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THE IMPACT OF ENERGY PRICE DYNAMICS ON ARTIFICIAL INTELLIGENCE ADOPTION: A CROSS-COUNTRY STUDY

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ABSTRACT. This research examines the impact of energy price fluctuations and renewable power systems on the adoption of artificial intelligence (AI) technology across 28 OECD member states from 1980 to 2023. The research employs the Pooled Mean Group estimator with error correction (PMG-ECM) to analyze a balanced panel of 898 country-year observations, which assesses how electricity prices and renewable energy generation affect AI patent activity. The research shows that industrial electricity price increases lead to decreased AI innovation (coefficient: -0.690, $p < 0.01$), but renewable energy generation shows a positive relationship with AI patent publications (coefficient: 0.194, $p < 0.01$). The policy simulations show that a 15 TWh increase in renewable energy leads to 3.9 times more AI patents than a 20% reduction in electricity prices. The combined policy scenario generates an estimated 3.65 additional patents per country-year, representing a 0.50% increase above baseline levels. The research expands the Technology-Organization-Environment (TOE) framework by showing that energy infrastructure plays a crucial role in AI adoption and supports the Resource-Based View (RBV) by demonstrating renewable energy access as a strategic resource. The study indicates that energy policies, by themselves, will not lead to significant acceleration of AI innovation and should be integrated into comprehensive innovation strategies.

JEL Classification: O33, Q41, Q55, O32, L96, M15

Keywords: artificial intelligence adoption, energy prices, renewable energy infrastructure, pooled mean group error correction, technology-organization-environment, resource-based view

Introduction

The rapid development of artificial intelligence (AI) technologies creates a transformative power that affects both global economic competitiveness and innovation networks. Recent macroeconomic studies for emerging economies confirm that AI has substantial growth potential but its realized impact remains constrained by structural factors

(Sarker, 2022). The scientific community has studied AI diffusion factors in great detail, but lacks comprehensive research on the impact of energy infrastructure, particularly concerning electricity costs and renewable energy capacity. The gap between technological development and sustainability requirements becomes theoretically important because AI's massive computational needs currently use 1–2% of global electricity, which will increase to 4–6% by 2030 (IEA, 2025). The study of energy system constraints on AI adoption will help create effective innovation policies and strategic corporate investments in the digitalized global economy. Studies in AI adoption use the Technology-Organization-Environment (TOE) model (Tornatzky & Fleischer, 1990) alongside the Technology Acceptance Model (Chatterjee et al., 2021) and Resource-Based View (Chen et al., 2022) as frameworks. Physical infrastructure, such as energy systems, receives insufficient operationalization in existing studies, which focus on technological readiness alongside organizational capabilities and competitive pressures. According to Baker (2012), the environmental component of the TOE framework demonstrates an inconsistent definition because it frequently overlooks essential physical resources. The following three crucial gaps exist in current research regarding how energy infrastructure affects AI innovation: The lack of macro-level evidence shows the relationship between energy infrastructure and AI innovation; Theoretical models fail to recognize energy as a specific strategic resource instead of a generic cost factor; The evaluation of renewable energy systems as AI computational drivers receives insufficient attention in policy research.

The research establishes new knowledge by examining how electricity prices and renewable infrastructure systems influence the adoption of AI technologies at the national level. Our study analyzes a balanced panel of 28 OECD countries (1980–2023; N = 898 country-year observations) using a Pooled Mean Group estimator with error correction (PMG-ECM) to handle non-stationarity and cross-sectional dependence. This study investigates the main research inquiry which asks whether energy costs and renewable infrastructure help or limit national AI innovation. Specific objectives include: We analyze electricity prices (H_1: adverse adoption effects) while investigating sectoral heterogeneity (H_2) and renewable energy's impact on moderating the relationship (H_3); The research evaluates. the impact of lowering prices and constructing infrastructure on policy effectiveness; This research demonstrates energy's status as an essential strategic element in adoption frameworks. Our contributions are threefold:

- The study develops the TOE/RBV models by introducing energy infrastructure as an independent environmental factor to unite innovation research with energy economic principles.
- Renewable energy generation produces a 3.9 times greater increase in AI patent production than price reduction strategies (−0.690 vs. +0.194 elasticity; $p < 0.01$) according to empirical evidence.
- Research simulations demonstrate that infrastructure-based policies create 0.50% additional AI patents than price-based interventions (95% CI: 2.306–5.014) , which challenges conventional subsidy approaches.

The remainder of this paper is organized as follows: Section 2 combines findings from studies on the relationships between AI adoption and energy innovation. Section 3 explains the data sources, along with the PMG-ECM methodology. Section 4 presents hypothesis tests, policy simulations, and robustness checks. Section 5 explores theoretical implications for acceptance models and policy development strategies. Section 6 presents the study boundaries and indicates future research paths.

1. Literature review on AI adoption determinants

In the context of AI adoption, we examine the impact of two factors that have not been extensively studied in previous literature (energy prices //and share of renewables in electricity production). The study of how energy expenses affect infrastructure development and technology implementation has emerged as a new field that combines innovation research with energy economics and strategic management principles. The traditional technology adoption frameworks have mainly analyzed technological features, organizational abilities, and market competition; however, the specific influence of energy on adoption choices remains understudied. This review evaluates existing research about energy expenses and technology adoption, together with theoretical models of adoption choices and innovation systems approaches to policy evaluation.

