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The impact of China's artificial intelligence development on urban energy efficiency

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Energy efficiency has become a central concern amidst shifting global economic conditions, intensifying climate variability, and geopolitical tensions that have fundamentally reshaped energy consumption and production patterns. Improving energy efficiency is vital for addressing these challenges and advancing the United Nations sustainable development goals (SDGs). Artificial intelligence (AI) has emerged as a transformative tool in this context, offering innovative solutions to complex energy-related problems. While prior research has examined the energy impacts of digital technologies broadly, few studies have isolated the specific contributions of AI. Addressing this gap, our study investigates the influence of AI development on energy efficiency and explores the mechanisms by which AI drives this improvement. Using a fixed-effects model based on prefecture-level data in China, we find that AI significantly enhances energy efficiency. This effect is primarily mediated through two channels: (1) promoting green technological innovation and (2) facilitating the rationalization of industrial structures. Moderation analyses reveal that AI's positive impact is more pronounced in cities with strong informal environmental regulations and less significant in those with weaker oversight. Additionally, AI adoption yields greater efficiency gains in declining and regenerating resource-based cities compared to their growing and mature counterparts. These findings highlight AI's pivotal role in advancing energy efficiency and provide actionable guidance for policymakers. To fully realize these benefits, decision-makers should strengthen informal environmental governance and prioritize AI deployment in transitioning resource-based cities. Such measures can help address pressing global energy challenges and accelerate progress toward sustainable development.

Keywords Artificial intelligence, Energy efficiency, Green technology innovation, Industrial structure rationalization, Informal environmental regulations, Resource-based cities

In recent decades, as globalization has accelerated and environmental challenges have intensified, sustainable development has emerged as a shared global priority[1]. In 2015, the United Nations launched the 17 Sustainable Development Goals (SDGs), urging countries to align economic growth with environmental responsibility and aiming for substantial progress by 2030 to ensure a safer and more equitable future[2]. Among these goals, energy efficiency plays a pivotal role in achieving sustainable development[3,4]. In the face of rising geopolitical tensions[5] intensifying climate change[6] and growing uncertainty, the efficient use of energy has become essential for national development.

Extensive research has identified multiple determinants of energy efficiency, including financial development[7,8] carbon emission trading[9–11] fiscal decentralization[12] manufacturing agglomeration[13,14] and policy uncertainty[15]. These factors, grounded in diverse theoretical frameworks, influence energy efficiency through different mechanisms. More recently, digital technologies have attracted growing scholarly attention for their transformative impact on energy systems. Technological advancements are reshaping energy production, operations, and transmission processes. Within the broader context of sustainable development, digital innovation is accelerating the transition toward greener, low-carbon practices[16]. These technologies have been shown to enhance energy efficiency, modernize energy infrastructure, and restructure energy consumption patterns[16–18]. Drawing on the theory of technological innovation, several studies underscore the beneficial effects of digital transformation—highlighting its role in upgrading industrial structures, optimizing energy use, and improving overall efficiency[19]. However, some scholars caution that the development of digital infrastructure may also entail adverse environmental consequences, potentially undermining sustainability objectives[6]. Among the emerging technologies, artificial intelligence (AI) has distinguished itself as a transformative driver of future

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innovation. In 2022, the number of AI-related patents granted annually has surpassed 62,000—more than seven times the figure recorded in 2018. By the end of 2023, AI systems had equaled or exceeded human performance on standardized assessments in domains such as image classification, basic reading comprehension, natural language reasoning, multilingual understanding, and visual reasoning. Only in areas such as visual common-sense reasoning and complex mathematical problem-solving does AI still lag behind human capabilities (Artificial Intelligence Index Report, 2024).

The integration of AI into the energy sector is increasingly recognized for its transformative potential to accelerate the transition to sustainable energy sources and enhance energy efficiency. Through advanced data analytics, predictive modeling, and automation, AI facilitates smarter decision-making, optimizes energy distribution, and promotes the adoption of renewable energy technologies, thereby contributing to a more resilient and sustainable energy system[20–22]. Proponents argue that AI is reshaping the landscape of energy management and sustainability, driving high-quality urban development and generating measurable environmental benefits, including improved energy efficiency and enhanced ecological outcomes[23,24]. However, despite these advantages, the energy-intensive nature of AI technologies poses potential risks to overall energy efficiency. Training and operating AI models require substantial computational resources[25] which can lead to increased carbon dioxide emissions and environmental degradation[19,26]. Furthermore, the dependence of AI systems on massive datasets indirectly amplifies the carbon footprint of the information technology sector. For example, data centers in the United States alone account for approximately 2% of national energy consumption. Globally, projections suggest that by 2030, the energy consumption of the information and communication technology (ICT) sector could reach 20% of total energy use, underscoring its growing role in the global energy landscape[17,27].

Given the rapid advancement of AI and its dual potential to both transform and challenge sustainable energy use, empirical investigation into its effects is critical. This study centers on China, offering valuable insights into the relationship between AI development and energy efficiency. According to the Ministry of Industry and Information Technology (China), the country's AI industry exceeded 500 billion RMB by 2023, encompassing over 4,500 enterprises. As the world's largest energy consumer and a leading developing nation[28,29] China's pursuit of energy efficiency holds significant implications for global sustainability, particularly for other developing economies. The rapid growth of AI in China presents a unique opportunity to assess its impact and to explore pathways for integrating AI into sustainable development strategies.

Previous studies have predominantly relied on metrics such as the number of industrial robots or AI-related patent applications to assess AI development[30–32] often focusing on production processes and technological innovation. While informative, these metrics tend to emphasize specific technologies and their direct effects on energy consumption, potentially overlooking AI's broader and more systemic influence across sectors. To address this gap, this study employs a fixed-effects model using prefecture-level data from Chinese cities to evaluate the relationship between AI development and energy efficiency.

