Original Research Article

A Cross-Country Analysis on Artificial Intelligence Diffusion, Energy Intensity, and Income

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ABSTRACT

This study sought to examine how national diffusion of artificial intelligence measured by the share of artificial intelligence job postings is related to energy intensity and income. The hypothesis in this study was that the greater the diffusion of artificial intelligence is, the lower energy intensity is, reflecting efficiency gains, and higher income, reflecting productivity gains. Using two publicly available datasets, this study, this study merged country-year records, analyzing the most recent year with broad coverage in cross-sectional design. Outcomes identified energy use per unit of economic output and income per person by applying artificial job posting share as a single explanatory variable. Models were estimated with bivariate ordinary lease squares for the purpose of replication. Results indicated that there was a positive but statistically inconclusive association between the diffusion of artificial intelligence and primary-energy intensity. In addition, when focusing on electricity intensity, there was a small and statistically null association, while there was a positive and precise association between the diffusion of artificial intelligence and income as confirmed by three light robustness checks, including a logarithmic specification and a leave-one-out influence analysis. The findings in this study were not casual but descriptive. Future work is recommended to focus on extending to a short panel with fixed effects, emphasizing outcomes specific to electricity and carbon to add readily available controls and examine heterogeneity by region or income group.

Keywords: Artificial intelligence diffusion; Energy intensity; Electricity intensity; GDP per capita; AI job postings; Cross-sectional analysis; Ordinary lease squares

INTRODUCTION

Artificial intelligence has been rapidly expanding across many sectors. With focus on economies, energy system and macroeconomic performance may witness great implications from the use of artificial intelligence. To be more specific, electricity demand has been on the rise from data centers as reported by energy agencies in an attempt to optimize artificial intelligence training and inference. This has left a question about how the diffusion of artificial intelligence may contribute to national energy intensity and prosperity. According to the Energy & AI Analysis Projects by the International Energy Agency (IEA), it is anticipated for the artificial intelligence electricity consumption from global data centers to roughly double by 2030 to around 945 TWh, estimating to the growth of around 15% per year and reaching to about 3% of global electricity by 2030 (1). In addition, IEA also reported that artificial intelligence

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workloads were expected to increase in the same magnitude with energy consumption with AI (2). In the United States, it was expected by the U.S. Energy Information Administration (EIA) that computing loads would become the most dominant end use in commercial buildings with an estimate of 8% of the entire commercial electricity consumption by 2024 and 20% by 2050 (3).

As many researchers argued how the electricity in data centers would have been kept near 1% of global consumption even with skyrocketed computation work thanks to improvements in hardware, cooling, and server utilization, these projections sound striking. According to a widely cited science analysis, the amount of electricity used in global data centers increased only around 6% between 2010 and 2018, constituting about 1% of global use, because of gains in efficiency (4). In addition, IEA also suggested that around 1 to 3% of global final electricity demand was from a combination of data centers and data transmission networks in 2022 with continued progress in efficiency in network (5). However, according to the most recent Energy & Artificial Intelligence overview from IEA, the amount of electricity used in data centers reached around 1.5% in 2024 in a faster growing pace in overall demand since 2017 (6).

With this trend of skyrocketing energy demand with artificial intelligence, economic effects of artificial intelligence have been actively documented by economists. According to quasi-experimental studies, worker productivity was known to be improved with an access to generative-AI tools. Furthermore, issue resolution rates improved, while reducing the handling times through a generative-artificial intelligence assistant (7). Furthermore, there was an experiment where participants with access to ChatGPT ended up showing higher quality of work with faster pace (8). According to a task-content assessment with focus on interventions rather than exposure, a large share of occupations in the United States witnessed great improvement in potential from LLM-enabled software (9). Putting all of these together, these results indicate how the use of GDP per capita as an appropriate macroeconomic outcome along with energy indicators would be relevant.

In the micro-level, efficiency has been emphasized through "Green Artificial Intelligence" from early work quantifying the energy and CO_2 implications of NLP models (10). In addition, more works have been done to show how training emissions would be reduced by orders of magnitude through data-center efficiency and hardware accelerators, etc. (11, 12). These results imply that energy growth may not be achieved in proportion to the expansion of artificial intelligence and also that the efficiency of system and the operational choices may influence the impact of it.