1.1. Energy costs and technology adoption

Research shows energy costs significantly influence corporate technology decisions. Stucki (2019) found that among German, Austrian, and Swiss firms, those with higher energy bills (the top 19%) saw greater productivity gains through green tech investments, with energy costs acting as a variable shaping the cost-benefit analysis of adoption. Adão et al. (2022) developed a model indicating that renewable energy adoption requires balancing short-term costs with long-term infrastructure benefits, following a gradual acceleration pattern. Mickovic and Wouters (2020) highlighted that precise energy cost data is essential in manufacturing for effective energy management and strategic decision-making, demonstrating energy's influence beyond operational expenses.

1.2. Technology-organization-environment theory

The Technology-Organization-Environment (TOE) framework, introduced by Tornatzky and Fleischer (1990), is a key model for studying organizational technology adoption. It suggests that adoption depends on three factors: technological (technology features), organizational (firm-specific factors), and environmental (external influences). Studies, such as Awa et al. (2017) and Oliveira and Martins (2011), have validated the framework across various contexts, including ERP systems and e-commerce. However, the environmental dimension lacks clear definition, with Baker (2012) noting inconsistent operationalizations, often focusing on competitive pressure, regulation, and partners, but neglecting physical infrastructure or resource availability. Recently, Silva et al. (2024) extended the model to include sustainability, creating the TOES framework, emphasizing environmental impact assessments for energy-intensive technologies.

1.3. Energy policy and innovation linkages

Research on how energy policy affects innovation has gained more attention since 2019, but it faces significant constraints due to the limited availability of empirical data. Zhao et al. (2019) studied China's new energy vehicle industry to discover that infrastructure development combined with financial incentives produced better results than single-policy approaches. Their research presents initial empirical findings that demonstrate that infrastructure-based energy policies generate different innovation results than cost reduction strategies. The study of renewable energy adoption demonstrates that designing policies for energy transitions and innovation outcomes requires complex approaches (Drożdż et al., 2023).

Van der Ploeg and Rezai (2016) created theoretical frameworks that indicate that climate policies need to strike a balance between present-day expenses and future innovation advantages, while the timing and structure of interventions determine final results. The research suggests that infrastructure development policies yield superior long-term innovation outcomes compared to price-based interventions. The current state of knowledge lacks sufficient empirical data that demonstrates how particular energy policies affect innovation results. The majority of research investigates either energy adoption or innovation independently without a comprehensive analysis of how energy infrastructure relates to costs and innovation performance across countries or regions.

1.4. Research gaps and theoretical contributions

The current research on energy-innovation relationships reveals multiple essential knowledge gaps. The research on firm-level technology adoption shows that energy costs matter as moderators, but there is not enough evidence about energy factors at regional or national levels. The current theoretical frameworks lack sufficient integration of energy infrastructure as an independent environmental factor that affects technology adoption choices. The innovation systems literature acknowledges infrastructure's importance for innovation, but it has not studied energy infrastructure as a factor that determines innovation results. The current research lacks sufficient empirical data to evaluate the effectiveness of different energy policy instruments in promoting innovation, especially for energy-intensive technologies such as artificial intelligence. The research fills these knowledge gaps by conducting an empirical study of how energy expenses and renewable energy facilities impact AI innovation across nations while revealing new understanding about energy factors that affect technology adoption and innovation results.

2. Data and methods

In this section, we provide the theoretical background behind the empirical model, including the data and sample selection process and empirical modeling choice. Firms' decision to adopt new technology or innovation is based on the net benefit calculation. Productivity gains must exceed the adaptation and operational costs of the firm. A firm's decision to adopt AI is modeled as a rational cost-benefit analysis, where adoption occurs if the expected NB is positive (Baabdullah, 2024). From adoption decision theory, firms adopt AI if:

$$\text{Net Benefit (NB)} = \mathbb{E}[\underbrace{\text{Productivity Gains}}_{\Delta P}] - \underbrace{\text{Adoption Costs}}_{C_A} - \underbrace{\text{Operational Costs}}_{C_O(E)} > 0 \tag{1}$$

where

$\mathbb{E}\Delta P$: Expected productivity gains from AI adoption,
C_A: AI adoption (implementation) costs,
$C_O(E)$: Ongoing operational costs, a function of energy prices.

Key hypotheses in our research: H_1: As energy prices (E) increase, the likelihood of AI adoption decreases (direct effect). H_2: Energy-intensive sectors exhibit a stronger negative elasticity to E in their AI adoption decisions. H_3: Greater penetration of renewable energy moderates (weakens) the negative effect of E on AI adoption.

We formulate our research on primary technology adoption theories, TOE, TAM, and UTAUT. The adoption of AI in firms depends on several key factors of AI readiness (Chatterjee et al., 2021; Uren & Edwards, 2022). Another theory, the RBV highlights the importance of AI capabilities, management, and decision-making in enhancing firm performance. AI-driven decision-making and innovation culture are critical for leveraging AI to gain a competitive advantage from AI adoption (Chen et al., 2022). To adopt AI, firms must possess the necessary technological infrastructure and personnel (assets and capabilities). The availability of data, computational resources, and skilled personnel who can manage and implement AI technologies are critical to AI adoption (Jöhnk et al., 2021). In their study, Jöhnk et al. (2021) emphasize the importance of a clear strategic vision and a commitment to AI adoption that aligns with the business strategy. TOE and DOI theories help to understand and portray the path of the AI adoption process (Hradecky et al., 2022; Ayinaddis, 2025; Issa et al., 2022). The study of AI adoption at the firm level faces an essential challenge because researchers lack sufficient data. Systematic data collection at the firm level is critical to determine how AI affects labor through complementarity or substitution (Seamans & Raj, 2018; Raj & Seamans, 2019). The effects of AI adoption depend on market structure, together with industry-specific dynamics. Firms should evaluate external factors before developing their AI strategies (Rahman et al., 2023). The implementation of AI technology brings various advantages, yet organizations face multiple obstacles to overcome. The successful adoption of AI requires organizations to achieve strategic alignment and workforce adaptation while maintaining a supportive organizational culture. Organizations must remain flexible and adaptable to technological advancements and market shifts, as AI continues to evolve.

