CHEMICAL ENGINEERING TRANSACTIONS
VOL. 120, 2025

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.cetjournal.it

Guest Editors: Bing Shen How, Viknesh Andiappan, Denny K.S. Ng, Hon Loong Lam, Petar S. Varbanov

ISBN 979-12-81206-21-2; **ISSN** 2283-9216

DOI: 10.3303/CET25120046

Harnessing AI for Sustainability: Evidence on Energy Efficiency and Green Innovation

Yong Zhou[a], Wei Bu[a,*], Sue Lin Ngan[b], Donghui Zhao[c]

[a]School of Economics and Management ,Beijing Jiaotong University, Haidian District,Beijing 100044,China
[b]The University of Tokyo, Organization for Programs on Environmental Sciences, Graduate School of Arts and Sciences, 3-8-1 Komaba, Meguro-ku, Tokyo 153-8902, Japan
[c]UKM-Graduate School of Business, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor MALAYSIA
bwei@bjtu.edu.

Despite the growing enthusiasm for artificial intelligence (AI) as a sustainability enabler, empirical evidence on its real-world environmental benefits, particularly in emerging markets, remains limited and fragmented. In particular, how AI adoption affects firm-level energy consumption, and through which mechanisms, has yet to be fully understood. This study examines the impact of artificial intelligence (AI) adoption on corporate energy consumption, utilizing panel data from over 32,000 firm-year observations of Chinese-listed firms between 2011 and 2022. AI adoption is measured via Word2Vec-based textual analysis of annual reports. Fixed-effects regressions show that higher AI adoption is associated with significantly lower firm-level energy consumption. The study identifies green innovation, proxied by the number of green patent applications, as a key mediating mechanism through which AI reduces energy use. Heterogeneity analysis further reveals that the energy-saving effect of AI is more pronounced among large firms, privately owned enterprises, firms in non-energy-intensive industries, and those operating in digitally underdeveloped regions. These findings enrich the literature on AI-driven sustainability by clarifying how and under what conditions AI adoption contributes to improved energy efficiency. The study also offers insights for business leaders and policymakers aiming to integrate digital technologies into national low-carbon development strategies.

1. Introduction

Amid intensifying environmental pressures and rapid digital transformation, artificial intelligence (AI) has emerged as a critical enabler of corporate sustainability (Yang et al., 2024). In particular, whether and how AI adoption contributes to reducing corporate energy consumption has gained increasing attention from both academia and policymakers. While earlier studies have recognized AI's potential to enhance operational efficiency and intelligent decision-making (Bai et al., 2024), empirical validation of its environmental impact, especially within developing economies, remains insufficient.

Energy consumption is a pivotal indicator of environmental performance. In China, industrial sectors account for more than 65 % of the country's national energy use and are significant contributors to carbon emissions (IEA, 2022). Improving energy efficiency has thus become central to the country's dual carbon goals and green development agenda. AI applications, such as predictive maintenance, energy demand forecasting, and smart manufacturing, are believed to reduce energy waste. However, large-scale empirical studies remain scarce.

To bridge this gap, this study examines the impact of AI adoption on firm-level energy consumption, utilizing a panel dataset comprising over 32,000 firm-year observations from Chinese A-share listed companies between 2011 and 2022. Drawing on the innovation-driven sustainability literature (Ibrahim et al., 2024), this study further examines whether green innovation acts as a mediating channel through which AI adoption enhances energy efficiency. Meanwhile, heterogeneity analyses explore whether the AI-energy nexus is shaped by firm size, ownership, industry energy intensity, and regional digital development.

