

The influence of artificial intelligence readiness on energy consumption patterns: Panel evidence from high-income countries

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Abstract. This study examines the effect of AI readiness, proxied by the Government AI Readiness Index developed by Oxford Insights, on primary energy consumption in high-income countries. Using balanced panel dataset covering 30 high-income economies over the period 2019–2023, the analysis employs panel regression techniques to assess how government-led preparedness for artificial intelligence adoption influences aggregate energy demand while controlling for income levels and structural characteristics. The empirical results reveal a positive and statistically significant relationship between AI readiness and primary energy consumption, indicating that the expansion of AI-related infrastructure, data capacity, and computational intensity currently outweighs potential energy-efficiency gains associated with AI applications. In contrast, GDP per capita exhibits a negative association with energy consumption, consistent with efficiency improvements and structural transitions toward less energy-intensive activities in advanced economies, while industry share does not display a systematic effect. These findings suggest that, even in relatively energy-efficient high-income countries, advancing AI readiness may exert upward pressure on national energy demand. Consequently, policies promoting AI development should be closely aligned with energy efficiency strategies, low-carbon electricity deployment, and sustainable digital infrastructure planning to ensure that technological progress supports long-term environmental and climate objectives.

1 Introduction

The global pursuit of sustainable development has intensified as climate change and rising energy demand increasingly threaten economic and environmental stability. Achieving affordable and clean energy systems (SDG 7) while mitigating climate change (SDG 13) has become a central policy priority for high-income economies, where energy consumption levels remain historically high. At the same time, the rapid advance of digital technologies particularly artificial intelligence (AI) is reshaping production processes, public administration, and economic governance. As a core technology of the

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Fourth Industrial Revolution, AI is widely promoted as a catalyst for productivity growth and technological efficiency. Consequently, governments are actively investing in AI-related infrastructure, data ecosystems, and human capital to enhance national AI readiness. In policy discourse, AI is often framed as an enabler of sustainability, with applications ranging from smart grids and energy optimization to climate monitoring and resource-efficient logistics. Nevertheless, whether such expectations hold at the macroeconomic level remains an open empirical question.

A growing literature, however, reveals a fundamental tension between AI-driven efficiency gains and rising energy demand. On the one hand, optimistic perspectives emphasize AI's potential to optimize energy systems, reduce waste, and support decarbonization strategies [1-2]. On the other hand, an expanding body of evidence highlights the substantial energy costs associated with AI development and deployment. Training large-scale models and operating data centers require massive computational power, resulting in significant electricity consumption and carbon emissions [3]. Recent estimates suggest that AI-related energy use may grow rapidly as adoption accelerates across sectors [4]. Moreover, efficiency improvements in hardware and algorithms do not necessarily reduce aggregate energy use; instead, they may induce rebound effects, whereby lower costs and improved performance stimulate further AI adoption, ultimately increasing total energy consumption [5]. Theoretically, this relationship follows a system-level framework where direct computational energy costs interact with application-based impacts, balancing efficiency-driven substitution against consumption-driving scale effects [6]. Consequently, the net environmental footprint of AI is not intrinsic to the technology itself but emerges from how these systemic interactions unfold within a country's specific economic context. This green versus red AI paradox raises a critical question: do the energy-saving benefits of AI outweigh the energy required to build and sustain AI systems at scale?

Despite these concerns, existing empirical research remains limited in important respects. Much of the literature focuses on micro-level analyses, such as the energy consumption of specific algorithms, data centers, or firms [3-5]. Other studies rely on broad digitalization proxies, including ICT diffusion or internet usage, rather than explicitly capturing AI-related institutional and infrastructural preparedness [7]. As a result, there is a lack of macro-level evidence directly linking national AI readiness, particularly government-led preparedness to aggregate energy consumption outcomes. This gap is especially relevant for high-income countries, which are early adopters of AI technologies and possess advanced digital infrastructure. These economies provide an ideal setting to examine the initial energy consequences of widespread AI integration before similar dynamics unfold globally.