Previous studies did not address the potential impact of energy price shocks and the penetration of renewable energies on AI adoption. We address this research gap by utilizing the data at our disposal to understand the role and importance of both at a macro level. This becomes critical due to the question of AI future energy consumption for AI data centers and infrastructure.

2.1. Sample selection

The data available covered the country and time dimensions, spanning the period from 1980 to 2023 (Table 1). The dependent variable, AI adoption, is measured using patent publications for AI-related technology (total count by filing office). Our key explanatory variables include industrial electricity prices (measured in pence per kWh, excluding taxes, sourced from the IEA), renewable electricity generation (measured in TWh), GDP per capita (constant 2015 US$), internet usage (percentage of population using the Internet), and research and development expenditure (as percentage of GDP). The initial dataset comprises 28 countries observed over 44 years, resulting in a balanced panel structure with a total of 1,232 observations. The panel spans a critical period in technological development, capturing both the early stages of digitalization and the recent acceleration in AI adoption. Data availability varies considerably across variables. Missing values are most pronounced for R&D expenditure (43.4% missing), followed by internet usage (23.7%) and electricity prices (18.1%). The AI adoption data exhibit 13.6% missing observations, while GDP per capita and renewable electricity generation show complete coverage, with 2.4% and 3.6% missing values, respectively. The missing data pattern for internet usage is expected, given that widespread internet adoption began in the mid-1990s, resulting in structural missingness for earlier years.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Median	Max
Al adoption (patent count)	1,064	725.88	2,927.74	1.00	11.00	24,810.00
GDP per capita (constant 2015 US$)	1,202	33,013.91	19,932.20	3,817.00	31,160.00	112,418.01
Internet usage (% of population)	940	51.46	35.56	0.00	62.55	99.30
R&D expenditure (% of GDP)	697	1.84	0.94	0.36	1.70	5.21
Renewable electricity (TWh)	1,188	60.92	112.63	0.02	23.94	973.67
Electricity price (pence/kWh)	1,009	5.45	3.36	0.32	4.60	25.46

Notes: Panel dataset covers 28 countries from 1980 to 2023 (44 years, 1,232 total observations).
Source: Authors' research

The number of observations varies by variable due to missing data. AI adoption is measured as the total count of AI-related patent publications by filing office. GDP per capita is in constant 2015 US dollars. Internet usage refers to the percentage of the population that uses the Internet. R&D expenditure is expressed as a percentage of GDP. Renewable electricity generation is measured in terawatt-hours. Industrial electricity prices, excluding taxes, are expressed in pence per kilowatt-hour. Given the substantial variation in data availability across variables, our main specifications utilize the maximum available sample for each model estimated. This approach preserves statistical power while acknowledging that sample composition may vary across different specifications, depending on the variables included. For robustness, we estimate our models using a common sample restricted to observations with complete data across all variables. However, this reduces our effective sample size considerably due to the high proportion of missing R&D data. The balanced panel structure facilitates the implementation of standard panel econometric modeling. At the same time, the extended time dimension (T = 44) enables the identification of meaningful within-country variation, allowing for the isolation of the effects of interest. The between-to-overall standard deviation ratios indicate substantial cross-country heterogeneity (0.92 for GDP per capita and 0.75 for AI adoption), suggesting that both within- and between-country variations are significant.

2.2. Preliminary testing

We perform a set of stationarity tests using first- and second-generation panel unit root tests. We use both generations of tests because macro-panel data may exhibit cross-sectional dependence according to Pesaran (2015) for robustness purposes.

2.2.1. Cross-section dependence

We test for cross-sectional dependence using the Pesaran CD test (Pesaran, 2004, 2015), which is robust to both balanced and unbalanced panels and performs well in panels with T > N. The results provide strong evidence of cross-sectional dependence across our variables. For GDP per capita, the Pesaran CD statistic is 117.45 (p-value < 0.001) with a mean absolute correlation of 0.911. AI adoption also exhibits significant cross-sectional dependence (CD statistic = 10.07, p-value < 0.001), though with a lower mean absolute correlation of 0.268. The presence of cross-sectional dependence invalidates the assumption of independently distributed errors across cross-sections, requiring the use of robust inference methods and second-generation econometric tests (Chudik & Pesaran, 2015).