This study draws upon two complementary perspectives. The Dynamic Capabilities Theory (Teece, 2007) posits that firms enhance performance by reconfiguring internal resources in response to environmental demands. Thus, AI adoption may enable energy efficiency through adaptive operations and data-driven optimization. The

Paper Received: 16 June 2025; Revised: 29 August 2025; Accepted: 4 October 2025
Please cite this article as: Zhou Y., Bu W., Ngan S.L., Zhao D., 2025, Harnessing AI for Sustainability: Evidence on Energy Efficiency and Green Innovation, Chemical Engineering Transactions, 120, 271-276 DOI:10.3303/CET25120046

Green Innovation Pathways Theory suggests that digital technologies contribute to sustainability indirectly by stimulating innovation, providing a logical basis for the mediating role of green innovation (Chen et al., 2025). Figure 1 illustrates the conceptual framework. Accordingly, the study proposes the following hypotheses: H1: AI adoption significantly reduces firm-level energy consumption. H2: Green innovation mediates the relationship between AI adoption and energy consumption.

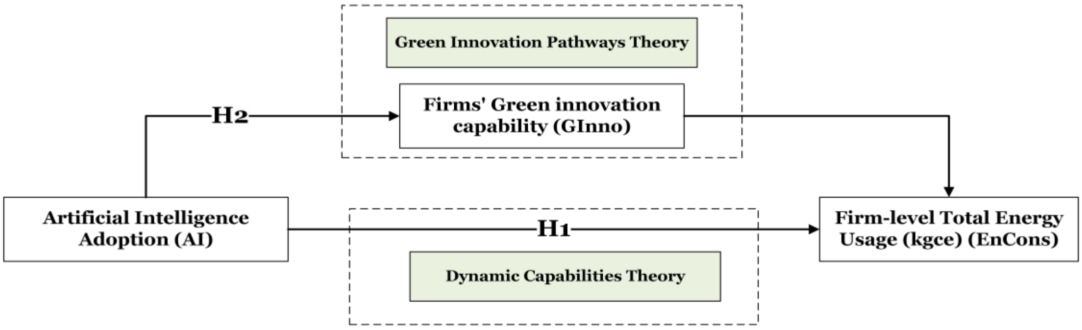

Figure 1: Conceptual Framework.

This paper makes three key contributions to the current literature. First, it provides robust evidence of the relationship between AI adoption and energy consumption, utilizing firm-level panel data. Second, it identifies green innovation as a key mechanism, expanding the understanding of how AI drives environmental outcomes. Third, it uncovers context-specific differences in the effectiveness of AI, offering practical insights for targeted policy and management strategies. The remainder of this paper is structured as follows: Section 2 introduces the empirical methodology and variable construction. Section 3 presents the main results, including mediation and heterogeneity analyses. Section 4 discusses the conclusions and policy implications.

2. Methodology

This section outlines the empirical strategy adopted to examine the relationship between AI adoption and corporate energy consumption， including details on the construction of the sample, variable definitions, and econometric specifications, with a particular focus on addressing endogeneity and identifying the mediating role of green innovation. To enhance the interpretability of the estimates, this research relies on a within-firm identification strategy. Firm fixed effects absorb all time-invariant unobservable heterogeneity (e.g., baseline technology endowments, management culture), and year-fixed effects capture common macroeconomic or policy shocks. This specification focuses on how within-firm changes in AI adoption are associated with subsequent changes in energy consumption, which mitigates concerns about spurious correlations driven by cross-sectional differences.

2.1 Data and Sample

The study utilizes a balanced panel dataset comprising all A-share listed firms in China over the period 2011–2022. Financial and operational data are drawn from the CSMAR databases, while green patent data are retrieved from the China National Intellectual Property Administration (CNIPA). To ensure consistency, this study excludes firms from the financial sector and those with missing values on key variables. The final dataset consists of over 32,000 firm-year observations.