This research advances the literature in four key ways: (1) Unlike prior studies that use proxies such as industrial robots or patent counts, we assess the influence of AI enterprises, offering a more robust reflection of the practical and commercial dimensions of AI implementation. (2) Moving beyond simplistic indicators like the energy-to-GDP ratio, we adopt a Data Envelopment Analysis (DEA) model based on the Charnes–Cooper–Rhodes (CCR) approach, allowing for a nuanced assessment of energy efficiency across multiple inputs and outputs. (3) We investigate the pathways through which AI impacts energy efficiency, providing an in-depth understanding of the mediating mechanisms that drive these effects. (4) By investigate the functional boundaries of AI in influencing energy efficiency, we offer a clearer picture of its potential scope. By addressing these research gaps, the study delivers critical insights into the direct effects of AI on energy efficiency, especially by unpacking the mechanisms that link AI development with sustainable energy outcomes. The findings offer actionable strategies for policymakers and industry stakeholders, fostering evidence-based decision-making in the integration of AI technologies to support global sustainability goals.

The structure of this paper is organized as follows: Section 2 presents a comprehensive review of the literature and introduces the theoretical hypotheses. Section 3 describes the data sources and research methodology. Section 4 reports the results of the empirical analysis. Section 5 provides extended analysis, focusing on the moderating effects. Finally, Section 6 summarizes the key conclusions and discusses the policy implications and limitations of the study.

Literature review and theoretical hypothesis

Literature review

Key driver of energy efficiency

Efficient and renewable energy systems have been widely recognized as essential contributors to sustainable development by strengthening environmental governance[33]. Numerous studies have investigated the factors influencing energy efficiency. Among these, environmental considerations have played a pivotal role in shaping financial strategies—particularly through green finance policies, which allocate capital to environmentally sustainable initiatives and lay the groundwork for improved energy performance[7,8]. Building on this foundation, institutional mechanisms such as carbon trading systems offer market-based incentives to reduce emissions and promote more efficient resource allocation[9–11]. Furthermore, the role of industrial agglomeration has garnered increasing attention. Researchers have found that clustering industries can create economies of scale and generate positive externalities—such as knowledge spillovers—that streamline production processes and enhance energy utilization[13,14].

The impact of digital technologies

Recently, , the global shift toward digital transformation—fueled by rapid advancements in digital technologies—has reshaped economic paradigms. Breakthroughs in artificial intelligence and other frontier technologies have emerged as key enablers of innovation and optimization in energy use across diverse sectors[19]. These advancements not only catalyze economic and social transformation but also foster further technological progress. As a result, growing academic interest is now directed toward understanding how digitalization influences production systems and alters energy consumption patterns.

Within the academic discourse, two divergent perspectives have emerged regarding the impact of digital technologies on energy transition. Proponents of the positive view argue that digital technologies have facilitated high-quality urban development while delivering measurable environmental benefits[34]. Enhanced innovation capacity[35] has improved total factor productivity by optimizing human capital, integrating advanced manufacturing with modern service industries, and implementing cost-reduction strategies[36,37], ultimately leading to gains in energy efficiency[23,24]. However, a contrasting view cautions that technological innovation may also drive-up carbon emissions due to the resource-intensive construction of digital infrastructure, thus exerting adverse effects on the ecological environment[19,26].

The impact of AI

Artificial intelligence (AI), as a foundational element of digital technologies, has the potential to profoundly transform energy utilization and enhance efficiency, particularly in the manufacturing sector [21,22,38]. Unlike other digital innovations, AI's core functionalities can be classified into six critical domains: learning, perception, prediction, interaction, adaptation, and reasoning[39]. For instance, AI's learning capability allows systems to improve performance over time, thereby increasing operational efficiency and effectiveness. Perception enables the interpretation of complex datasets and dynamic environments, supporting more informed decision-making[40]. Predictive capabilities facilitate accurate outcome forecasting, which is essential for strategic planning[41]. Interaction fosters seamless communication between humans and machines, enhancing user engagement and system responsiveness[42]. Adaptation allows AI systems to respond to novel conditions and tasks, maintaining their relevance and functionality[40,43]. Finally, reasoning enables AI to draw logical inferences and solve complex problems, effectively augmenting human cognitive capabilities. Empirical studies underscore AI's impact on energy efficiency. For example, AI-driven ventilation control systems have achieved energy savings of approximately 26% in commercial buildings in the United States[44]. Unlike conventional digital tools, AI's ability to autonomously make decisions, recognize patterns, and exhibit "human-like" scientific reasoning enables more nuanced management of production processes, thereby supporting greener manufacturing practices[45]. Collectively, these capabilities establish AI as a versatile and powerful enabler of innovation and efficiency across diverse industrial and technological domains. Nevertheless, the development and deployment of AI systems are energy-intensive, particularly during manufacturing, model training, and operational phases, potentially resulting in a substantial carbon footprint[20].

A growing body of literature explores the complex relationship between AI and energy efficiency, yielding a range of perspectives. Several studies highlight AI's potential to enhance energy performance, particularly in regions characterized by high levels of green innovation[25], and within high-performing organizations where AI integration is more advanced[46]. However, these benefits are counterbalanced by the substantial energy demands associated with AI model development and training. High-performance computing for algorithm development, training cycles, and data center cooling consumes vast computational resources, contributing to elevated carbon emissions and environmental degradation[19,25,26,47]. The expansion of digital infrastructure, particularly at scale, exacerbates these challenges, as it entails considerable energy inputs for both construction and maintenance[17,28,48,49].

Despite these concerns, AI presents transformative opportunities to address energy-related challenges through predictive analytics, real-time monitoring, and automated control systems. As AI technologies are increasingly adopted across sectors such as manufacturing, transportation, and utilities, they offer sophisticated mechanisms to detect inefficiencies in energy consumption and enable precise, data-driven interventions to enhance operational efficiency[50]. These applications yield both direct and indirect environmental benefits. For instance, AI can optimize the timely input of production factors to maximize resource utilization[51]. Furthermore, the integration of intelligent automation within large-scale industrial ecosystems enables production lines to become more flexible, adaptive, self-aware, self-regulating, and capable of autonomous optimization[52–54]. Such advancements significantly reduce resource consumption and promote sustainability, yielding substantial gains in both environmental performance and industrial efficiency.