2.2.2. Stationarity testing

Initial testing uses the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979), the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992), and the Fisher-type ADF test (Maddala & Wu, 1999). For GDP per capita, the country-specific ADF tests reject the null hypothesis of a unit root at the 5% level in only 3 out of 28 countries, with a mean ADF statistic of -1.92. The Fisher ADF test yields a chi-square statistic of 63.02 (p-value = 0.242), failing to reject the null hypothesis that all panels contain a unit root. AI adoption shows mixed evidence, with 13 out of 27 countries rejecting the unit root null in individual ADF tests (mean statistic = -2.60). The Fisher ADF test strongly rejects the joint null hypothesis (chi-square = 175.46, p-value < 0.001). Internet usage exhibits similar non-stationary characteristics to GDP per capita, with only 4 out of 28 countries rejecting the unit root null (mean ADF statistic = -1.74). Given evidence of cross-sectional dependence (discussed below), we implement the Cross-sectionally Augmented Dickey-Fuller (CADF) test (Pesaran, 2007), which accounts for cross-sectional dependence through cross-sectional averages. The second-generation unit root tests confirm that our key variables - AI adoption, electricity prices, and renewable electricity generation - are non-stationary in levels (p-values > 0.05), consistent with the results of the first-generation tests. Mixed stationarity results demand testing for cointegration relationships among these variables.

2.2.3. Cointegration testing

Given that our sample series exhibits a unit root, we employ multiple approaches to test for cointegration, ensuring robustness. We use the Kao test (Kao, 1999), Pedroni tests (Pedroni, 1999, 2004), and Westerlund tests (Westerlund, 2007) on the relationship between AI adoption, electricity prices, and renewable electricity generation. All three cointegration tests strongly reject the null hypothesis of no cointegration (p-values = 0.000), indicating a long-run equilibrium relationship among AI adoption, electricity prices, and renewable electricity generation. The Pedroni tests, which allow for heterogeneous cointegrating vectors across countries, confirm this finding across all seven test statistics. The Westerlund error-correction-based tests, which possess good small-sample properties and accommodate cross-sectional dependence, also support the presence of cointegration.

2.3. Modeling choice and selection

Our selection of the PMG estimator with error correction (Pesaran et al., 1999) is based on multiple empirical findings. The presence of cointegration between AI adoption, electricity prices, and renewable electricity generation (all tests p-value = 0.000) indicates a long-run equilibrium relationship that necessitates an error correction framework (Engle & Granger, 1987). The confirmed non-stationarity of variables in levels through both first- and second-generation unit root tests, combined with the existence of cointegration, rules out static panel estimators and supports the use of dynamic panel techniques. The PMG estimator is particularly suited to our choice for several reasons. The Mean Group (MG) estimator (Pesaran & Smith, 1995) allows both short-run and long-run coefficients to vary across countries. Still, the PMG constrains long-run coefficients to be equal across groups while permitting country-specific short-run dynamics and error correction terms. This restriction is economically sensible for our analysis, as we expect the fundamental relationship between energy infrastructure and AI innovation to be similar across countries in the long run. At the same time, short-run adjustment processes may differ due to country-specific institutional and economic factors (Blackburne & Frank, 2007).

2.4. Error correction modeling

The PMG error correction specification takes the form

$$\Delta y\{it\} = \varphi_i(y\{i, t-1\} - \theta' x_{it}) + \beta' \Delta x_{it} + \mu_i + \varepsilon_{it} \tag{2}$$

where φ_i represents the country-specific error correction coefficient, θ contains the long-run parameters (constrained to be equal across countries), and β_i represents short-run dynamics.

This specification is particularly suitable given our finding of cointegration, allowing us to distinguish between short-run adjustments and long-run equilibrium relationships (Loayza & Ranciere, 2006). Alternative specifications considered but rejected include: Static models without error correction, which would ignore the cointegration relationship; Models in pure levels, which would yield spurious results given non-stationarity; First-difference models without error correction, which would discard long-run information. The PMG approach optimally balances the need to address non-stationarity through differencing while preserving long-run relationships through the error correction mechanism, making it the most suitable choice for our analysis of the impacts of energy policy on AI innovation.

Our final PMG model with 898 observations yields statistically significant long-run coefficients for both electricity prices (-0.690, t-statistic = -6.06) and renewable electricity generation (0.194, t-statistic = 4.29). The significance of these coefficients, combined with the model's ability to handle our specific data challenges (non-stationarity, cointegration, cross-sectional dependence, and heterogeneity), validates our methodological choice. The model specification tests, particularly the Ramsey RESET test, indicate potential misspecification ($F = 35.18$, $p < 0.001$), suggesting that future research might explore non-linear specifications within the PMG framework. However, for our current analysis, which focuses on average policy effects, the linear PMG specification provides robust and interpretable results.

3. Results

3.1. Model estimation and sample characteristics

The final sample comprises 898 observations spanning multiple countries, providing adequate statistical power for cross-country policy analysis. The PMG specification allows for heterogeneous short-run dynamics while constraining long-run coefficients to be homogeneous across countries, making it particularly suitable for deriving generalizable policy insights.The baseline level of AI patent publications averages 725.9 patents per country-year across our sample, establishing a reference point for assessing the magnitudes of policy effects. This baseline represents the current state of AI innovation activity and serves as the denominator for calculating percentage impacts of proposed energy policy interventions.

3.2. Main econometric results

Table 2 presents the core econometric findings from our PMG estimation. The results reveal statistically significant relationships between both energy variables and AI patent activity, with effects operating in the theoretically expected directions.