2.2 Measurement of Key Variables

AI Adoption (AI_intensity): Following Zhong et al. (2022) and Chen and Srinivasan (2024), this study applies a Word2Vec-based textual analysis to construct a firm-level AI adoption index (Chen and Srinivasan, 2024). Annual report texts (2011–2022) are collected from Sina Finance and supplemented with patent texts from the IRPDB database. The AI keyword dictionary is generated in three steps: (1) manually selecting 52 seed terms from industry reports and WIPO lists (e.g., “artificial intelligence,” “machine learning”), (2) expanding these terms using a Skip-gram Word2Vec model trained on annual reports and patent texts, and (3) removing duplicates and irrelevant items, yielding a final dictionary of 73 AI-related terms. This study incorporates this dictionary into the Jieba tokenizer to improve segmentation accuracy and calculate the frequency of AI terms in each firm’s annual report. The AI adoption index equals the natural logarithm of (1 + AI term frequency). This index captures the breadth and depth of AI engagement beyond binary disclosure measures.

Energy Consumption (EnCons): Firm-level energy consumption is measured in kilograms of coal equivalent (kgce), derived from reported energy usage and standardized across different sources (e.g., electricity, fuel, gas) using national conversion coefficients. The natural logarithm of energy consumption (ln_EnCons) is used to stabilize variance.

Green Innovation (GreenInno): To explore the mediating mechanism, this study uses the annual count of green invention patents as a proxy for firms' green innovation output (Fang and Li, 2024). Patents are filtered based on CPC codes aligned with climate-related technologies.

This research includes a comprehensive set of control variables following established literature (Kulkov et al., 2024): Firm Size (lnAssets), Profitability (ROA), Leverage (Lev), Growth (Sales growth rate), Firm Age (Age since listing), Board Size (lnBoard), firm-level and year fixed effects.

2.3 Econometric Strategy

To examine the effect of AI adoption on corporate energy consumption, this study estimates the following baseline fixed-effects Model (1). Where, μ_i and λ_t Capture firm and year fixed effects, respectively, and $Control_{i,t}$ Denotes the control variables. Standard errors are clustered at the firm level to adjust for autocorrelation and heteroscedasticity.

$$ln\_EnCons_{i,t} = \alpha_0 + \alpha_1 AI_{i,t} + Control_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{1}$$

To assess the mediating role of green innovation capability, this study follows a multi-step estimation procedure consistent with Baron and Kenny (1986) and further confirms the mediation pathway using bootstrapped indirect effects and Sobel tests (Baron and Kenny, 1986). The first-stage model estimates the impact of AI on green innovation:

$$GInno_{i,t} = \beta_0 + \beta_1 AI_{i,t} + Control_{i,t} + \mu_i + \lambda_t + \nu it \tag{2}$$

The second-stage model assesses the joint impact of AI and green innovation on energy consumption:

$$EnCons_{i,t} = \theta_0 + \theta_1 AI_{i,t} + \theta_2 GInno_{i,t} + Control_{i,t} + \mu_i + \lambda_t + \xi it \tag{3}$$

If β_1 and θ_2 are significant, the coefficient θ_1 is reduced in magnitude compared to the main effect model, the indirect effect $\beta_1 * \theta_2$ is statistically significant based on bootstrapping or Sobel statistics. This study further explores heterogeneity by examining whether the impact of AI adoption varies across different firm contexts. The sample is divided into subgroups based on firm size (large vs. small), ownership type (SOEs vs. non-SOEs), industry energy intensity (high vs. low, per NEA classification), and regional digital development (high vs. low digital index). Separate regressions are conducted for each subgroup to assess variation in AI's effectiveness across institutional and structural dimensions.

3. Empirical Results

3.1 Descriptive Statistics and Correlation Analysis

Table 1 presents summary statistics for key variables. The dependent variable, firm-level energy consumption (EnCons), averages 1,512 kgce with a standard deviation of 300.6, indicating substantial variation across firms. The AI adoption index has a mean of 0.837 but a median of 0, highlighting a skewed distribution—most firms show minimal engagement, while a smaller subset demonstrates intensive AI activity. This skewness reflects the uneven diffusion of emerging technologies and motivates later heterogeneity analysis. Firm size (log of assets) centres around 22.17, indicating the sample is composed mainly of large firms. Other control variables, including profitability (ROA: mean 4.25 %), leverage (41.3 %), growth, board size, and firm age, show distributions consistent with financial norms and prior literature. No extreme outliers are observed, and the variation is sufficient to support regression-based inference.