Literature gap

This literature review synthesizes current scholarship on energy efficiency and offers a comprehensive analysis of its influencing factors. Although considerable research has examined the impact of digital technologies and AI on energy efficiency, several critical gaps remain. Notably, much of the existing literature conflates AI with broader digital technologies, with limited studies isolating AI to examine its distinct effects. Furthermore, prior research often quantifies AI through proxies such as industrial robot density or patent data. In contrast, this paper emphasizes the practical application of AI technologies[55–57]. Additionally, prevailing studies typically assess energy efficiency using a unidimensional framework, such as the ratio of energy input to GDP output. This study adopts a more robust approach by employing the CCR model, which enables a multidimensional assessment of energy efficiency[25,56]. Most importantly, the underlying mechanisms through which AI influences energy efficiency remain underexplored. These research gaps underscore the need for further empirical investigation—particularly in China, where a nuanced understanding of AI's role in energy consumption could enhance its applicability in developing economies.

Theoretical background and hypothesis

As outlined above, the relationship between AI and energy efficiency is multifaceted, encompassing both opportunities and challenges. When AI technologies transition from patent registration to real-world deployment, their energy usage dynamics evolve. Practical implementation often leads to system optimization and energy consumption reduction. This implies that AI's capacity to improve energy efficiency is best realized through active application rather than theoretical modeling alone. In this regard, AI offers a unique advantage by integrating energy efficiency with adaptability, interactivity, and creativity[22]. This phenomenon aligns with the Solow paradox, which posits that the productivity gains from technological innovation are not immediately apparent but emerge gradually over time[58]. Innovation theory further supports the view that widespread adoption of AI can lead to significant improvements in productivity and operational efficiency. Given AI's demonstrated potential to reduce energy consumption and disrupt conventional energy use patterns, this study advances the following hypothesis:

H1: AI development can improve energy efficiency.

Green technological innovation refers to enterprise-driven innovations aimed at conserving energy, reducing emissions, mitigating climate-related environmental damage, and enhancing ecological benefits. These innovations also contribute to the modernization of production technologies[59]. Empirical evidence suggests that AI development positively influences green innovation outcomes[9]. From the perspective of technological innovation, green innovation can reduce emissions from fossil fuels while promoting the adoption of renewable energy sources[11]. While green innovation may increase research and development expenditures, it simultaneously enhances productivity and enables effective management of wastewater, exhaust emissions, and solid waste during manufacturing. The implementation of stringent environmental regulations to stimulate technological innovation can significantly reduce environmental pollution without compromising production efficiency[60]. Accordingly, this study proposes Hypothesis 2:

H2: AI development enhances energy efficiency through fostering green technological innovation.

Prior research has established that energy intensity varies significantly across industrial sectors and that structural transformation can influence aggregate energy efficiency[61]. Notably, industrial structure is a critical determinant of carbon emissions. The configuration and composition of industries—particularly their dependence on energy-intensive technologies and processes—substantially shape the overall carbon footprint. As such, industrial restructuring has become increasingly central to sustainable development and climate change mitigation strategies[62]. Upgrading the industrial structure can reduce total carbon emissions by decreasing the share of high-energy-consuming sectors while expanding low-carbon and renewable energy industries. This structural shift not only curtails emissions but also fosters a more resilient and sustainable economic system, aligning with global efforts to combat climate change and advance environmental sustainability[63]. Artificial intelligence (AI) plays a catalytic role in driving industrial upgrading by optimizing and reshaping industrial configurations. The widespread deployment of AI is expected to revolutionize traditional technologies, thereby enabling a more rational, efficient, and innovation-driven industrial structure. AI and related innovation technologies accelerate industrial adaptation and advancement by promoting industrial clustering and enhancing operational efficiency through the adoption, integration, and diffusion of new technological paradigms[64–67]. Technological progress also generates significant capital reallocation and innovation-driven transformation. On one hand, capital—including physical, human, and institutional—tends to flow out of high-energy-intensive sectors and into knowledge-intensive, low-carbon industries. On the other hand, the advancement of emerging industries—characterized by superior energy efficiency and environmental performance—contributes to overall improvements in energy use. Based on this rationale, the present study proposes the following hypothesis:

H3: AI development boosts energy efficiency by rationalizing the industrial structure.

In exploring the mechanisms through which AI affects energy efficiency, it is equally important to examine the contextual conditions under which its influence may vary. Drawing on the theory of environmental regulation, prior empirical research indicates that such regulations exert a pronounced influence on both firms' intentions to innovate and their actual innovation behaviors. This suggests that the effectiveness of AI in enhancing energy efficiency may be contingent upon the regulatory environment and the extent to which firms are incentivized to adopt green technologies. Environmental regulations heighten firms' awareness of ecological concerns and promote engagement in green innovation activities. For instance, stringent policies can enhance firms' recognition of the importance of environmental responsibility, thereby increasing their motivation to pursue green innovations[68]. In developing countries—where formal regulatory frameworks are often weak or inconsistently enforced—informal environmental regulation (IER) emerges as a pivotal mechanism for compelling polluters to take corrective action[69]. We argue that in such contexts, the impact of AI on energy efficiency is likely to be more substantial in environments characterized by higher levels of IER. Social pressure and public scrutiny, as key drivers of informal regulation, can incentivize firms to adopt AI technologies that reduce emissions and improve operational sustainability. These regulatory dynamics may foster a more conducive environment for AI adoption, thereby amplifying its potential to enhance energy efficiency. On this basis, we propose the following hypothesis:

H4: Informal environmental regulation amplifies the positive impact of AI on energy efficiency.