At the macro-level, it requires much more to measure the diffusion of artificial intelligence. For example, the share of job postings with artificial intelligence is a widely used public proxy in measuring the diffusion of artificial intelligence, and this has been used by the OECD and research partners to keep track of the artificial intelligence diffusion across countries and also occupations (13, 14). Share of AI Job Postings from Our World in Data (OWID) provides the measure of Lightcast/Artificial Intelligence (15) (Figure 1). Specifically on the energy and macroeconomic side, the OWID Energy Dataset provides a consolidated set of variables for electricity and primary energy with GDP and population in a long panel, regularly updating the data from Energy Institute Statistical Review, Ember Electricity, and Maddison Project GDP (16).

Under these circumstances, whether the diffusion of artificial intelligence estimated by job-posting shares would be related to lower energy intensity and also to higher income still remains a central policy question.

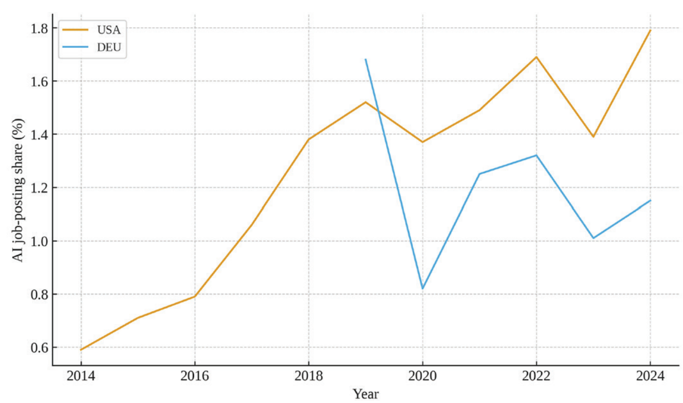

Figure 1. Share of artificial intelligence job posting (%) over time for the United States (USA), Germany (DEU), Japan (JPN), and South Korea (KOR). The line shows the diffusion dynamics in advanced economies, ensuring the appropriateness of the artificial intelligence-share proxy used in the cross-section. According to the upward trajectories, the demand for artificial intelligence skills has been growing, providing the context for the year 2022 snapshot used in the regressions. Data source: Our World in Data (15, 16).

On one hand, artificial intelligence can contribute to optimization, such as predictive maintenance and better industrial controls, that will reduce energy per unit output. On the other hand, there would be a rebound effect that gains with efficiency offset effective costs, ending up increasing total activity through reverse expected savings at the macro level (17).

There has been a growing literature with generative artificial intelligence to productivity improvements on the macroeconomic side (7, 8), most of them support the use of GDP per capita as a macro-level proxy for the aggregate benefits of diffusing artificial intelligence in current economic situations. A possibility of broad impacts of artificial intelligence across occupations has been reinforced by exposure metrics (9). In addition, OECD/Lightcast provided a skill-demand evidence, showing that competencies from artificial intelligence have been widely diffused and consistently measured by job-posting shares across countries (13, 14). Therefore, job-posting shares of artificial intelligence are regarded as valid artificial intelligence diffusion metric instead of a direct measure of artificial capital. However, they are useful for research as they are replicable, transparent, and internationally comparable. OWID's job-posting shares from Lightcast through the Artificial Intelligence Index may be aggregated to annual country values compatible with the OWID Energy Excel File (15). In addition, OWID Energy File contains information about primary energy, electricity consumption and demand, GDP, and population in a single workbook (16).

In spite of growing literature about electricity of artificial intelligence data centers and also productivity in worker-level, there still remains a question about the diffusion of artificial intelligence across countries in connection with energy intensity and GDP per capita only with little macro-level evidence. There was a study projecting the energy consumptions in data centers by employing model-based scenarios with assumptions (18). Furthermore, prior studies examining the productivity only focused on outcomes from firms or workers instead of national aggregates (7, 8).

In response to this literature gap, this study specifically asks how the shared of artificial intelligence job postings are related to energy intensity (primary energy per unit of GDP) and GDP per capita across countries in the most recent year with broad coverage. This study hypothesized that countries with higher shares of artificial intelligence job postings will show lower energy intensity and higher GDP per capita. It was also acknowledged that scale effects may be weakened or reverse the energy-intensity association in some years (17). This study contributes by explicitly connecting the national diffusion of artificial intelligence to both energy and economic performance by using publicly available datasets. Unlike prior studies focusing mostly on separated firm-level productivity or data-oriented demand based on the mode-based projections, this study integrated outcomes in energy and income in a reproducible framework in cross-country analysis. This contribution offered a macro-scale benchmark for dual relationship of artificial intelligence with energy intensity and prosperity.