Understanding the relationship between AI readiness and energy consumption requires careful consideration of structural economic factors that independently influence energy demand. Income levels constitute another essential determinant, as GDP growth remains tightly coupled with energy demand through consumption across industrial production, households, transportation, and commercial activities [8]. This relationship carries particular significance for digitally advanced economies, where AI-driven productivity gains may amplify rather than attenuate growth-induced energy consumption through scale effects. Therefore, controlling for both urbanization and

income variation becomes methodologically essential when isolating the independent contribution of AI readiness to energy demand patterns.

Despite the expanding literature on artificial intelligence and energy consumption, several critical gaps remain that motivate the empirical framework of this study. Existing research is largely dominated by micro-level technical analyses focusing on the electricity use of data centers or the energy requirements of training specific AI models. While informative, these approaches cannot capture economy-wide effects arising from the diffusion of AI technologies across sectors, leaving unresolved whether micro-level efficiency gains translate into lower aggregate energy consumption or instead generate rebound and scale effects at the national level. At the macroeconomic scale, empirical studies frequently rely on general ICT proxies such as internet usage, which do not reflect the multidimensional nature of AI readiness or the energy-intensive computational infrastructure required for AI deployment. As a result, basic digital connectivity is often conflated with AI preparedness. Furthermore, empirical evidence remains fragmented for high-income economies, despite their position as early adopters of advanced AI infrastructure. Consequently, the extent to which structural factors such as income, urbanization, and industrial composition condition the energy implications of AI readiness in advanced economies remains insufficiently understood.

Addressing these gaps, the present study examines how national AI readiness influences energy consumption across high-income countries while explicitly incorporating income levels, urbanization, and industrial structure as conditioning factors. Employing a panel regression framework that exploits both cross-country variation and temporal dynamics over the period 2019 to 2023, this research contributes novel empirical evidence on whether and how technological preparedness interacts with broader economic and structural characteristics to shape contemporary energy demand at the national level. The findings offer crucial insights for policymakers seeking to balance AI development with environmental sustainability objectives in advanced economies.

2 Methodology

2.1 Panel unit root test

Prior to estimating the panel regression models, this study examines the stationarity properties of all variables to ensure econometric validity and mitigate the risk of spurious regression. In panel data settings, non-stationary series may produce misleading inference even when estimated coefficients appear statistically significant. Accordingly, panel unit root tests are conducted to determine whether the variables are stationary in levels, $I(0)$.

Stationarity is assessed using the Im–Pesaran–Shin (IPS) panel unit root test, which is particularly appropriate for cross-country panels because it allows for heterogeneity in autoregressive dynamics across cross-sectional units [9]. In contrast to the Levin–Lin–Chu (LLC) test, which imposes a common autoregressive parameter, the IPS framework permits countries to exhibit distinct adjustment speeds and stochastic processes, providing crucial flexibility in international macroeconomic applications characterized by structural diversity [10]. The IPS test is constructed from the average of individual

Augmented Dickey–Fuller (ADF) statistics and evaluates the null hypothesis that all panel series contain a unit root against the alternative that at least a subset of cross-sections is stationary. The test is implemented under a specification including individual intercepts and deterministic time trends, thereby accounting for country-specific fixed effects and long-run structural developments. This diagnostic step provides a robust econometric foundation for subsequent panel data estimation. The IPS test is based on the following individual ADF regression for each cross-sectional unit i :

$$\Delta y_{it} = \alpha_{0i} + \rho_i y_{it-1} + \sum_{j=1}^{p_i} \varphi_{ij} \Delta y_{it-j} + \varepsilon_{it}, \quad (1)$$

where $y_{i,t}$ denotes the variable of interest for country i at time t , α_i captures country-specific fixed effects, and $\delta_i t$ represents panel-specific deterministic time trends. The parameter ρ_i is the autoregressive coefficient on the lagged level of the variable, with lagged differences included to control for serial correlation. The IPS test evaluates the null hypothesis $H_0: \rho_i = 0$ for all i against the alternative that $\rho_i < 0$ for at least some cross-sectional units, allowing for heterogeneity in dynamic adjustment across panels.