The developmental stage of a city significantly influences the extent to which AI can enhance energy efficiency. In China, approximately 44% of urban areas are classified as resource-based cities—urban centers whose economies rely heavily on the extraction and processing of natural resources such as minerals, water, and forests[70]. According to the resource curse theory, the finite nature of these resources implies that sustained extraction will eventually lead to their depletion[71]. Resource-based cities generally follow four developmental stages: growing, mature, declining, and regenerating. Each stage presents distinct challenges and opportunities for energy use and technological adoption. Growing resource-based cities possess abundant resources and are in the early phases of industrial expansion. These cities are increasingly exploring sustainable practices alongside resource development. Mature cities, having reached peak resource output after years of intensive exploitation, face the challenge of balancing economic growth with environmental preservation. Achieving this balance is vital for long-term sustainability, requiring deliberate efforts to mitigate environmental degradation while maintaining economic performance[72]. Declining resource-based cities confront the compounded challenges of resource exhaustion and economic instability. These cities must transition from a resource-dependent economy to one that is diversified and sustainable. This transition demands innovative policy measures and strategic interventions. AI can play a critical role in this transformation by identifying inefficiencies, optimizing remaining resources, and facilitating the shift toward sustainable practices. In regenerating cities, resource extraction has largely ceased, and efforts focus on ecological restoration and sustainable urban development. For these cities, AI is essential to supporting smart city initiatives, energy management systems, and environmental monitoring, all of which are key to achieving sustainable urban planning[73]. Empirical research indicates that the digital economy has a pronounced positive effect on energy efficiency in resource-dependent cities. However, this impact is less significant in cities with more diversified economies. The heightened responsiveness of resource-based cities may be attributed to their centralized industrial structures and initially lower energy efficiency baselines[74]. Consequently, these cities exhibit both a greater capacity and a more urgent need to leverage AI and other innovative technologies to optimize energy use. As natural resources inevitably dwindle, the priorities of resource-based cities evolve across different stages. In the early stages, the emphasis may be on maximizing extraction efficiency, while in later stages, the focus shifts toward sustainability and ecological recovery. Thus, the demand for AI applications to improve energy efficiency varies across stages, with the need becoming most acute in cities experiencing resource depletion and economic decline. Based on this context, we propose the following hypothesis:

H5: The stage of resource development in a resource-based city moderates the impact of AI on energy efficiency.

Figure 1 shows the conceptual framework.

Methods

Data source

The focus of our study is on the impact of AI on energy efficiency across Chinese cities. To empirically test our hypotheses, we employ a fixed-effects model using data compiled from five major sources. Because city-level energy consumption data are not publicly available, we follow established methodologies and use nighttime light intensity data from NOAA as a proxy for energy consumption[75,76]. Official energy data, standardized in tons of standard coal, are drawn from the China Energy Statistical Yearbook to facilitate calculation and comparison. Additional control variables—including GDP, industrial structure, income levels, educational attainment, population density, and demographic composition—are extracted from the China City Statistical Yearbook. AI enterprise data are identified using a keyword extraction technique applied to the business scope descriptions listed in the Tianyancha enterprise database. Furthermore, green patent data sourced from CNIPA provide insight into the level of technological innovation. All continuous variables are logarithmically transformed to stabilize variance and normalize distributions. After data collection and preprocessing, the final dataset comprises 4177 observations spanning the years 2006 to 2020.

Model settings

Drawing on existing research, we employ a two-way fixed effects panel model to control for both individual (city-level) and time-specific effects[25]. This model offers significant advantages in handling complex panel

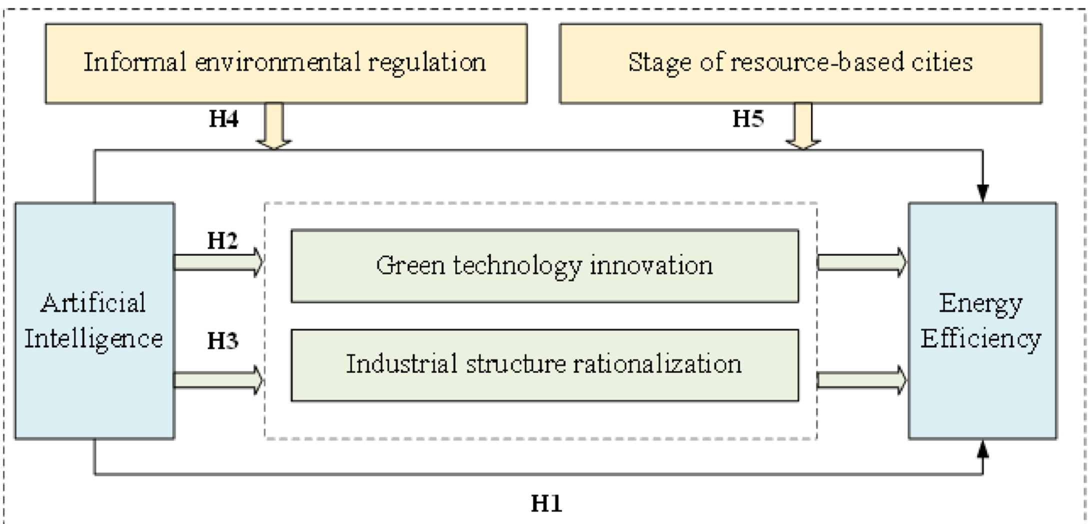

Fig. 1. Shows the conceptual framework.

data by effectively reducing omitted variable bias and enhancing the precision of causal inference. The baseline specification is as follows:

$$\mathrm{EE_{it}} = \alpha_0 + \beta_1 \mathrm{AI_{it}} + \beta_2 \mathrm{density_{it}} + \beta_3 \mathrm{structure_{it}} + \beta_4 \mathrm{pgdp_{it}} + \beta_5 \mathrm{so2_{it}} + \beta_6 \mathrm{energy_{it}} + \mu_i + \gamma_t + \epsilon_{it} \quad (1)$$

where i denote the city and t the year. The dependent variable, EE, represents energy efficiency, while the key explanatory variable, AI, captures the artificial intelligence development index. Control variables include population density, industrial structure, per capita GDP (pgdp), sulfur dioxide emissions (so2), and energy consumption. City and year fixed effects are denoted by μ_i and γ_t respectively.