METHODS AND MATERIALS

Data Sources and Study Design

This study used two publicly available data: Artificial intelligence diffusion proxy as a share of artificial intelligence job posting (%, country-year) from Out World in Data (OWID) derived from Lightcast/AI Index and Energy and Economy Panel (single workbook) as OWID energy dataset with primary energy consumption (TWh), electricity consumption per demand (TWh), GDP, and population by country-year.

To harmonize the files, ISO-3 country code and calendar year were matched, keeping observations with non-missing artificial intelligence share and appropriate energy and economic series. Keeping the workflow accessible while balancing the coverage and recency, the analysis was limited to the latest broad-coverage year, 2022, yielding n = 21 countries after listwise deletion.

Variables

The index *i* was used to indicate a country with the year *t*.

For artificial diffusion ($\text{AIShare}_{i,t}$), the share of job postings mentioned at least one artificial intelligence-related skills was measured in percentage point (pp). The original percent scale was maintained to preserve intuitive interpretation as a one-unit change to be equal to +1 pp.

For primary-energy intensity ($\text{PEI}_{i,t}$), primary energy was transformed from TWh into kWh per \$1,000 of GDP to make magnitudes conveniently interpretable.

$$\text{PEI}_{i,t} = \frac{\text{PrimaryEnergy}_{i,t}(\text{TWh}) \times 10^9 \text{kWh/TWh}}{\text{GDP}_{i,t}} \times 1000 \quad (1)$$

This indicated "kWh of primary energy needed per \$1,000 of output.

Electricity intensity ($EI_{i,t}$) was calculated as follows for robustness.

$$EI_{i,t} = \frac{ElectricityConsumption_{i,t}(TWh) \times 10^9}{GDP_{i,t}} \times 1000 \quad (2)$$

This formula was interpreted as kWh of final electricity per $1,000 of GDP.

For income ($GDPpc_{i,t}$), GDP per capita was calculated as GDP/population, and also formed natural log of it, ln ($GDPpc_{i,t}$) for a log-scaled robustness check to mitigate heteroskedasticity. GDP units in OWID were kept to maintain the internal consistency, while avoiding rebasing across the system.

Modeling Strategy

Two bivariate ordinary least squares (OLS) models were estimated on the 2022 cross-section by using AIShare as the sole predictor. With x_i as $AIShare_{i,2022}$ (pp), energy model (baseline) and economic model (baseline) were generated as follows.

For energy model (baseline), the following equation was used.

$$PEI_i = \alpha + \beta x_i + \varepsilon_i \quad (3)$$

Where β indicates the change in kWh per $1,000 related to a +1-pp increase in the artificial intelligence posting share.

For economic model (baseline), the following equation was used.

$$GDPpc_i = \gamma_0 + \gamma_1 x_i + u_i \quad (4)$$

Where γ_1 indicates the change in GDP per capita (OWID units) per +1-pp artificial intelligence share.

With only one regressor, the slope units and policy meaning are reproducible since, for each regression, the intercept, slope, standard error, and 95% confidence interval were reported by using the t critical value for df = n − 2, R^2, and sample size. Significance thresholds were defined as $p < 0.05$ as strong evidence, while $p < 0.1$ for marginal evidence, and $p \geq 0.01$ as insignificant.

In the data analysis, three light robustness checks were added to examine the sensitivity to reasonable analytic choices. First, PEI was replaced with electricity intensity (EI), while re-estimating $EI_i = \alpha' + \beta'^{x_i} + \varepsilon'_i$. Since artificial intelligence demand was electrical, this showed whether energy results relied on the choice of primary vs. final energy accounting. Second, regression was performed with ln ($GDPpc_i$) on x_i. The slope b was a semi-elasticity, while 100 × b was the percent change in GDP per capita related to a +1-pp artificial intelligence share. Lastly, slopes were re-estimated after removing each country in turn to both baseline models specified above, indicating whether the sign turned out to be the same with the range of slope magnitudes.

All the procedures in the data analysis, such as data merge, OLS fits, and robustness checks, were conducted by using only two publicly available files. By using listwise deletion for missing values, the workflow was kept transparent and reproducible in Excel. In the main analysis, no outlier trimming was applied.