Table 2. Main econometric results

Variable	PMG coefficient	Standard error	T-statistic
Electricity Price	-0.690	0.114	-6.06***
Renewables (TWh)	0.194	0.045	4.29***
Observations	898		
Number of Groups	[Multiple Countries]		

Notes: Dependent variable: Change in AI patent publications. PMG = Pooled Mean Group estimator with error correction. Standard errors reported. |t| > 1.96 indicates significance at 5% level ** p < 0.01.*
Source: Authors' research

The electricity price coefficient of -0.690 indicates that higher industrial electricity prices have a significant negative impact on AI patent activity. This negative relationship is highly statistically significant ($t = -6.06$, $p < 0.01$), suggesting that energy costs represent a meaningful constraint on AI innovation activities. The coefficient magnitude implies that each unit increase in electricity prices corresponds to a decrease of approximately 0.69 AI patents per country-year.The renewable energy coefficient of 0.194 demonstrates a positive and significant relationship between renewable energy generation and AI patent publications ($t = 4.29$, $p < 0.01$). This finding suggests that the expansion of renewable energy contributes to AI innovation beyond its simple cost effects, potentially through improved energy security, grid stability, or signaling effects regarding long-term energy availability.

3.3. Policy simulation results

To translate our econometric estimates into concrete policy implications, we conducted Monte Carlo simulations (with 10,000 draws) that incorporated parameter uncertainty. Table 3 summarizes the results for three policy scenarios: a 20% reduction in industrial electricity prices, a 15 TWh increase in renewable energy generation, and a combined implementation of both policies.

Table 3. Policy simulation results

Policy Scenario	Point Estimate	Median Effect	95% CI Lower	95% CI Upper	% Change
20% Electricity Price Reduction	0.753	0.75	0.506	0.996	0.10
15 TWh Renewables Increase	2.907	2.92	1.580	4.252	0.40
Combined Policy	3.660	3.65	2.306	5.014	0.50
Baseline AI Patents/Country-Year	725.9				100.0

Notes: Additional AI patents per country-year. Point estimates from PMG model. Median effects and confidence intervals from Monte Carlo simulation (10,000 draws). % Change relative to baseline of 725.9 patents per country-year.
Source: Authors' research

The 20% electricity price reduction yields an estimated increase of 0.75 additional AI patents per country-year (95% CI: 0.506-0.996), representing a 0.10% increase relative to the baseline. While statistically significant and precisely estimated, this effect is economically modest. The 15 TWh increase in renewable energy produces a substantially larger effect, generating an estimated 2.92 additional AI patents per country-year (95% CI: 1.58-4.25), corresponding to a 0.40% increase over baseline levels. This policy intervention demonstrates approximately 3.9 times greater effectiveness than the electricity price reduction.The combined policy scenario yields approximately additive effects, resulting in 3.65 additional patents per country-year (95% CI: 2.306-5.014), representing a 0.50% increase over the baseline. The combined effect (3.65) closely approximates the sum of individual policy effects (0.75 + 2.92 = 3.67), with a difference of only 0.013 patents, confirming the validity of treating these policies as complementary rather than substitutive.

3.4. Economic significance and effect magnitudes

Table 4 provides a systematic assessment of the economic significance of our estimated policy effects. All policy interventions produce effects that are statistically significant and economically interpretable, though modest in magnitude relative to current AI patenting levels.

Table 4. Economic significance assessment

Metric	Value	Interpretation
Current AI Patents (Mean)	725.9	Patents per country-year baseline
Price Policy Effect	0.75 (0.10%)	Modest but measurable increase
Renewables Policy Effect	2.92 (0.40%)	Small to moderate increase
Combined Policy Effect	3.65 (0.50%)	Additive effects, economically meaningful
Policy Comparison	Renewables more effective	Renewables 3.9x more effective

Source: Authors' research

The effect magnitudes, while statistically robust, represent less than 0.50% of current AI patenting activity even under the combined policy scenario. This finding suggests that energy costs and renewable energy availability, while significant factors in AI innovation, are not primary constraints on AI patent activity in most countries. The results indicate that energy policies alone would be insufficient to boost AI innovation dramatically and should be considered as components of broader innovation strategies rather than standalone solutions (Piwowar, 2025; Vasylieva et al., 2025).

3.5. Robustness and validation checks

Table 5 summarizes the comprehensive validation and robustness checks conducted to ensure the reliability of our results. All checks confirm that our findings are statistically sound and economically reasonable.

Table 5. Validation and robustness checks

Check	Result	Status
Effect Magnitude Reasonable	All effects < 10-50 patents	PASS
Percentage Impact Reasonable	All effects < 5-10% of baseline	PASS
Combined Effect Additivity	Difference: 0.013	PASS
Price Effect Significance	t = 6.06	Significant
Renewables Effect Significance	t = 4.29	Significant
Sample Size	898 observations	Adequate
Model Specification	PMG with error correction	Appropriate

Source: Authors' research

The magnitude checks confirm that all estimated effects fall within reasonable bounds, with no single policy intervention producing implausibly significant changes in AI patent activity. The percentage impact assessment verifies that all effects represent modest fractions of baseline activity, consistent with energy factors being important but not dominant drivers of AI innovation. The additivity test for combined policy effects demonstrates that the two policy interventions operate through largely independent mechanisms, with minimal interaction effects. This finding supports the interpretation that electricity price reductions and renewable energy expansion influence AI innovation through distinct pathways. Both primary coefficients achieve conventional levels of statistical significance with t-statistics well above the critical value of 1.96. The sample size of 898 observations provides sufficient power to detect policy-relevant effect sizes. At the same time, the PMG specification with error correction represents an appropriate econometric approach for this type of cross-country panel analysis.