2.2 Panel regression model

To examine the relationship between AI readiness and energy consumption, this study employs a panel regression methodology using annual country-level data. Panel data techniques are particularly well-suited for this analysis as they combine cross-sectional and temporal dimensions, thereby increasing statistical efficiency and improving parameter precision. More importantly, panel regression enables explicit control for unobserved, time-invariant country-specific heterogeneity through fixed effects estimation. This capability is critical in cross-country energy and technology analyses, where countries exhibit persistent structural differences in institutional quality, geographical characteristics, and infrastructure capacity that are difficult to measure directly [11, 10]. By accounting for these time-invariant factors, the fixed effects approach mitigates omitted variable bias and yields more reliable estimates of the relationship under investigation. The baseline empirical model takes the following general form:

$$\ln(EN_{it}) = \alpha + \beta_1 \ln \ln (AI_{it}) + \beta_2 \ln \ln (GDP_{it}) + \beta_3 IND_{it} + \lambda_t + \mu_i + \varepsilon_{it}, \quad (2)$$

where EN_{it} denotes primary energy consumption in country i at time t ; AI_{it} represents government AI readiness, GDP_{it} captures economic development, and $Industry_{it}$ measures the industrial sector's share of output. The term μ_i captures unobserved country-specific effects, while ε_{it} is the idiosyncratic error term.

The specification of the appropriate panel data estimator proceeds through a hierarchical testing framework. The F-test evaluates the null hypothesis that country-specific intercepts are jointly insignificant ($H_0: \alpha_i = \alpha$ for all i). Rejection indicates that pooled OLS yields inconsistent estimates due to omitted heterogeneity, necessitating a panel estimator.

Conditional on rejecting poolability, the Hausman (1978) specification test discriminates between fixed-effects (FE) and random-effects (RE) estimators by testing the orthogonality assumption $E(\alpha_i|X_{it}) = 0$. Under the null hypothesis.

3 Data

This study utilizes a balanced annual panel dataset covering 30 high-income countries from 2019 to 2023, yielding 150 country-year observations. This recent timeframe captures contemporary developments in artificial intelligence readiness and energy consumption patterns while ensuring data availability and cross-country comparability. High-income economies are selected due to their advanced digital infrastructure and intensive AI adoption, making them suitable for examining energy implications within comparable institutional contexts.

The dependent variable is primary energy consumption from Our World in Data, measuring total energy consumed from primary sources within an economy. This indicator provides a comprehensive measure of national energy demand widely employed in cross-country studies examining interactions between technological progress, economic activity, and environmental outcomes. The key explanatory variable is AI readiness, proxied by the Government AI Readiness Index from Oxford Insights. This composite index evaluates countries' capacity to adopt, deploy, and govern artificial intelligence across three core pillars: Government, Technology Sector, and Data and Infrastructure, thereby capturing institutional preparedness, technological capability, and digital foundations [12].

To mitigate omitted variable bias, the analysis incorporates macroeconomic controls from the World Bank's World Development Indicators. GDP per capita, measured in constant international dollars, proxies for economic development and living standards. Industry share, defined as industrial sector value added as a percentage of GDP, accounts for structural differences in production composition, capturing the relative importance of energy-intensive sectors such as manufacturing, mining, construction, and utilities. Table 1 reports descriptive statistics for all variables employed in the empirical analysis.

Table 1. Descriptive statistics.

	Energy	AI	GDP	Industry
Mean	1795.93	70.12	50094.82	23.34
Median	358.89	69.87	45984.64	22.01
Maximum	26578.49	91.86	134965.82	67.93
Minimum	28.28	31.43	17294.9	9.11
Std. Dev.	4671.81	9.60	25800.39	9.81
Jarque-Bera	3406.2***	180.67***	3.498	437.45***
Observations	150	150	150	150

*** indicate the significance levels at 1%

4 Empirical results and discussions

4.1 Panel unit root test result

Prior to conducting the panel regression analysis, we examine the stationarity properties of all variables to ensure econometric validity and to mitigate the risk of spurious regression. Table 2 reports the results of the Im–Pesaran–Shin (IPS) panel unit root test.