RESULTS

Descriptive Statistics (2022 cross-section)

The merged sample in the year of 2022 had 21 countries with non-missing values for artificial intelligence share and outcomes. Key ranges confirmed enough variation for bivariate fits as follows. Mean, minimum, and maximum values of artificial intelligence share (pp) were 1.239 0.17, and 3.61, respectively. Mean, minimum, and maximum values of primary energy intensity (kWh/$1,000) were 1,147.42, 531.81, and 2,250.91, respectively. In addition, mean, minimum, and maximum values of GDP per capita (OWID units) were 45,695.74, 15,810.51, and 81,737.13, respectively (Table 1).

Baseline Associations

Primary-Energy Intensity vs. Artificial Intelligence Share (Model A)

After fitting $PEI_i = \alpha + \beta x_i + \varepsilon_i$, the slope was calculated to be β = +231.49 kWh per $1,000 per +1-pp artificial intelligence share. Standard error was 135.77, 95% confidence interval was [-52.68, +515.67], and R^2 = 0.133 (n = 21).

The point estimate turned out to be positive, showing how countries with larger artificial intelligence-posting shares had a tendency to indicate higher primary-energy intensity of GDP. However, the 95% confidence interval contained zero, and the associated p-value (around 0.10) did not pass the conventional thresholds. Therefore, the statistical evidence was inconclusive. Substantively, this pattern was compatible with how artificial intelligence-enabled optimization may reduce per-unit energy of output in particular processes, while the scale of expanded digital activity may increase overall requirements of primary-energy. The fitted line and R^2 (y = 860.7 + 231.5x, R^2 = 0.133) exactly matched with aforementioned estimates (Figure 2, Table 2).

Table 1. Descriptive statistics (Year 2022)

Variable	Mean	Standard Deviation	Min	Max	N
AI Share (%)	1.24	0.66	0.17	3.61	21
Energy Intensity (kWh/$1,000)	1147.42	419.98	531.81	2250.91	21
GDP Per Capita (OWID Unit)	45695.74	15792.73	15810.51	81737.13	21

Summary statistics for the analytic sample (n = 21), containing artificial job posting share (%), primary-energy intensity (kWh per $1,000 of GDP), and GDP per capita (OWID units). Means, standard deviations, minima, maxima, and sample sizes were reported in the table. Data source: Our World in Data (15, 16)

Table 2. Sample OLS regressions (Year 2022).

Model	Slope	SE (Slope)	95% CI (Slope)	R^2	N
Energy Intensity (kWh/$1,000)	231.49	135.77	[-52.68, 515.67]	0.133	21
GDP Per Capita – AI Share (%)	17,306	3,781	[9,393, 25,218]	0.524	21

Bivariate OLS results for primary-energy intensity (kWh per $1,000) (A) were reported as regressed on artificial intelligence job-posting share (%), and the ones for GDP per capita (%) (B) were also reported as regressed on artificial intelligence job posting share (%), containing slope, standard error, 95% confidence interval, , and sample size n (n = 21). Data source: Our World in Data (15, 16).

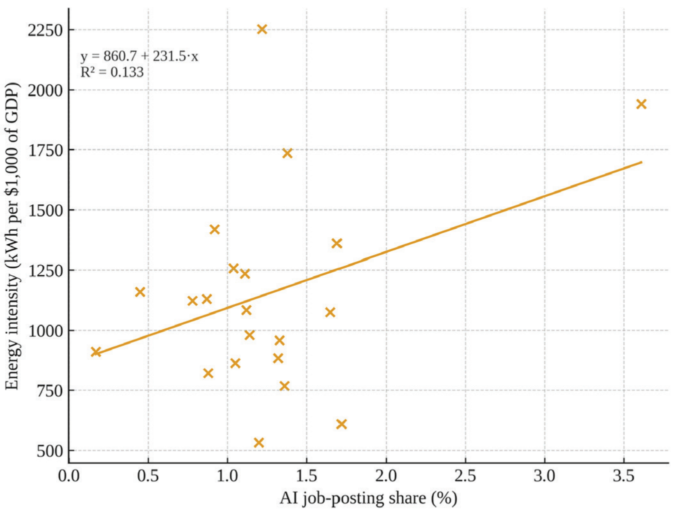

Figure 2. Scatter plot of artificial intelligence job-posting share (%) with primary-energy intensity (kWh per $1,000 of GDP) along with the fitted linear trend and (year 2022; n = 21). The slope of the fitted line was positive as reported in the Model A (Table 2), showing that the higher the artificial intelligence share was, the more it was likely for a country to have higher primary-energy intensity on average. Though the relationship was statistically inconclusive, it was still consistent with the offsetting efficiency at the macro level. Data source: Our World in Data (15, 16).