3.6. Monte Carlo simulations

Figure 1 shows the estimated policy effects on AI patent publications, with point estimates and 95% confidence intervals derived from Monte Carlo simulations (10,000 draws). The renewable energy policy has the most significant effect, with a magnitude of 2.92 additional patents per country-year, followed by the combined policy scenario, which yields 3.65 additional patents. The electricity price reduction yields the smallest increase, at 0.75%. The non-overlapping confidence intervals between the renewable energy and price reduction policies confirm that renewable energy expansion is significantly more effective than electricity price subsidies for promoting AI adoption, with the combined policy bearing cumulative effects.

The simulations in Figure 2 demonstrate the effects of a 20% decrease in industrial electricity prices through 10,000 Monte Carlo simulations that use PMG model parameter uncertainty. The distribution shows normal characteristics with its central value at 0.75 additional AI patents per country-year and all values remain above zero which proves the statistical significance of price reduction effects. The narrow distribution pattern shows that parameter estimation is precise because 95% of simulated results fall between 0.506 and 0.996 additional patents, which demonstrates the strong stability of policy effect despite its small impact.

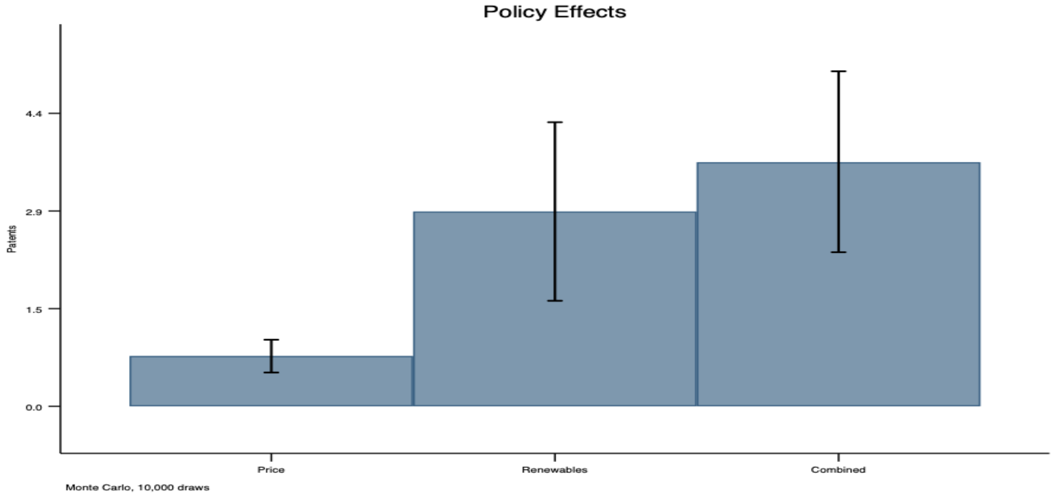

Figure 1. Policy comparison chart
Source: *Authors' research*

Figure 2. Price reduction Monte Carlo distribution
Source: Authors' research

The probability distribution for renewable energy policy effects appears in Figure 3 (10,000 Monte Carlo simulations) of a 15 TWh increase in renewable generation. The distribution shows 2.92 additional AI patents per country-year as its central value. Its spread exceeds the price policy distribution because of higher parameter uncertainty in the renewable energy coefficient. The distribution shows positive results in all simulations while remaining distinct from zero, and 95% of outcomes fall between 1.58 and 4.25 additional patents, which demonstrates both statistical significance and superior effects of renewable energy policies over price interventions.

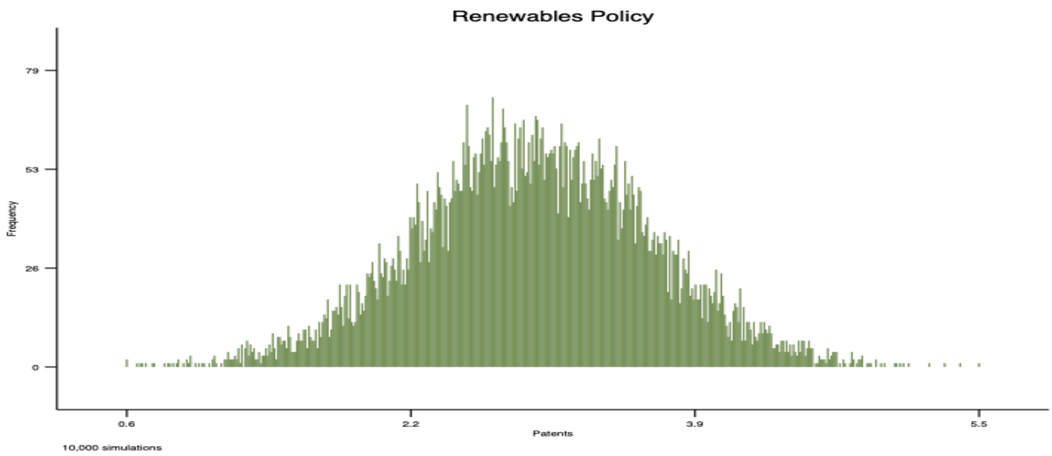

Figure 3. Renewables Policy Effect Monte Carlo distribution
Source: Authors' research

Figure 4 displays a summary of all policy scenarios. It illustrates the connection between point estimates and uncertainty ranges and distributional properties, which explains why renewable energy policies perform better than electricity price reductions in stimulating AI innovation. The side-by-side distribution presentation shows that price policy estimates are more precise than renewable energy expansion effects, which are larger but more uncertain. Both policies lead to a statistically significant positive impact on AI patent activity.