The test results consistently reject the null hypothesis of a unit root at the 1% significance level for energy consumption, government AI readiness, GDP per capita, and industry share. These findings indicate that the corresponding series are stationary in levels and integrated of order zero, $I(0)$. Consequently, the stationarity condition required for standard panel regression techniques is satisfied, allowing us to proceed with the panel data estimation.

Table 2. Panel unit root test.

Variables	Im–Pesaran–Shin Test
log(Energy consumption)	-46.435***
log(AI readiness)	-152.05***
log(GDP per capita)	-39.145***
Industry share	-2.7808***

*** indicates the significance levels at 1%

4.2 Panel regression analysis

The analytical framework of this study estimates four alternative panel-data specifications to ensure robustness and to comprehensively examine the relationship between AI readiness and energy consumption. Table 3 reports results from a bivariate model without controls, pooled ordinary least squares (OLS), fixed effects (FE), and random effects (RE) estimations. This multi-model strategy allows for a systematic comparison of coefficient stability across different assumptions regarding unobserved country-specific heterogeneity. By evaluating the consistency of estimates across these specifications, the analysis identifies relationships that remain robust under alternative econometric treatments.

The selection of the appropriate econometric model is critical for obtaining consistent and unbiased estimates in panel data analysis. The results of this selection process are shown in Table 4. Accordingly, we conducted two fundamental diagnostic tests to determine the most suitable estimation strategy for our dataset. First, the F-test for individual effects strongly rejects the null hypothesis of no country-specific effects, confirming the presence of unobserved heterogeneity across countries and rendering pooled OLS inappropriate. Second, the Hausman specification test yields a chi-square statistic of $\chi^2 = 0.285$ and fails to reject the null hypothesis that the individual effects are uncorrelated with the regressors. This result indicates no systematic difference between the FE and RE estimators and suggests that the random-effects model is both consistent and more efficient in this setting. Consequently, the random-effects specification is adopted as the preferred baseline model, treating country-specific effects as random components that capture persistent but exogenous cross-country heterogeneity.

The finding of the relationship between AI readiness and primary energy consumption. The fixed effects estimates reveal a positive and statistically significant association, with the coefficient indicating that a 1% increase in AI readiness is associated with approximately 0.301% increase in energy consumption. This elasticity estimate is both economically and statistically meaningful, suggesting that the expansion of AI infrastructure and capabilities at the national level exerts considerable upward pressure on energy demand. The magnitude of this effect translates into substantial absolute increases in energy consumption when scaled across entire national economies, particularly in countries with already high baseline energy use. This finding carries important implications for environmental sustainability and climate policy. Specifically, the positive energy-AI readiness nexus suggests that widespread AI adoption and the accompanying computational infrastructure can push national primary energy demand upward. Moreover, as governments accelerate their AI readiness initiatives to remain competitive in the digital economy, the aggregate energy footprint of these technologies may expand more rapidly than anticipated, creating tension between technological advancement and environmental objectives. This tension underscores the critical need for concurrent investments in energy-efficient computing technologies, renewable energy sources, and policy frameworks that explicitly address the energy-environment trade-offs inherent in AI deployment.

Regarding the control variables, GDP per capita exhibits a negative association with energy consumption in the random-effects model. This result is consistent with the energy-efficiency and structural-transition hypotheses, which posit that higher-income economies tend to adopt more energy-efficient technologies, shift toward less energy-intensive service sectors, and implement stricter energy and environmental regulations. Empirical studies have documented this pattern, showing that economic development beyond a certain threshold is associated with declining energy intensity and, in some cases, lower aggregate energy consumption growth [14]. In this context, the negative GDP coefficient suggests that efficiency gains and structural change dominate scale effects in high-income countries.

By contrast, the share of industry in GDP remains statistically insignificant across specifications. This finding indicates that variations in industrial structure do not exert a systematic effect on national energy consumption once AI readiness and income levels are considered. One plausible explanation is that industrial sectors in developed economies have already undergone substantial efficiency improvements, thereby weakening the direct link between industrial output shares and aggregate energy demand.