GDP Per Capita vs. Artificial Intelligence Share (Model B)

After fitting GDP$pc_i = \gamma_0 + \gamma_1 x_i + u_i$, the slope γ_1 was calculated to be +17,305.79 (OWID currency units per person) per +1-pp artificial intelligence share, standard error was 3,780.51, 95% confidence interval was [9,393.10, 25,218.48], and $R^2 = 0.524$ (n = 21).

The income association turned out to be positive, large, and precise that the single predictor explained about 52% of cross-country variation in GDP per capita. This was not a causal estimate. However, it aligned with how early diffusion of artificial intelligence occurred with complementary capabilities, such as digital infrastructure, human capital, and supportive institutions. The fitted line (y = 24,261 + 17,306x, R^2 = 0.524) matched with the tabulated statistics (Figure 3, Table 2).

Robust Checks

Alternative Outcomes for Electricity Intensity

After replacing PEI with electricity intensity, the slope β' was calculated to be -21.49 kWh per $1,000 per +1-pp artificial intelligence share, standard error was 18.41, 95% confidence interval was [-60.03, +17.05], and =0.067 (n = 21). Focusing on final electricity, the association turned out to be slightly negative but small,

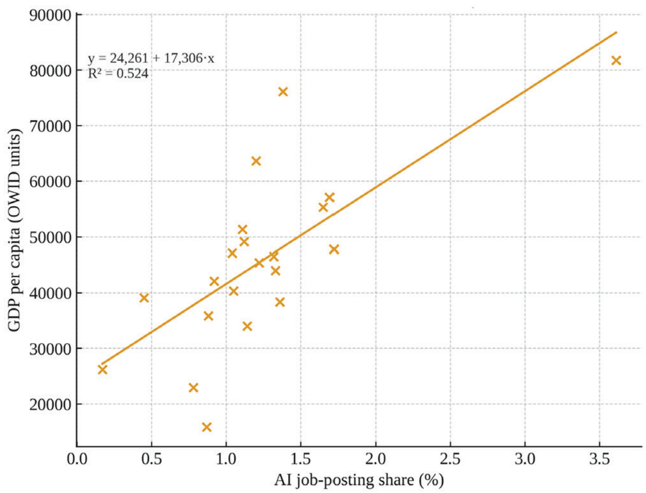

Figure 3. Artificial intelligence job-posting shares vs. GDP per capita, 2022. Scatter plot of artificial intelligence job-posting share (%) with GDP per capita along with fitted linear trend and (year 2022; n = 21). The strong and positive association was visualized as reported in Model B (Table 2). The higher the artificial intelligence-posting share was in a country, the more the country tended to be richer. This pattern was robust, though not causal, and aligned well with the co-movement between the adoption of the artificial intelligence and complementary capabilities, such as digital infrastructure. Data source: Our World in Data (15, 16).

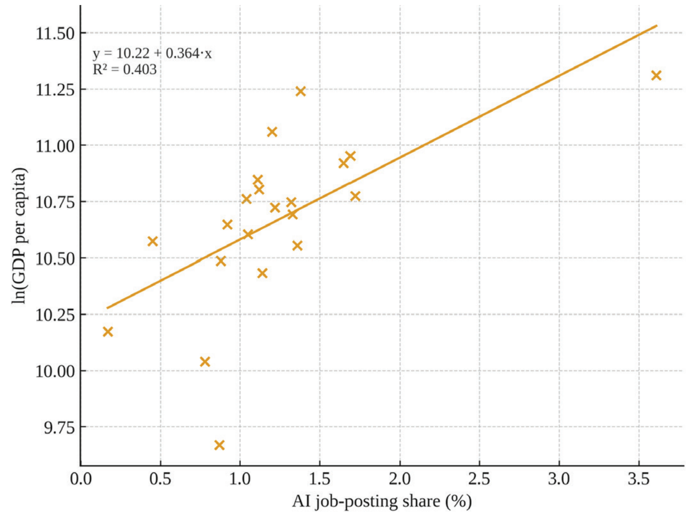

Figure 4. Artificial intelligence job-posting share vs. ln(GDP per capita), 2022. Scatterplot of artificial intelligence job-posting share (%) with the natural log of GDP per capita along with fitted linear trend and (year 2022; n = 21). The slope of the fitted line indicated that each additional increase in the percentage point of artificial intelligence share was associated with a significantly higher GDP per capita in percentage terms. This confirmed that the sign and strength of income under standard transformation were robust. Data source: Our World in Data (15, 16).