Description of variables

Explained variable

Energy efficiency is a multifaceted concept with no universally accepted metric. Broadly, it refers to achieving the same level of output or service with reduced energy input—for example, using the ratio of energy consumption to GDP output as a proxy[25]. However, such single-factor indicators provide a limited, one-dimensional view that neglects interactions among multiple inputs and the presence of multiple outputs[77,78].

These indicators typically focus solely on the energy–output relationship, overlooking the influence of other production factors such as labor and capital. To address this limitation, we adopt the CCR model within the Data Envelopment Analysis (DEA) framework, which evaluates relative efficiency using a non-parametric approach. This model incorporates a broader set of inputs—namely energy, labor, and capital—and a single output (GDP) to estimate each decision-making unit's (DMU's) position relative to a production frontier[74]. This methodology provides a holistic view of energy efficiency by comparing the performance of a DMU with peers that optimize input use for a given output or maximize output for a given level of input[79]. By integrating both technical and scale efficiency under the assumption of constant returns to scale[80] the CCR model captures input–output interactions more comprehensively, providing a more accurate and holistic assessment of energy efficiency. Therefore, we construct our measure of energy efficiency using the CCR model rather than relying on single-factor indicators. For robustness checks, we further construct a measure of total factor energy efficiency using the SBM (Slack-Based Measure) model[81–83].

Explanatory variable

Prior studies have commonly measured the level of AI development using two main approaches. The first relies on industrial robot data from the International Federation of Robotics (IFR)[30–32,84,85]. While widely used, this method offers only a partial view and fails to capture the full spectrum of AI applications. The second approach uses AI-related patent data as a proxy for AI development. As a direct reflection of technological innovation, patent data enables precise identification of AI-specific technologies and has been increasingly employed to assess technological advancement[86,87]. Nevertheless, the number of AI-related patents is often used as a proxy for the level of R&D activity and the cumulative technological achievements in the AI domain. However, when examining energy consumption, the number of AI enterprises may serve as a more direct and relevant indicator. This is because enterprise count reflects the degree of industrial agglomeration and the extent to which the AI sector has matured in a given city. A growing number of AI enterprises typically signals the translation of R&D efforts into real-world applications and market-driven innovations[25,88]. Therefore, compared to patent counts, the number of AI enterprises offers a more comprehensive measure of both innovation output and its practical implementation.

Mediating variables

Green technology innovation (GTI). At the city level, green technology innovation is measured by taking the natural logarithm of the number of green patent applications plus one, to account for the potential of zero values and to normalize the data[89].

Industrial Structure Rationalization (ISR). Following prior research, this study adopts the Theil index to evaluate the rationalization of industrial structure by assessing both sectoral coordination and resource allocation efficiency[62]. The Theil index quantifies disparities in output and employment across sectors, capturing the extent of structural imbalance at the city level, as shown in Eq. (2):

$$TL = \sum\nolimits_{i=1}^{n} \left[\left(\frac{Y_i}{Y} \right) \ln\left(\frac{Y_i}{L_i} / \frac{Y}{L} \right) \right] \quad (2)$$

In Eq. (2), *TL* denotes the Theil index, *with Y* and *L* representing total industrial output and labor force, respectively. *Yi* and *Li* refer to the output and employment of sector *i*, where *i* ranges from 1 to n, the total number of sectors. A lower Theil index approaching zero indicates a more rational industrial structure. This study calculates ISR for 284 cities over the period 2006–2020.

Moderating variables

Informal environment regulation (IER). To assess the moderating role of informal environmental regulation, the study employs a composite index constructed from indicators such as per capita income, population density, age structure, and educational attainment. These variables jointly capture the socio-economic conditions that influence public awareness and pressure for environmental protection, thus serving as proxies for informal regulatory mechanisms operating outside formal institutions.

To explore how informal environmental regulation moderates the impact, this research draws on the methodology of selecting a series of indicators such as income level, educational background, population density, and age structure to measure the extent of informal environmental regulation in cities[90,91].

Stage of Resource City (SRC). Based on the National Resource-Based City Sustainable Development Plan (2013), resource-based cities are classified into four developmental stages: Growing, Mature, Declining, and Regenerating. In this study, these stages are numerically coded from 1 to 4, respectively, following the classification framework proposed by previous research[70].

Control variables

In addition, we control for several variables commonly identified in the literature as influencing energy efficiency: (1) Population Density (density): Areas with higher population density often exhibit greater energy demand[26]. Population density is calculated based on the year-end total population[57,92]. (2) Industrial Structure (structure): This is measured by the share of tertiary industry value added in GDP, capturing the economic composition and its implications for energy use patterns. (3) GDP per Capita (pgdp): Reflecting regional economic development, GDP per capita is associated with higher living standards and greater awareness of sustainability concerns[93]. It is measured as the per capita GDP of urban residents. (4) Total Energy Consumption (energy): This variable captures the absolute scale of energy usage within a city, serving as a key control for evaluating energy efficiency[94]. (5) Environmental Pollution (so_2): Given that highly polluted regions often allocate more resources to environmental management, sulfur dioxide (so_2) emissions—one of the most prominent industrial pollutants—are used as a proxy for environmental pressure and are included as a control variable[94]; therefore, this study controls it, considering the environmental pollution status, and measures it by the amount of sulfur dioxide emissions.

Table 1 outlines the definitions and calculation methods of all variables.

Empirical analysis

Benchmark regression analysis

Due to the Hausman test results, with a p-value of 0.000, we choose the fixed effects model to control for unobserved individual heterogeneity. The analysis begins by examining the impact of AI development on energy efficiency (EE), with regression results presented in Table 2. Column (1) reports baseline estimates without control variables, while column (2) introduces controls. Column (3) further refines the model by clustering standard errors at both the city and calendar year levels to mitigate potential intra-group error correlation. The progressive increase in R-squared values across columns (1) through (3) indicates improved model fit with the inclusion of controls and robust error adjustments. In all specifications, the coefficient of AI on EE remains positive (0.049) and statistically significant at the 1% level, providing preliminary evidence that AI development positively influences energy efficiency.

