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The Impact of Artificial Intelligence Development on Urban Energy Efficiency—Based on the Perspective of Smart City Policy

Xiangyi Li [1], **Qing Wang** [1] and **Ying Tang** [2,*]

[1] Hubei Recycling Economy Development Research Center, Hubei University of Technology, Wuhan 430068, China; 20211041@hbut.edu.cn (X.L.); 2110811130@hbut.edu.cn (Q.W.)
[2] School of Business Administration, Zhongnan University of Economics and Law, Wuhan 430073, China
* Correspondence: 202101080007@zuel.edu.cn; Tel.: +86-13717950877

Abstract: China's economy is stepping into a new stage of high-quality development. The shift not only marks the optimization and upgrading of the economic structure, but also reflects the in-depth implementation of the concept of sustainable development. In this context, the development of AI technology is playing an important role in balancing economic growth and ecological protection with its unique advantages. This paper empirically studied the impact of AI development on urban energy efficiency by constructing panel data for 282 prefecture-level cities from 2006 to 2019 and then using the super-efficiency SBM model based on non-expected outputs to evaluate the urban energy efficiency indicators of prefecture-level cities. It was discovered that the development of AI had a key influence on increasing urban energy efficiency and the optimization of the energy structure by speeding up green technology innovation and digital economy development, which in turn improved urban energy efficiency. In terms of heterogeneity analysis, AI development had a greater impact on urban energy efficiency in the eastern region, which has higher levels of human capital, financial independence, and government intervention. This study combined the smart city pilot policy with a multi-period DID model, based on the treatment of endogeneity issues, in order to perform a parallel trend test and investigate further the effects of policy implementation on the advancement of AI in the context of improving urban energy efficiency. Accordingly, to achieve green and sustainable urban development, the relevant government departments should increase funding for AI research and development, pay attention to the introduction and cultivation of professionals, establish a platform for international exchanges and cooperation between AI and energy management, and continue to advocate for the pilot development of smart cities to increase urban energy efficiency.

Keywords: AI; energy efficiency; smart city policy; DID; sustainable development

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1. Introduction

Due to the deep integration of modern information technologies such as the internet of things (IoT), big data, artificial intelligence (AI), and cloud computing (CC) with the energy industry [1], energy production has gradually transformed from monolithic to centralized and decentralized. The construction and development of smart cities is advancing rapidly around the world. More and more cities are trying to apply AI technology to energy management in order to reduce energy consumption and environmental pollution, and to provide a new impetus for sustainable urban development. At the same time, to expedite the growth of the digital economy and allocate resources more efficiently, in 2022 the Chinese government pointed out that it is necessary to make use of AI or other emerging technologies to enhance the management mechanisms of energy systems and accelerate the construction of a modern energy market to maximize the promotion of energy conservation and carbon reduction. However, as China's economy enters a high-quality development stage, the contradiction between energy usage and economic growth has become increasingly prominent; improving urban energy efficiency has become an important issue in balancing the sustainable development of both [2].

In this context, the rapid development of AI technology brings new growth opportunities for the energy industry. The application of this technology tends to prompt the exponential growth of data volume in smart cities [3], which will expand the scope of data extraction, fusion, cleaning, and processing. And then, this may generate higher demand for computing resources and exacerbate the problem of energy consumption to some extent. However, existing AI algorithms and computing power are still unable to meet the demands of large-scale energy optimization, so more advanced technologies are urgently needed in the fields of smart grids, smart buildings, and intelligent transportation to improve the rational allocation of resources. Therefore, the construction of smart cities has become a hot issue. As the resource centers and core carriers of policy implementation, cities and AI play different roles, respectively. The latter is a key tool for achieving optimal energy management, while the former provides a wide range of application scenarios for AI technologies [4]. Therefore, it is of great significance to study the impact of AI development on urban energy efficiency and promote the implementation of smart city pilot policies for the realization of national energy revolution and urban green and low-carbon transformation.

On this basis, this study constructed a panel dataset of 282 prefecture-level cities from 2006 to 2019, and conducted a series of robustness tests to ensure the accuracy and reliability of the research data. Meanwhile, from the perspectives of green technology innovation and digital economy, this paper comprehensively examined the impact mechanism of AI on energy utilization and analyzed the impact of AI development on urban energy efficiency for different regions and levels of the economy to enrich existing theories. In addition, this paper also utilized the multi-period DID model to test the parallel trend of the smart city policy to further explore its impact on urban energy efficiency and rule out endogeneity issues, with a view to providing a new direction of thinking for future urban planning and construction.