and statistically indistinguishable from zero. The difference related to the (imprecise) positive primary-energy slope was informative as fuel conversion and thermal losses may have been introduced by primary-energy, while the electrical load relevant to artificial intelligence infrastructure may have been isolated by electricity intensity. According to the electricity-based results, it was implied that energy findings in this study may not robustly positive in macro-level across energy metrics.

Log-Income Specifications

After regressing ln(GDPpc) on artificial intelligence share, the slope was calculated to be 0.364 (semi-elasticity), standard error was 0.102, 95% confidence interval was [0.151, 0.577], and R^2 = 0.403 (n = 21) (Figure 4).

This means that a +1-pp increase in artificial intelligence share was correlated with an estimated 36% higher GDP per capita (100 × 0.364), indicating the strength and sign of the income in a transformation with stabilizing variance. R^2 differed because of scale, but the positive and statistically strong inference was unchanged.

Leave-One-Out Influence

Each baseline model was refit after taking one country out at a time to verify that results did not rely on a single country. For income model, the slope turned out to be still positive in all 21 re-fits in a range from +16,247 to +21,703, while the median was calculated to be +17,312. The sign and significance were stable, even though the magnitude slightly varied. This indicated that there was no single leverage point that generated the association. For primary-energy model, the slope was still positive in all 21 re-fits in a range from +17.7 to +270.1, while the median was calculated to be +233.8. This was consistent with the positive but imprecise findings in the baseline.

Putting all of these findings together, the income relation turned out to be robust, indicating that countries with higher artificial intelligence posting shares were systematically richer. This reflected a co-movement with broader development with new technologies in terms of skills, digital capital, management, and institutions, instead of a causal effect of artificial intelligence alone.

In addition, at the macro scale, the energy relationship still remained ambiguous, indicating that the point estimate was positive but statistically inclusive with primary energy. With electricity intensity, it was statistically null and small. This pattern explained that there was an accounting difference between primary energy and final electricity, while there were offsetting forces between artificial intelligence efficiency gains and scale/rebound. Due to this, the net cross-sectional association was weak in a modest sample.

DISCUSSION

This paper focused on the assessment of how national diffusion of artificial intelligence approximated by the share of artificial intelligence job postings related to the energy intensity and income by using two publicly available datasets. First, there was a positive but statistically inconclusive association between artificial intelligence share and primary-energy intensity of GDP in the 2022 cross-section. The slope was +231.5 kWh per $1,000 per +1 Percentage point [pp] artificial intelligence, 95% confidence interval was [-52.7, +515.7], and R^2 = 0.133. Second, there was a large, positive, and precise association between artificial intelligence share and GDP per capita. The slope was +17,305.8 per +1 pp artificial intelligence, 95% confidence interval was [$9,393.1, $25,218.5], and R^2 = 0.524. With three light robust checks, these patterns were supported, indicating that using electricity intensity instead of primary energy gave a small and statistically null slope of -21.5, with 95% confidence interval [-60.0, +17.1]. When modeling the log GPD per capita, there was a strong positive semi-elasticity of 0.364 and near 36% per +1 pp artificial intelligence. With leave-one-out influence, the sign was kept the same across all refits for both outcomes.

Interpretation of the Energy Evidence

At face value, the positive point estimate of primary-energy intensity may be interpreted in a way that more primary energy per unit of output may be achieved with more artificial intelligence. However, the confidence interval included zero, and the robustness of the electricity-intensity also indicated a near-zero (slightly negative) estimate. Putting these two results, there was no clear and robust signal of the diffusion of artificial intelligence from the macro-level energy intensity in the year of 2022.

With an inquiry about why primary energy indicated positive, but electricity intensity did not, there may be two reasons. First, there would be accounting differences. There would be upstream conversion losses and fuel-mix assumptions with primary energy, while the final electricity used by load may be isolated by electricity intensity. Second, there may be offsetting mechanisms. Artificial intelligence may reduce energy per unit of output through optimization, such as process control, predictive maintenance, and grid dispatch. However, the scale and rebound of digital services may increase aggregate outcomes. These forces may offset to a weak and also uncertain slope in a small cross-section.