Regarding the control variables, the coefficient on population density is positive and significant at the 1% level, suggesting that higher population density is associated with greater energy efficiency. This may be attributable to the intensified economic activity and more diversified industrial structures typically found in densely populated regions. Additionally, such regions often adopt stricter energy efficiency regulations, incentivizing firms to implement advanced energy-saving technologies. Likewise, the coefficient on per capita GDP is both positive and significant at the 1% level, indicating that higher income levels are linked to enhanced energy efficiency. This relationship likely reflects the increased capacity of wealthier regions to invest in technological innovation and R&D, along with heightened public awareness of environmental sustainability and energy conservation.

In contrast, the coefficients for so_2 emissions and total energy consumption are negative, implying that greater pollutant emissions and energy usage are detrimental to energy efficiency. These findings are consistent with empirical patterns observed in real-world contexts.

Type of variables	Variables	*N*	Mean	Sd	min	max
Dependent variable	Energy efficiency	4177	0.54	0.14	0.27	0.99
Explanatory variable	Artificial intelligence development	4177	4.12	1.79	0	10.37
Mediating variable	Green technology innovation	4177	4.30	1.87	0	10.25
	Industrial structure rationalization	4177	0.28	0.21	−0.03	1.72
Moderating variable	Informal environment regulation	4177	0.18	0.06	0.07	0.88
	Stage of resource-based city	1681	2.35	0.86	1	4
Control variable	Population density	4177	5.73	0.93	0.68	7.88
	Industry structure	4177	0.40	0.10	0.09	0.84
	Per capita GDP	4177	10.45	0.72	4.61	13.06
	Sulfur dioxide	4177	10.14	1.27	1.10	13.43
	Total energy consumption	4177	13.67	1.27	9.30	17.53

Table 1. Summary statistics. The VIF value for EE, AI and control variables range from 1.28 to 4.83, the mean VIF is 2.69. There is no significant multicollinearity problem among the variables.

Model	(1)	(2)	(3)
DV	EE_t	EE_t	EE_t
AI	0.025***	0.049***	0.049***
	(20.709)	(20.109)	(7.083)
Density		0.028***	0.028***
		(8.638)	(3.009)
Structure		−0.135***	−0.135
		(−4.178)	(−1.731)
pgdp		0.070***	0.070***
		(13.373)	(4.828)
so2		−0.019***	−0.019***
		(−7.195)	(−3.062)
Energy		−0.087***	−0.087***
		(−26.219)	(−10.725)
Contant	0.435***	0.883***	0.883***
	(81.637)	(16.658)	(6.100)
Province FE	YES	YES	YES
Year FE	YES	YES	YES
N	4177	4177	4177
R^2	0.100	0.510	0.510

Table 2. Results of the regression analysis. Parentheses contain robust standard errors in columns (1) and (2), with standard errors clustered by city and calendar year in column (3). ***, ** and * indicate significance at the 1, 5, and 10% levels, respectively.

Robustness checks

Robustness test

To verify the robustness of these results, the study undertakes three validation approaches. First, it replaces the CCR model-derived measure of energy efficiency with a single-factor energy efficiency (EE) measure[81]. This shift allows us to assess energy efficiency through a more straightforward metric, calculated as the ratio of energy input to economic output[10]. Although this approach oversimplifies the multidimensional nature of energy performance, it aligns the analysis with conventional metrics frequently used in existing literature, enabling comparability across studies. As shown in column (1) of Table 3, the positive and significant relationship between AI development and EE persists, lending further credibility to the baseline findings.

Second, a subsample analysis is conducted to account for regional heterogeneity. The cities of Beijing, Shanghai, Guangzhou, and Shenzhen—China's leading megacities—exhibit advanced economic development, robust infrastructure, and strong capabilities in AI innovation, placing them well ahead of cities in central and western China, which face structural and infrastructural limitations. To mitigate potential bias introduced by these outliers, a regression is performed after excluding the four first-tier cities. The results, presented in Column (2) of Table 3, are consistent with those of the full sample, further reinforcing the robustness and generalizability of the core conclusions.

Third, the effects of AI development on energy efficiency may exhibit a time lag due to delays in policy interpretation and implementation. To account for this, we introduce one- and two-period lags of AI development as robustness checks, as shown in columns (3) and (4) of Table 3, respectively. The results remain consistent with our baseline findings and provide further empirical support for Hypothesis 1, reaffirming that AI development is positively associated with improvements in urban energy efficiency.

Endogenous processing

To address potential endogeneity, we adopt an instrumental variable (IV) approach. Drawing on established methodologies in the literature, we construct two instruments: (1) a one-period lag of AI development, and (2) a Bartik shift-share instrument. The latter is derived by interacting the lagged first-order AI index with its first-order difference, thereby generating a theoretically grounded IV[25,95,96]. Table 4 presents the results of the IV regressions, which include the same set of control variables used in the baseline model to mitigate confounding effects. The results demonstrate that AI remains positively and significantly associated with energy efficiency under both IV strategies. Specifically, columns (1) and (3) report the first-stage regression outcomes, confirming a strong correlation between the instruments (IV1 and IV2) and AI. Columns (2) and (4) show the second-stage estimates, where the coefficients on AI are 0.051 and 0.049, respectively, both significant at the 1% level. These findings confirm the robustness and consistency of the main regression results.