Table 1: Descriptive Statistics of Key Variables

Variable	N	Mean	SD	Min	p50	Max
EnCons	32,967	1,512	300.6	874.1	1,545	2,097
AI	36,353	0.837	1.179	0	0	4.860
Size	36,415	22.17	1.297	19.68	21.98	26.09
ROA	36,414	0.0425	0.0650	-0.221	0.0411	0.216
Lev	36,415	0.413	0.207	0.0521	0.402	0.894
Growth	36,395	0.159	0.374	-0.573	0.103	2.213
Board	36,374	2.118	0.198	1.609	2.197	2.708
FirmAge	36,415	2.916	0.338	1.386	2.944	3.526

In support of the model's empirical validity, this research conducts preliminary correlation and multicollinearity diagnostics. Pairwise correlations (Table 2) reveal that AI adoption is negatively associated with energy consumption and positively correlated with green innovation, consistent with the hypothesized direction of effects. These relationships are moderate in strength and align with theoretical expectations regarding the dual environmental and innovation roles of AI. To assess potential multicollinearity, this research further calculates Variance Inflation Factors (VIFs) for all independent variables. As shown in Table 2, all VIF values are well below the conventional threshold of 10, with most values under 2.0, indicating that no severe multicollinearity exists among the covariates. These diagnostics confirm the appropriateness of the regression model specifications and enhance confidence in the estimation results.

Table 2: Multicollinearity Test

	Pairwise Correlation Matrix								VIFs Test	
	EnCons	AI	Size	ROA	Lev	Growth	Board	FirmAge	VIF	1/VIF
EnCons		0.310***	0.130***	-0.029***	-0.019***	-0.041***	-0.141***	0.431***	—	—
AI	0.281***		0.027***	0.033***	-0.066***	0.042***	-0.110***	0.073***	1.040	0.966
Size	0.131***	0.003		-0.031***	0.495***	0.042***	0.245***	0.204***	1.500	0.667
ROA	-0.054***	-0.016***	0.027***		-0.404***	0.358***	-0.004	-0.110***	1.360	0.737
Lev	-0.026***	-0.086***	0.487***	-0.362***		-0.001	0.134***	0.155***	1.670	0.599
Growth	-0.033***	0.018***	0.041***	0.269***	0.020***		-0.007	-0.107***	1.110	0.905
Board	-0.143***	-0.114***	0.264***	0.019***	0.140***	-0.008		0.038***	1.090	0.917
FirmAge	0.447***	0.064***	0.175***	-0.094***	0.166***	-0.070***	0.033***		1.060	0.948
t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1									MeanVIF	1.260

3.2 Main Regression Results

Table 4 presents the baseline regression results assessing the impact of AI adoption on firm-level energy consumption, using the full sample of A-share listed firms from 2011 to 2022. Across all model specifications (Columns 1-4), the coefficient on AI is consistently negative and statistically significant at the 1 % level. The result confirms that increased AI engagement is associated with lower energy use, supporting Hypothesis 1. In the preferred model, a one-unit increase in the AI intensity index corresponds to a 0.1 % reduction in energy consumption, holding other factors constant. While the effect appears small in magnitude, it can translate into sizable aggregate savings given the scale of industrial energy demand. Control variables behave as expected: more profitable and less leveraged firms consume less energy. The stability of estimates across models with year and industry-fixed effects strengthens the robustness of the findings. Overall, the results suggest that AI adoption enhances energy efficiency at the firm level, highlighting AI's potential as a technological enabler of low-carbon operations in emerging markets.