This result is supported by the leave-one-out influence. When one particular country was omitted in turn, the slope of the primary-energy turned out to be positive but widely varied (+17.7 to +270.1). This was consistent with the wide confidence interval.

Interpretation of the Income Evidence

Unlike the energy evidence, the income relation was clear and robust. In levels, the slope indicated that a 1-pp higher artificial intelligence job posting share was related to around $17.3k higher GDP per capita, and the model explained nearly half of cross-country income variation. In logs, around 36% higher GDP per capita per +1 pp artificial intelligence share was suggested by the semi-elasticity. This remained strong even after a transform for stabilizing variance. The leave-one-out range from +16,247 to +21,703 turned out to be positive across all refits.

However, all these results shall not be read causally. Omitted variables, such as education, research and development, institutions, and digital infrastructure, and also measurement error in the posting proxy may contribute to the association. Seen in this perspective, the findings in this study may be more conservatively interpreted that the diffusion of artificial intelligence may move with the capabilities of advanced economies. This means that artificial intelligence-related skills may appear more often in postings, and income may be higher where complementary assets were abundant. This may be informative for comparative policy and planning as a descriptive benchmark.

Limitations

Even though this study provided an important insight about the diffusion of artificial intelligence and the energy intensity and GDP per capita, there are limitations. This study used a single year (2022) with a modest sample (n = 21) that contained power, while preventing the separation of persistent national attributes by using fixed effects. Job-posting share was the artificial intelligence proxy that captured demand for artificial intelligence skills without computing the intensity or modeling the deployment of artificial intelligence. In addition, issues related to coverage and taxonomy may add noise. In this study, no-control variables were employed to preserve accessibility, leaving estimates exposed to confounding by climate, industrial structure, energy prices, or policy regimes. Furthermore, this study treated OWID's GDP units consistently rather than going through the rebasing process to PPP or a different currency. This made it possible to avoid mixing systems, but it still limited certain welfare comparisons.

However, despite these limits, credibility was strengthened by three features. First, this study performed light robustness check, indicating that the income result was not the outcome from one observation or scale. Second, transparency was secured. Ever step in this study may be replicated in a spreadsheet from two files. Lastly, this study consistently avoided casual claims, while emphasizing uncertainty where applicable as conservative framing.

CONCLUSION

With two publicly available datasets, this study examined if national diffusion of artificial intelligence estimated by the share of artificial intelligence job postings was associated with energy intensity and income in the year of 2022. According to the evidence, there was a positive but statistically inconclusive association with primary-energy intensity (kWh per $1,000 GDP). When using electricity intensity, there was a small and non-significant association. When using GDP per capita, there was a large and precise positive association. Based on three light robustness checks, including electricity-intensity outcome, a log specification for income, and leave-one-out influence, confirmed that income was a factor with uncertainty for energy at the macro scale. All findings in this study were descriptive, not causal, while reflecting the constraints of a single-year (2022) cross-section, modest sample size, and proxy with artificial intelligence job postings.

From a policy perspective, the findings in this study emphasized the importance of aligning the digitalization driven by artificial intelligence with sustainable energy strategies. Government and international agencies may support this evidence to expect how national energy demand profiles would be reshaped by rapid diffusion of artificial intelligence, while promoting inclusive economic growth at the same time. Integrating policies of innovation with artificial intelligence with renewable energy targets and digital-efficiency standards may support the achievement of well-balanced technological and environmental goals.

Given limitations of this study, it is recommended for future study to focus on extending to a multi-year panel with country as well as year-fixed effects to decrease confounding and emphasizing outcomes specific to electricity and carbon-intensity (kWh/$1,000 and gCO_2/kWh), including log-log variants, and also adding a small set of controls from the same source, such as renewable share, energy prices, and manufacturing share. Lastly, it is also suggested for future work to explore heterogeneity by region or income group.

CONFLICT OF INTERESTS

The author declares no conflicts of interest related to this work.