Mechanism test

Green technology innovation

Table 5 reports the mediating role of green technological innovation (GTI) in the AI–energy efficiency relationship. Column (1) presents the total effect of AI on energy efficiency, while column (2) shows that AI

Model	(1)	(2)	(3)	(4)
DV	EE_t	EE_t	EE_{t+1}	EE_{t+2}
AI	0.403***	0.051***	0.045***	0.041***
	(17.529)	(7.007)	(6.369)	(5.775)
Density	0.058*	0.017	0.028**	0.027**
	(2.012)	(1.643)	(3.008)	(2.901)
Structure	−1.024***	−0.187*	−0.090	−0.027
	(−4.925)	(−2.040)	(−1.067)	(−0.302)
pgdp	0.094**	0.059***	0.066***	0.062***
	(2.364)	(3.562)	(4.447)	(4.049)
so2	0.071***	−0.013*	−0.018**	−0.017**
	(4.754)	(−2.084)	(−2.810)	(−2.424)
Energy	−0.841***	−0.093***	−0.078***	−0.070***
	(−34.961)	(−11.122)	(−8.850)	(−7.553)
Contant	10.774***	1.066***	0.805***	0.742***
	(24.969)	(6.856)	(5.159)	(4.490)
Province FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	4177	2900	3895	3613
R^2	0.508	0.511	0.462	0.430

Table 3. Results of the robust test. Parentheses with standard errors clustered at the city and calendar year. ***, ** and * indicate significance at the 1, 5, and 10% levels, respectively.

Model	(1)	(2)	(3)	(4)
DV	AI_t	EE_t	AI_t	EE_t
IV1	0.978***			
	(224.806)			
IV2			0.584***	
			(11.318)	
AI		0.051***		0.049***
		(19.278)		(7.997)
Control	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	3895	3895	3895	3895
R^2		0.269		0.269
F	50537.522	172.801	128.099	121.609
C-D Wald F	102617.616		849.228	
K-P LM	1070.288		350.629	
K-P LM P-val	0.000		0.000	

Table 4. Endogeneity test results. Parentheses with standard errors. ***, ** and * indicate significance at the 1, 5, and 10% levels, respectively.

significantly promotes GTI at the 1% level. This suggests that AI development exerts a substantial and positive influence on the advancement of green technologies, underscoring its capacity to catalyze sustainable innovation. In column (3), when both AI and GTI are regressed on energy efficiency, the coefficient for GTI remains positive and statistically significant at the 5% level. This indicates that GTI contributes to enhancing energy efficiency and functions as a partial mediator. The clustering of AI enterprises appears to foster green innovation, which in turn drives improvements in energy efficiency. These results support Hypothesis 2 regarding the mediating role of GTI.

Rationalization of industrial structure

Table 6 presents the mediating mechanism analysis involving the rationalization of the industrial structure (ISR). Column (1) shows the total effect of AI on energy efficiency, while column (2) reveals that AI significantly promotes ISR at the 1% level, suggesting that AI contributes to industrial upgrading and structural optimization. In column (3), when AI and ISR are jointly regressed on energy efficiency, both variables show positive and

Model	(1)	(2)	(3)
DV	EE_t	GTI_t	EE_t
AI	0.049***	0.672***	0.044***
	(20.109)	(46.782)	(13.576)
Density	0.028***	0.122***	0.028***
	(8.638)	(6.317)	(8.452)
Structure	−0.135***	0.168	−0.137***
	(−4.178)	(1.042)	(−4.205)
pgdp	0.070***	0.273***	0.069***
	(13.373)	(10.248)	(12.735)
so2	−0.019***	0.114***	−0.020***
	(−7.195)	(8.065)	(−7.415)
Energy	−0.087***	0.175***	−0.089***
	(−26.219)	(9.608)	(−26.614)
gti			0.007**
			(2.364)
Contant	0.883***	−5.633***	0.923***
	(16.658)	(−19.659)	(16.659)
Province FE	YES	YES	−0.001
Year FE	YES	YES	(−0.691)
N	4177	4177	4177
R^2	0.510	0.910	0.510

Table 5. The mediating roles of GTI. Parentheses with standard errors. ***, ** and * indicate significance at the 1, 5, and 10% levels, respectively.

Model	(1)	(2)	(3)
DV	EE_t	ISR_t	EE_t
AI	0.049***	0.021***	0.048***
	(20.109)	(6.187)	(19.665)
Density	0.028***	0.021***	0.028***
	(8.638)	(4.849)	(8.375)
Structure	−0.135***	−0.630***	−0.116***
	(−4.178)	(−13.851)	(−3.520)
pgdp	0.070***	−0.187***	0.076***
	(13.373)	(−19.912)	(12.896)
so2	−0.019***	−0.020***	−0.019***
	(−7.195)	(−5.922)	(−6.928)
Energy	−0.087***	−0.029***	−0.086***
	(−26.219)	(−5.940)	(−25.654)
ISR			0.031***
			(2.597)
Contant	0.883***	2.876***	0.793***
	(16.658)	(31.788)	(12.082)
Province FE	YES	YES	YES
Year FE	YES	YES	YES
N	4177	4177	4177
R^2	0.510	0.538	0.511

Table 6. The mediating roles of industrial structure rationalization. Parentheses with standard errors. ***, ** and * indicate significance at the 1, 5, and 10% levels, respectively.

statistically significant coefficients at the 1% level. These findings indicate that ISR serves as a significant mediating pathway through which AI enhances energy efficiency. Thus, the results provide empirical support for Hypothesis 3, confirming that AI facilitates energy efficiency improvements by driving the rationalization of the industrial structure.

Model	(1)	(2)
DV	EE_t	EE_t
AI	0.033***	0.057***
	(7.694)	(9.428)
IER	−0.596*	
	(−1.857)	
AI x IER	0.090***	
	(4.445)	
Mature		−0.064***
		(−3.288)
Declining		−0.192***
		(−9.371)
Regenerative		−0.246***
		(−10.500)
AI x Mature		0.005
		(0.884)
AI x Declining		0.026***
		(4.195)
AI x Regenerative		0.041***
		(6.409)
Density	0.028***	0.014***
	(8.499)	(2.760)
Structure	−0.136***	−0.053
	(−4.193)	(−1.003)
pgdp	0.069***	0.084***
	(13.140)	(10.183)
so2	−0.018***	−0.005
	(−6.710)	(−1.400)
Energy	−0.087***	−0.085***
	(−26.082)	(−19.078)
Contant	0.986***	0.630***
	(13.137)	(6.997)
Province FE	YES	YES
Year FE	YES	YES
N	4177	1681
R^2	0.513	0.625

Table 7. Moderate roles of informal environment regulation and the types of resource-based city. ***, ** and * indicate significance at the 1, 5, and 10% levels, respectively; industry and Year fixed effects are controlled for in all columns. Robust standard errors are presented in parentheses.