2. Literature Review

In recent years, scholars have deeply considered the application of AI to various production fields, but the implications of AI use in the academic world have yet to result in a unified definition. Most of the existing literature regards AI as a computer program with autonomous learning characteristics, which mainly uses intelligent environmental sensors and big data to continuously analyze, adapt, and regulate the environment [5,6]. However, some scholars believe that AI is a technology designed and developed for energy internet systems that combines machine learning, swarm intelligence algorithms, and other hybrid techniques like artificial neural networks [7,8]. On this basis, the applications of AI in the energy field are mainly reflected in the following several areas. First, optimization of smart energy management systems. Through the analysis of big data and AI algorithms, the relevant decision-making departments can further grasp urban energy utilization and improve the accuracy and feasibility of resource allocation so as to realize refinement of urban energy management [9]. Second, the fostering of green technology innovation. If the strength to implement environmental regulations and policies exceeds a certain threshold, the development of AI can promote the application of new energy technologies and reduce the cost of energy consumption [10]. Third, acceleration of the construction of the energy internet (EI). Via the control system of the EI, a distributed control method based on AI can improve the stability and aging of an EI system more quickly, and ensure the sustainable operation of the EI system [11]. Fourth, expansion of the application scenarios of smart energy. AI is widely applied to energy consumption, production, storage, and transmission by utilizing smart technologies for scheduling, management, and optimization [12,13]. It can realize the potential of the smart grid to expand the energy network and accelerate the speed of the energy decarbonization transition.

There are still some controversies in the research regarding the impact of AI development on urban energy efficiency. In concrete terms, excessively fast update repetition rates and unreasonable treatment of outdated artificial intelligence equipment may intensify energy consumption and hinder the balanced development of urban ecosystems [14]. However, in the process of the establishment of smart cities, there is no doubt that AI technology can provide cities with a more efficient and intelligent management service system [15]. Ullah Z et al. believed that the smart city represents the efficient use and optimal allocation of urban resources through informatization, digitization. and networking technology, so as to improve the efficiency of urban operation and the quality of life of residents [16]. And energy management is the management paradigm for realizing the complex energy system of the smart city [17]. In terms of mechanism testing, Li et al. discussed the effect of AI development on Chinese energy transformation and upgrading under the promotion of 5G technology based on an energy system analysis model (GCAM) and concluded that smart interconnection will reshape China's energy system [18]. Guo and Li considered the impact of urban economic development on energy saving optimization through the construction of an environmental effect input-output index system [19]. They adopted a spatial econometric model to study the heterogeneity of the impact of urban development on energy saving and exhaust reduction efficiency. Guo et al. experimentally analyzed the smart city pilot policy by quantifying energy and environmental performance with the non-radial directional distance function (NDDF) model [20]. It was found that implementation of the policy significantly promoted the improvement of energy and environmental performance. Many of these scholars' views directly or indirectly indicate that AI can help improve energy efficiency through various impact channels and mechanisms.

However, there are some gaps in the existing research on the impact of AI development on urban energy efficiency. Although most of the existing studies have explored the relationship between AI and regional energy efficiency at the macro level, such as the provincial level, there is a lack of in-depth studies on prefecture-level cities from the micro perspective. Considering also that China is a vast country with large differences in resource endowments between regions, the impact of AI on energy efficiency is not the same in different regions. Accordingly, this paper conducted group regressions of prefecture-level cities across four dimensions to further explore their heterogeneity. In addition, most current studies tend to overlook the importance of national policy factors when exploring the relationship between AI and energy efficiency. In fact, government intervention and the implementation of related policies have a significant impact on energy efficiency, so future research should pay more attention to the interaction of national policies with AI development and its impact on energy efficiency.

Currently, some research results have shown that AI can reduce the cost of energy consumption and improve the efficiency of energy use by optimizing the energy management system [9–13]. At the same time, the construction and development of smart cities also promotes the application of AI technology in the energy sector [16]. Therefore, to explore the impact of AI development on urban energy efficiency in more depth, based on the findings of existing studies, the possible marginal contributions of this paper compared to the existing literature are as follows: (1) Exploration of the impact of AI development on urban energy efficiency from the perspective of prefecture-level cities to enrich existing theories. (2) Based on the perspectives of the human capital level and government intervention, etc., this paper analyzes the heterogeneity of the impact of AI on urban energy efficiency across different regions, so as to provide a reference resource for the relevant departments to formulate tailored development policies. (3) This paper introduces the smart city pilot policy and uses a multi-period DID model to treat it as an endogeneity issue in order to further explore the impact of AI on urban energy efficiency and provide some theoretical support to the construction of a modernized environmental maintenance system in the future.

3. Theoretical Analysis and Research Hypothesis

3.1. The Impact of AI Development on Urban Energy Efficiency

The development of AI has a direct or indirect impact on urban energy efficiency. Analyzed from the angle of its direct impact, AI technology can identify the problems existing in the present environment through the identification and analysis of a large amount of historical data [21], which can help city managers conclude decision-making judgments more quickly. It also formulates a reasonable energy allocation plan to avoid energy mismatch and waste at the source to further improve urban energy utilization efficiency [22]. From the perspective of indirect impact analysis, the combination of AI with information technologies in the field of energy production and energy storage could form an integrated regional energy system that would improve the efficiency of renewable energy outputs by monitoring and adjusting the operating parameters of wind and solar power plants in real time [23]. At the same time, with the help of a variety of integrated sensors and intelligent equipment, AI technology for smart grid construction and management can help the relevant government departments achieve the intelligent scheduling and distribution of electricity [24], reduce energy transmission losses, minimize the negative impact of economic development on the environment, and prompt the green and sustainable development of urban energy. Accordingly, Hypothesis 1 is formulated:

