technological dividend. In particular, Singapore should be experiencing all positive effects from 2023, while the United States is already reducing emissions due to AI, and could reach the $570-$580 threshold in 2031. Korea would reach the $220 threshold in 2035 and $570-$580 in 2043 following latest trends. By contrast, European countries might have to wait several decades to reach positive continent-wide effects.

These results have quite clear policy implications, calling for a more coordinated global AI and energy governance, for national AI strategies adapted to the level of digital maturity, the need for innovative funding mechanisms (including the aforementioned *digital development bonds*), and enhanced transparency and standards measuring and reporting the use of energy by AI.

Our research faced some limitations stemming mostly from data availability that prevented us from addressing some critical questions. First, our AI measure captures overall usage intensity, but not the specific demand for development and training of AI tools, which are highly energy intensive, nor the diverse types of AI. Second, as a usage proxy, our AI variable may still not be fully capturing the environmental effect since the data centers used in the process may be located abroad. Third, due to data aggregation we could not break down AI by application (e.g., energy, industry, agriculture, digital services). Finally, our panel extends through 2023 (again due to data availability not only in AI demand but also on energy consumption), which means we could not fully address the latest wave of technological development, especially in terms of generative AI. Actually, after a brief slowdown, corporate investment in AI has rebounded, and newly funded generative AI startups nearly tripled in 2024 (Stanford Institute for Human-Centered AI, 2025). In this race, some leading AI companies announced the adoption of nuclear energy in US plants (pending regulatory approval and other technological issues) as a clean, sustainable power source for their data centers. Also, many countries have launched billion-dollar national AI infrastructure initiatives, including major efforts to expand energy capacity to support AI development.

As for potential research extension, we would like to expand the sample as soon as more data becomes available. This would make it possible to study longer-term dynamics as well as conduct regressions by

[20] In a similar line, see the recently published ITU (2025), stemming from the *Green Digital Action initiative*. This report examines the environmental footprint of AI systems across their lifecycle stages—training, inference, and supply chain—highlighting significant gaps and inconsistencies in current measurement practices. It reveals an over-reliance on estimates rather than real-time data, inconsistent lifecycle boundaries, underreported Scope 3 emissions, and a narrow focus on carbon overlooking water use, e-waste, and resource depletion. ITU advocates for standardized metrics, enhanced transparency, and comprehensive lifecycle assessments to drive accountability and sustainability. It further recommends developing real-time telemetry tools, improving hardware efficiency, and modeling user behavior to better understand and minimize AI's environmental impacts, urging collaborative action among developers, consumers, and regulators to embed sustainability into every stage of AI development and deployment.

[21] UNFCCC and UNIDO (2025) released targeted recommendations for middle-income countries to effectively leverage AI for climate action. The recommendations emphasize building robust digital infrastructure and local capacity, improving access to high-quality climate and environmental data, and establishing clear governance frameworks to ensure ethical, transparent, and inclusive AI deployment. Prioritizing open-source AI solutions, supporting inclusive stakeholder participation, and developing robust monitoring and evaluation mechanisms are highlighted as key actions to maximize AI's climate benefits and manage its risks in middle-income contexts.

country-groups according to certain characteristics, in order to analyze heterogeneous effects.[23] Second, we would like to include a specific analysis on nuclear energy, if recent announcements materialize. Third, water consumption – needed both for semiconductors and batteries production and datacenters is an additional environmental impact dimension. Fourth, as energy has assumed strategic geopolitical implications, the empirical analysis could include security, covering both the reliability of the service and its privacy and cybersecurity dimensions given its speed digitization. Fifth, beyond decarbonization AI also supports inclusive development. Therefore, we could address the impact of AI on electricity coverage, on energy transmission and distribution losses (to proxy for grid efficiency and investment gaps), and on urban–rural access gaps. Sixth, it would be desirable to study the role of energy policies, trying to find out how having an active green agenda can accelerate energy transition or to reduce the thresholds required for AI to yield positive environmental outcomes. Finally, it would be interesting to work on a cost-benefit analysis to compare the cost per ton of emissions avoided through AI with the direct investment in renewables or energy infrastructure that may yield a similar effect.

CRediT authorship contribution statement

Angel Melguizo: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Raúl Katz:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Formal analysis. **Juan Jung:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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