REFERENCES

1. International Energy Agency (IEA). Energy and AI: Energy demand from AI. *Paris: IEA*. 2025. Available from: https://www.iea.org/reports/energy-and-ai/energy-demand-from-ai (accessed on 2025-06-30).
2. International Energy Agency (IEA). AI is set to drive surging electricity demand from data centres while offering the potential to transform how the energy sector works. News release; 2025 Apr 10. Available from: https://www.iea.org/news/ai-is-set-to-drive-surging-electricity-demand-from-data-centres-while-offering-the-potential-to-transform-how-the-energy-sector-works (accessed on 2025-07-01).
3. U.S. Energy Information Administration (EIA). Electricity use for commercial computing could surpass space cooling, ventilation. Today in Energy; 2025 Jun 25. Available from: https://www.eia.gov/todayinenergy/detail.php?id=65564 (accessed on 2025-07-01).
4. Masanet E, Shehabi A, Lei N, Smith S, Koomey J. Recalibrating global data center energy-use estimates. *Science*. 2020; 367 (6481): 984–986. doi:10.1126/science.aba3758.
5. International Energy Agency (IEA). Data centres and data transmission networks. Tracking Clean Energy

Progress; 2023 Jul 11. Available from: https://www.iea.org/energy-system/buildings/data-centres-and-data-transmission-networks (accessed on 2025-07-01).

6. International Energy Agency (IEA). Energy and AI: Executive summary. Paris: IEA; 2025. Available from: https://www.iea.org/reports/energy-and-ai/executive-summary (accessed on 2025-07-01).
7. Brynjolfsson E, Li D, Raymond L. Generative AI at Work. *Q J Econ*. 2025; 140 (2): 889–944. doi:10.1093/qje/qjae044.
8. Noy S, Zhang W. Experimental evidence on the productivity effects of generative AI. *Science*. 2023; 381 (6654): 187–192. doi:10.1126/science.adh2586.
9. Eloundou T, Manning S, Mishkin P, Rock D. GPTs are GPTs: An early look at the labor market impact potential of large language models. arXiv preprint arXiv:2303.10130; 2023. Available from: https://arxiv.org/abs/2303.10130 (accessed on 2025-07-01).
10. Strubell E, Ganesh A, McCallum A. Energy and policy considerations for deep learning in NLP. In: Proceedings of ACL 57; 2019. Available from: https://aclanthology.org/P19-1355/ (accessed on 2025-07-01). https://doi.org/10.18653/v1/P19-1355
11. Patterson DA, Gonzalez J, Le Q, *et al*. Carbon emissions and large neural network training. arXiv preprint arXiv:2104.10350; 2021. Available from: https://arxiv.org/abs/2104.10350 (accessed on 2025-07-01).
12. Henderson P, Hu J, Romoff J, Brunskill E, *et al*. Towards the systematic reporting of the energy and carbon footprints of machine learning. *J Mach Learn Res*. 2020; 21 (248): 1–43. Available from: https://www.jmlr.org/papers/volume21/20-312/20-312.pdf (accessed on 2025-07-01).
13. Organisation for Economic Co-operation and Development (OECD). Emerging trends in AI skill demand across 14 OECD countries. Paris: OECD; 2023. doi:10.1787/7c691b9a-en. Available from: https://www.oecd.org/en/publications/emerging-trends-in-ai-skill-demand-across-14-oecd-countries_7c691b9a-en.html (accessed on 2025-07-01).
14. Organisation for Economic Co-operation and Development (OECD). Artificial intelligence and the changing demand for skills in the labour market. Paris: OECD; 2024. doi:10.1787/88684e36-en. Available from: https://www.oecd.org/en/publications/artificial-intelligence-and-the-changing-demand-for-skills-in-the-labour-market_88684e36-en.html (accessed on 20 25-07-01).
15. Our World in Data. Share of artificial-intelligence job postings (Lightcast via AI Index). Dataset; 2025. Available from: https://ourworldindata.org/grapher/share-artificial-intelligence-job-postings (accessed on 2025-07-01).
16. Our World in Data. OWID Energy dataset (codebook and releases). Repository; 2024. Available from: https://github.com/owid/energy-data (accessed on 2025-07-01).
17. Sorrell S. Jevons' Paradox revisited: The evidence for backfire from improved energy efficiency. *Energy Policy*. 2009; 37 (4): 1456–1469. doi:10.1016/j.enpol.2008.12.003.
18. IEA Technology Collaboration Programme 4E (EDNA). Data Centre Energy Use: Critical Review of Models and Results. 2025 Mar 26. Available from: https://www.iea-4e.org/wp-content/uploads/2025/05/Data-Centre-Energy-Use-Critical-Review-of-Models-and-Results.pdf (accessed on 2025-07-01).