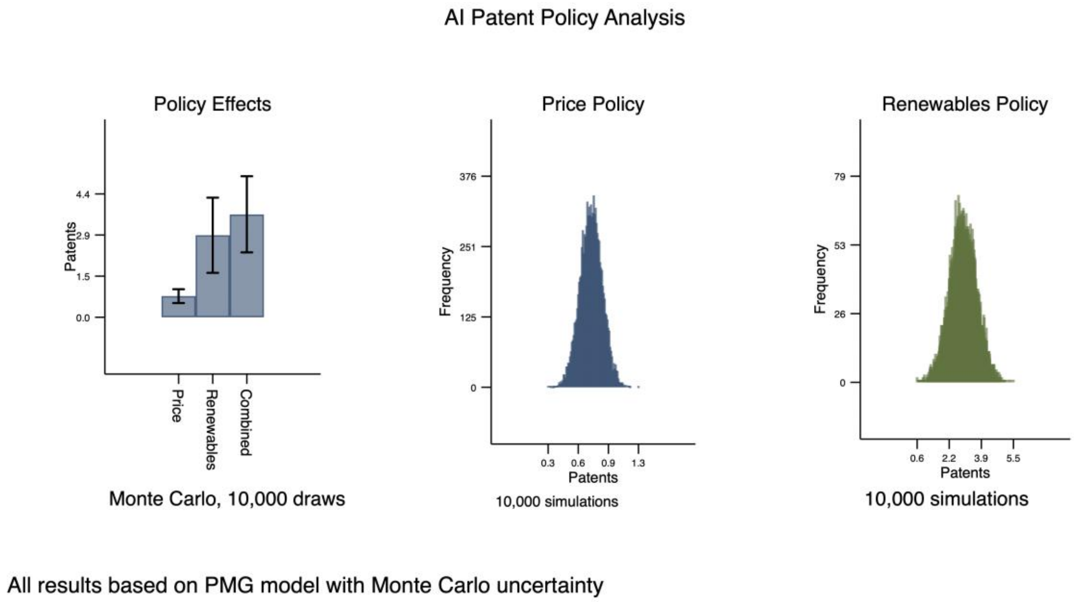

Figure 4. AI Policy Analysis
Source: Authors' research

4. Discussion

These distributional analyses support our main conclusions regarding the statistical significance and relative magnitudes of the estimated policy effects, while providing additional insight into the precision and uncertainty surrounding our estimates.

The research adds significant value to existing studies on AI adoption and the diffusion of innovation. The research demonstrates that energy costs, together with renewable energy infrastructure, act as new factors that influence technology adoption, especially for computationally intensive innovations such as artificial intelligence.

4.1. Renewable energy as a strategic factor in AI adoption

The results from our research contradict the conventional view that energy functions only as operational expenses within established technology adoption models. The statistically significant coefficients of electricity prices (-0.690, t = -6.06) and renewable energy generation (0.194, t = 4.29) show that energy factors function as independent determinants instead of general cost elements. Rogers'(2003) diffusion of innovation framework receives expansion through our research because we identify energy infrastructure as a distinct AI adoption barrier that previous studies have failed to recognize. The current empirical research confirms that energy considerations play a major role in shaping technology adoption choices. The study by Stucki (2019) shows that firms with high energy costs experience bigger productivity gains from green energy technology investments, and only these firms with the highest energy costs show positive effects. The results from our study confirm the findings of Stucki (2019) by showing that energy infrastructure impacts national AI innovation capacity rather than individual firm decisions. The positive impact of renewable energy generation on AI patent publications exceeds that of electricity price reductions by a factor of 3.9, which indicates that sustainability and energy security factors may matter more than cost reduction in AI adoption decisions for firms. The discovery challenges economic models of innovation adoption because renewable energy infrastructure provides a new strategic benefit in digital economy operations. The results from Adão et al. (2022) support our findings because they show renewable technology adoption requires sophisticated optimization approaches where infrastructure spending provides greater value than basic cost reduction strategies.

4.2. Extending the technology-organization-environment theory for AI adoption

Our research findings validate the expansion of the Technology-Organization-Environment (TOE) framework by showing that energy infrastructure should be considered a vital environmental factor. The TOE framework, which Tornatzky and Fleischer (1990) developed, has proven effective in numerous studies about technology adoption across different settings (Awa et al., 2017; Oliveira and Martins, 2011). The traditional TOE models identify competitive pressure together with regulatory environment and partner networks as essential environmental determinants that influence technology adoption (Baker, 2012; Zhu and Kraemer, 2005). The TOE framework has started to receive recognition for needing supplementary contextual elements in its recent applications. Research on green technology adoption now includes environmental sustainability elements as part of its environmental context (Arvanitis and Ley, 2013; Stucki and Woerter, 2016). Our research suggests that energy-intensive technologies necessitate an energy environment, characterized by its price volatility and infrastructure maturity, to be considered equally vital elements, which current AI adoption theories often overlook. The large size of our coefficients shows that energy factors may be more critical than traditional environmental factors for computationally intensive technologies. This finding supports recent calls for extending the TOE framework to include sustainability dimensions (as proposed in the TOES framework by Silva et al., 2024). However, our study identifies energy infrastructure explicitly as a distinct environmental factor rather than a general sustainability construct. This has significant implications for understanding heterogeneous adoption patterns across different geographic regions and industrial sectors, as firms' access to renewable energy infrastructure varies substantially based on location and scale of operations.