Further analysis

After establishing the fundamental connection between artificial intelligence (AI) development and energy efficiency, this study proceeds to examine the nuanced dynamics of this relationship under varying boundary conditions[97]. Specifically, we investigate how environmental regulations and the developmental stage of resource-based cities moderate the impact of AI on energy efficiency. This focus is grounded in the recognition that environmental regulation significantly shapes the technological and operational landscape of cities[57]. Previous research suggests that technological innovation tends to be more effective in regions with stringent environmental oversight[60]. Likewise, the economic trajectory of resource-based cities—categorized as growing, mature, declining, or regenerative—is closely tied to the energy sector, and each stage exhibits distinct characteristics[56]. These structural differences create divergent incentives and capacities for integrating AI to enhance energy efficiency. By exploring these moderating factors, we aim to refine our understanding of the contextual conditions under which AI contributes most effectively to energy efficiency.

Moderate role of informal environment regulation

We begin by analyzing the role of informal environmental regulation (IER). Table 7, column (1), presents the moderating effects of IER on the relationship between AI development and energy efficiency. The interaction term between IER and AI development is both positive and statistically significant at the 1% level, indicating that AI's impact on energy efficiency is more pronounced in areas with strong informal regulatory mechanisms. These findings support Hypothesis 4.

Moderate role of the stage of resource development

Next, we consider how the developmental stage of resource-based cities influences the effectiveness of AI in improving energy efficiency. Our analysis reveals that AI exerts a stronger positive effect in declining and regenerative cities compared to growing and mature ones, likely due to their heightened need for transformation and greater potential for system optimization. In Table 7, column (2), the moderation analysis indicates that mature cities are less energy efficient than growing cities, with declining and regenerative cities performing even worse. However, the interaction term between AI and mature cities is not statistically significant, suggesting no meaningful difference in AI's impact on energy efficiency between mature and growing cities. In contrast, the significantly positive interaction terms for declining and regenerative cities indicate a more substantial effect of AI in these contexts. This may reflect the targeted application of AI technologies to enhance efficiency amid resource depletion in declining cities, and to optimize energy management in regenerative cities transitioning from historical resource dependency. These results empirically validate our assumption that AI's contribution to energy efficiency varies across different stages of resource-based urban development.

Conclusion and implication

Conclusion

Amid growing global emphasis on sustainable development, the role of AI in advancing energy efficiency has garnered considerable attention from both policymakers and researchers. This study assesses the extent to which AI development facilitates sustainable practices in China, particularly in the energy domain. Three key findings emerge from our analysis. First, AI development positively influences energy efficiency. Second, this effect operates primarily through two channels: green innovation and industrial structure rationalization. Specifically, AI promotes the development and deployment of green technologies while also enabling a more balanced and efficient allocation of industrial resources. Third, the moderating analysis reveals that AI's impact on energy efficiency is significantly amplified in cities with strong informal environmental regulations, and is comparatively muted in cities with looser regulatory environments. Additionally, AI has proven particularly effective in enhancing energy efficiency in resource-based cities that are either in decline or undergoing regeneration, relative to their growing or mature counterparts. Our study's results align with existing research, emphasizing the significant impact of AI on energy efficiency. By comparing our findings with other studies, we have identified the mechanisms through which AI affects energy efficiency and the conditions under which these effects are most pronounced. This comparison not only validates our results but also highlights the unique contributions of our study.

These findings contribute significantly to the scientific understanding of AI's role in sustainable development by offering empirical evidence of its impact on energy efficiency. By elucidating the mechanisms linking AI to energy efficiency, our research provides critical insights for policymakers and industry stakeholders, underscoring the importance of incorporating AI into strategic frameworks to advance sustainable development. The practical implications are particularly salient for China, given its energy scarcity and uneven resource distribution. In light of China's ambitious targets to peak CO_2 emissions by 2030 and achieve carbon neutrality by 2060, harnessing AI to enhance energy efficiency and drive industrial transformation in resource-based cities is imperative. This strategy not only facilitates the attainment of domestic sustainability goals but also strengthens China's position as a global leader in sustainable development.

Policy implication

Based on the above findings, several key policy implications emerge for promoting sustainable development through AI adoption. First, the positive impact of AI on energy efficiency is significantly amplified in cities with robust informal environmental regulations. Policymakers should therefore prioritize the reinforcement of environmental governance by implementing formal regulations, enhancing public awareness, supporting environmental NGOs, and cultivating a culture of sustainability at the community level. Second, AI exerts a stronger influence on energy efficiency in declining and regenerating resource-dependent cities. Targeted investments in AI infrastructure and applications during these critical transition stages can support industrial restructuring. Simultaneously, efforts should be made to cultivate conducive environments for AI adoption in growing and mature cities. Early integration of AI technologies in these areas can yield long-term benefits by embedding sustainable practices and mitigating future transition risks. Third, AI enhances energy efficiency primarily through green technological innovation and industrial structure optimization. Policymakers and industry leaders should leverage AI to drive innovation and streamline industrial operations, thereby promoting sustainability and unlocking the full potential of AI-driven transformation.

Limitations and future research

Our analysis is based on data from China, which may limit the generalizability of the findings to other regions or developed countries. Future research should incorporate cross-national datasets to validate and expand upon our conclusions, enabling a broader understanding of AI's role in global energy efficiency improvements. Furthermore, this study does not delve into the differential impacts of various AI subtypes. For instance, generative AI may present unique implications worth exploring in greater depth in subsequent research.

Data availability

The datasets analysed during the current study are available from the corresponding author on reasonable request.

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Jun Zeng and Tian Wang designed the study, drafted the article, acquired the data, completed the analysis, critical revision for important intellectual content together.

Competing interests
The authors declare no competing interests.

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