Table 4: Baseline Regression: Effect of AI on Energy Consumption

	(1)	(2)	(3)	(4)
VARIABLES	ln_EnCons	ln_EnCons	ln_EnCons	ln_EnCons
AI	-0.001***	-0.001***	-0.001**	-0.001***
Year	Yes	Yes	Yes	Yes
Ind			Yes	
Id				Yes
Observations	32,943	32,932	32,932	32,710
R-squared	0.001	0.001	0.001	0.960
Number of years	12	12	12	12
r2_a	0.000141	0.000289	0.000205	0.954
F	16.66	3.931	1.657	2.037
	t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1			

3.3 Mediation Test: The Role of Green Innovation

To examine the mediating role of green innovation, this study estimates a two-stage regression model (Table 5). In the first stage, AI adoption significantly increases green innovation output ($\beta = 0.003$, $p < 0.01$), measured by the number of green patent applications. In the second stage, when both AI intensity and green Innovation are included in the regression, the coefficient on green Innovation is negative and significant ($\beta = -0.006$, $p < 0.05$), while the coefficient on AI remains negative but becomes smaller in magnitude, suggesting partial mediation. To formally validate the mediation pathway, a Sobel test is conducted, yielding a statistically significant Z-value of -2.369 ($p < 0.05$), which confirms the presence of an indirect effect. Moreover, the bootstrap confidence interval for the indirect effect [-0.00055, -0.00033] does not include zero, reinforcing the robustness of the mediation result. These findings suggest that green innovation acts as a transmission mechanism through which AI adoption enhances energy efficiency. Overall, the empirical evidence supports Hypothesis 2 (H2), highlighting innovation-driven pathways in the digital sustainability transformation.

Table 5: Mediation Effect of Green Innovation

VARIABLES	(1) GreenInno	(2)GreenInno
AI	0.003***	-0.001**
	(0.001)	(-2.54)
GreenInno		-0.006**
		(-2.09)
Control variables	Yes	Yes
Sobel Z	-2.369**	
Bootstrap (95 % conf. interval)	[-0.00055, -0.00033]	
Observations	35,795	32,212
R-squared	0.001	0.960
Number of firms	4,885	
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		

3.4 Heterogeneity Analysis

To investigate whether the energy-saving effect of AI adoption varies across firm contexts, this study conducts subgroup regressions based on four dimensions: firm size, ownership type, industry energy intensity, and regional digital economy development (DEI). Specifically, large versus small firms are split at the annual median of total assets, ownership type distinguishes state-owned enterprises (SOEs) and private firms based on CSMAR classifications, energy-intensive versus non-energy-intensive industries are identified using policy definitions and industry codes from the National Energy Administration, and regions with high versus low DEI are defined by the provincial-level digital economy index, using the annual median as the cutoff.