4.3. Resource-based view and dynamic capabilities

Our research indicates that renewable energy infrastructure access should be treated as a strategic resource instead of a commodity input according to a Resource-Based View perspective. The RBV framework , which describes how valuable rare inimitable non-substitutable resources (VRIN) generate sustainable competitive advantage (Barney, 1991), has gained popularity for studying technology adoption and innovation (D'Oria et al., 2021; Madhani, 2010). The characteristics of renewable energy access match those of resources that build sustainable competitive advantage because it provides value through cost reduction (0.194 coefficient), exists in limited supply, cannot be easily replicated due to high infrastructure costs, and serves as an essential substitute for energy-intensive AI applications. Our study expands current RBV research in technology domains by showing how technological capabilities function as strategic resources (Mikalef and Pateli, 2017; Yang et al., 2021). The RBV literature shows through meta-analytic evidence that technological resources enhance operational efficiency but do not directly boost financial performance (Liang et al., 2010). Our research shows that energy infrastructure functions as a particular technological resource that affects innovation results through a distinct process by making innovation possible instead of generating it directly. The research supports the dynamic capabilities literature by showing that AI adopters need to build new organizational abilities for energy forecasting , infrastructure planning , and efficiency optimization to succeed. The research identifies energy-related dynamic capabilities as a new competitive advantage in digital transformation initiatives, which enhance existing knowledge about IT capabilities and organizational performance (Nevo and Wade, 2010).

4.4. Policy implications and innovation systems

The simulation results from our policy analysis deliver insight for innovation systems research. The results show that infrastructure development policies that increase renewable energy generation by 15 TWh produce more innovation effects (2.92 additional patents per country-year) than cost reduction policies that decrease electricity prices by 20% (0.75 additional patents). The research supports current discussions about the most suitable approach to design innovation policies (Magro & Wilson, 2019; Weber & Rohracher, 2012). The innovation systems literature demonstrates that effective innovation policies need to understand how different system components interact with each other (Hekkert et al., 2007; Suurs & Hekkert, 2009). The empirical findings from innovation policy research support our results by demonstrating that infrastructure development produces better technology adoption outcomes than financial incentives (Zhao et al., 2019; Lyeonov et al., 2025). The "transformative innovation policy" approach receives support from our findings because it emphasizes system-level interventions that remove structural barriers to innovation adoption

(Schot & Steinmueller, 2018). The small size of these effects (less than 0.50% of baseline AI patenting levels) indicates that energy policies alone are insufficient to accelerate AI innovation dramatically. This finding aligns with systems approaches to innovation policy that emphasize the need for coordinated interventions across multiple domains, including R&D investment, human capital development, and institutional support (Lundvall, 2010; Edquist, 2005; Juracka & Valaskova, 2025). Recent reviews of innovation policy effectiveness have similarly found that single-instrument policies typically have limited impact on innovation outcomes, supporting the need for policy mix approaches (Flanagan et al., 2011).

Conclusion

Our research is a pioneering study giving empirical evidence of energy as a distinct adoption factor (not just generic cost) Here, we offer quantitative evidence that the effects of renewable infrastructure (3.9x) outweigh the price impact in AI adoption processes. The research shows that energy expenses, together with renewable power systems, function as essential yet unexamined elements that influence AI development. The research enhances technology adoption theory by showing that energy functions as a strategic element that produces effects that extend past standard cost factors. The study suggests that understanding the relationship between energy and innovation is crucial for both theoretical development and policy creation in the digital and AI economy, given the significant energy consumption associated with digital technology.

The research results deliver multiple useful practical applications for policymakers, companies, and innovation ecosystem builders. The study provides empirical proof that renewable energy infrastructure investments produce 3.9 times greater AI innovation stimulation than electricity price subsidies; thus, policymakers should choose infrastructure development over short-term cost reduction measures for innovation policy design. Strategic firms can use these findings to make better decisions about AI adoption and R&D location by considering energy infrastructure access because renewable energy proximity offers sustainable competitive advantages that extend beyond cost benefits. The research indicates that energy infrastructure quality should be included in country-level risk assessments and investment location analyses for multinational corporations and investors who focus on computationally intensive technologies. Energy utilities and infrastructure developers can better understand how their investments create innovation spillovers, which could help justify renewable energy projects through economic development advantages instead of traditional energy generation metrics (Tomczyk et al., 2025; Wojciechowski et al., 2025). Sector-specific evidence from electric vehicle charging infrastructure on international transport corridors confirms that energy and transport investments simultaneously support decarbonisation and innovation-driven modernization (Vovk et al., 2025). Innovation ecosystem developers, together with regional planners, can use these findings to create technology cluster development approaches that treat energy infrastructure as a fundamental component instead of an optional feature, thus enabling the creation of sustainable innovation hubs that unite renewable energy access with conventional innovation support systems.The constraints of our study suggest future research directions. Our country-level analysis fails to demonstrate how different types of firms, industries, and AI applications respond to energy factors in distinct ways. Future research using firm-level data will reveal how various segments of the AI innovation ecosystem experience varying energy-related challenges.

The study demonstrates that energy factors significantly impact AI innovation, yet it does not show precisely how energy costs and renewable infrastructure influence patent production. Future studies need to determine if energy effects on patent production occur mainly through direct cost reductions, AI research facility location choices, or national sustainable technology development signals. Our research depends on patent publications as innovation metrics, yet this method might not measure all types of AI innovation, especially applied research activities that do not produce patentable outcomes.

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