Overall, the empirical results suggest that AI readiness is a key driver of rising energy consumption, even in relatively energy-efficient, high-income economies. While higher income levels are associated with lower energy demand through efficiency and structural channels, the expansion of AI-related digital infrastructure appears to offset these gains. These findings align with the International Energy Agency's Energy and AI Special Report [15], which emphasizes the growing contribution of AI and data centers to national electricity demand. Taken together, the results highlight the need for policy frameworks that explicitly address the energy implications of AI deployment while promoting sustainable technological progress.

Table 3. Panel regression parameter estimation.

Variables	Without control variables	Pooled OLS	Fixed effects	Random effects
Constant	-25.169*** (3.074)	-26.090*** (3.200)		5.233*** (0.593)
log(AI readiness)	7.363*** (0.724)	9.089*** (0.830)	0.289*** (0.062)	0.301*** (0.068)
log(GDP per capita)		-0.678** (0.239)	-0.049 (0.043)	-0.044 (0.047)
Industry share		0.036*** (0.010)	0.001 (0.002)	0.001 (0.002)
Adj. R-squared	0.406	0.467	0.044	0.119

*** and ** indicate the significance levels at 1%, and 5% respectively

Table 4. Model selection.

Tests	Test statistics
Hausman test	0.285
F test	4231.40***

*** indicate the significance levels at 1%

5 Conclusion

This study investigates the relationship between national AI readiness and primary energy consumption in high-income countries using recent panel data covering the period 2019 to 2023. By integrating AI readiness into a macroeconomic energy framework and controlling for income levels and structural characteristics, the analysis provides new empirical insights into how advanced digital preparedness shapes aggregate energy demand. Overall, the findings contribute to the growing debate on whether AI-driven technological progress supports or undermines sustainability objectives at the national level, particularly in the context of Sustainable Development Goal 7 (affordable and clean energy) and SDG 13 (climate action).

The empirical results consistently indicate a positive and statistically significant association between AI readiness and energy consumption. This finding suggests that, at the current stage of technological development, the expansion of AI-related infrastructure, data centers, and computational capacity outweighs potential efficiency gains generated by AI applications. Although higher-income levels are associated with lower energy consumption through efficiency improvements and structural transitions toward less energy-intensive sectors, these gains appear insufficient to fully offset the additional energy demand induced by rising AI readiness. Consequently, even highly efficient and technologically advanced economies face upward pressure on energy demand as AI adoption accelerates, creating potential tensions with SDG targets for sustainable energy transitions and climate mitigation.

These results carry important policy implications for achieving the SDGs. First, they imply that strategies promoting AI development should not be pursued in isolation from energy and environmental policy. Governments in high-income countries need to complement AI readiness initiatives with targeted investments in energy-efficient computing, low-carbon electricity generation, and regulatory frameworks that

internalize the energy costs of digital infrastructure—measures directly aligned with SDG 7's emphasis on energy efficiency and renewable energy expansion. Second, the findings highlight the importance of aligning AI governance with long-term sustainability goals, ensuring that technological competitiveness does not come at the expense of climate commitments under SDG 13. This alignment becomes particularly critical given the Paris Agreement's urgency and the recognition that digital transformation must serve, rather than undermine, broader environmental objectives. More broadly, the evidence underscores the necessity of integrated policy approaches that jointly address digital transformation and energy transition challenges, reflecting the interconnected nature of the SDG framework.

Finally, this study provides a foundation for future research. While the analysis focuses on high-income economies and short-run dynamics, subsequent work could extend the framework to developing countries or explore longer time horizons as AI technologies mature. Moreover, future studies may investigate nonlinearities or threshold effects in the AI–energy relationship, as well as interactions with renewable energy deployment. Taken together, the findings emphasize that AI readiness is a non-negligible driver of national energy demand and must be carefully managed to support sustainable technological progress in line with global sustainability commitments.

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