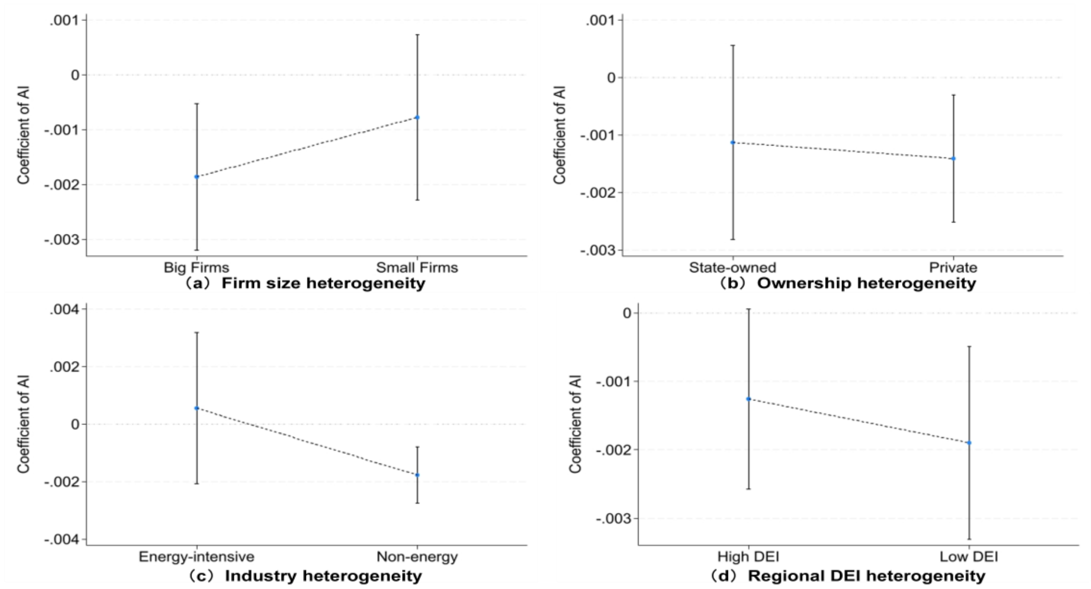

Figure 2: Heterogeneous Effects of AI on Energy Consumption

Figure 2 summarizes the estimated coefficients of AI across subgroups, along with 95 % confidence intervals. In Figure 2 (a), AI has a significantly more substantial negative effect on energy consumption among large firms, suggesting that scale enables more effective deployment of AI technologies for energy optimization. Private firms exhibit a more pronounced reduction in energy use than state-owned enterprises, as shown in Figure 2 (b), which may reflect more substantial market incentives and less rigid governance structures. Next, the AI effect is more pronounced in non-energy-intensive industries than in heavy industries (Figure 2. (c)). This implies that flexible manufacturing systems or service-oriented sectors may be more adaptable to intelligent process optimization. Lastly, firms located in digitally underdeveloped regions exhibit stronger responsiveness to AI, suggesting that the marginal gains from digital adoption are larger where baseline digitalization is weaker (Figure 2. (d)). These findings confirm that firm-level and regional heterogeneity play a critical role in shaping the environmental returns to AI adoption, reinforcing the value of targeted digital sustainability strategies.

4. Conclusion and Policy Implications

This study examines the environmental implications of artificial intelligence (AI) adoption in emerging economies, with a focus on firm-level energy consumption. By constructing a novel AI intensity index from corporate annual reports and employing fixed-effects panel regressions on Chinese listed firms (2011–2022), this study finds robust evidence that AI adoption significantly reduces energy consumption. Mediation analysis further reveals that green innovation serves as a key transmission mechanism, while heterogeneity analysis highlights that firm size, ownership, industry type, and regional digital development moderate the strength of AI's environmental impact. Some scholars note that AI development may raise energy use due to computational demands, but firm-level evidence in this study shows operational AI applications deliver net savings by improving efficiency.

From a theoretical perspective, this study contributes to the growing literature on digital sustainability by shifting the focus from macro-level efficiency gains to micro-level energy behavior (Guandalini, 2022). It extends prior work by quantifying the environmental return on AI investment and identifying green innovation as an endogenous pathway linking digital transformation to energy efficiency. Moreover, the results provide new evidence on conditional effects under organizational and contextual variation, responding to calls for more disaggregated ESG analyses (Donghui et al., 2025). Practically, the findings offer clear implications for managers and policymakers. Firms should align AI adoption not only with operational goals but also with sustainability, particularly through innovation-driven strategies. Policymakers are advised to support digital infrastructure and incentives in lagging regions and sectors where AI can deliver higher marginal energy gains. Limitations of this study include its reliance on disclosed AI-related information in corporate reports, which may not fully capture the actual depth of implementation or internal adoption dynamics. Future research could benefit from incorporating more granular, machine-level AI deployment data, extending the analysis to include social and governance dimensions of sustainability beyond environmental performance alone.

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