Hypothesis 1: *The development of AI can improve urban energy efficiency.*

3.2. The Indirect Effects of AI Development on Urban Energy Efficiency

3.2.1. Green Technology Innovation

Green technology innovation is an important route to enhance energy savings and emission reduction capacity in the process of industrial production and economic development [25]. In the context of industrial intelligence, enterprise activities are no longer limited to the concentrated application of traditional labor but focus more on technology development, output efficiency, factor inputs, and cost savings [26]. Through the development and improvement of green technologies, the production departments of relevant enterprises can establish management models and control mechanisms that harmonize the economy, resources, and the environment to reduce unnecessary processes. This will minimize energy losses in production processes and improve the efficiency of resource allocation. Therefore, AI development can accelerate the digitalization and green transformation of enterprises by promoting green technological innovation and, in turn, increase the energy efficiency of cities.

3.2.2. Digital Economy

The development of AI has not only changed the traditional production management model, but also promoted the rapid growth of the digital economy [27]. In terms of industrial digitization, as an important representative of the new generation of information technology, AI has been applied to prompt production intelligence, service personalization, and scientific decision-making in various industries. It will increase the market entry efficiency and core competitiveness of enterprises. And, against the backdrop of the digital economy, the development of AI will expand the theoretical system in areas such as quality transformation, efficiency transformation, and power transformation to a certain extent. It can help government departments better grasp the rules of digital economic development and play a decisive role in market resource allocation to improve energy efficiency [28]. Meanwhile, as an important engine of the digital economy era, AI empowers the digital economy and exercises the advantages of intelligent power grids, which will expand the coverage of the energy network and promote the development of green energy and low-carbon circulation. On this basis, this paper proposes Hypothesis 2:

Hypothesis 2: *AI can improve urban energy efficiency by accelerating the development of green technology innovation and the digital economy.*

3.3. Heterogeneity in the Impact of AI Development on Urban Energy Efficiency

The impact of AI development on urban energy efficiency is not singular or undifferentiated. There are some differences in its effect on urban agglomerations in different regions. So, to make the study more comprehensive and objective, this paper further analyzed the heterogeneity from four perspectives, including the East, Central, and West regions of China, and the human capital level.

3.3.1. Analysis of Regional Heterogeneity

Considering the disparities in resource endowments between regions and the fact that infrastructure and institutional development are not well developed in the low- and medium-growth regions, the implementation of the same policy may not have the same effect in different regions [29]. Specifically, although the midwestern area is rich in natural resources, there may be a certain delay in the development and application of AI technology due to the limitations of the geographical environment and the lack of capital, talent, and technology. In contrast, cities located in the eastern region tend to have a stronger economic base, a more open market environment, and a more adequate pool of professionals, enabling AI technology to develop rapidly and provide strong support for the optimization of urban energy management systems.

3.3.2. Heterogeneity Analysis of Human Capital Level

According to Schultz's (1960) theory of human capital [30], economic development depends primarily on improvements in the quality of people rather than on the abundance of natural resources or capital. As an important factor in driving energy technology innovation, the level of human capital directly affects the development of AI technology. In the construction process of modern industrial systems, the improvement of the human capital level provides high-quality professionals for the development of modern service systems and stimulates the potential productivity of various types of capital, including human capital [31,32]. This helps foster economic development and the coordinated allocation of energy utilization, so as to increase the reuse rate of related production factors and promote the efficiency of urban energy utilization.

3.3.3. Heterogeneity Analysis of Financial Independence

Under the local fiscal framework, the fiscal independence of the government is defined as the decision-making autonomy of the government in the process of formulating and implementing fiscal policies, which mainly represents the level of financial self-sufficiency. In general, urban government departments with a high degree of financial self-sufficiency usually provide sufficient funds to support the R&D of AI technology and attract more innovative talent and enterprises [33]. On the contrary, enterprises in relevant departments of cities with low financial self-sufficiency may face limitations in terms of special R&D funds, and this makes it difficult to invoke resources, technology, and manpower, thus hindering the application and development of AI technology in the field of urban energy management.

3.3.4. Heterogeneity Analysis of Government Intervention

Many government interventions are aimed at improving industrial process productivity and technological innovation [34], and there are also some differences in the focus and objectives of government interventions in different regions. Influenced by the national policy environment, cities with greater government intervention have a better constructed system and more stable cooperation between enterprises, universities, and research institutes, which provides a favorable environment for the development of AI technology [35]. In cities with lower government intervention, enterprises and research institutions may face problems such as an unclear market direction and unreasonable resource allocation, leading to the misallocation and waste of resources. This will directly affect the overall development of AI technology and the effective use of urban resources. Therefore, to further analyze the impact of AI on urban energy utilization, Hypothesis 3 is proposed in this study:

Hypothesis 3: *The development of AI has a positive effect on urban energy efficiency in the eastern region where the levels of human capital, financial independence, and government intervention are higher.*

4. Research Model and Variable Interpretation

4.1. Empirical Model Setting

The empirical study in this paper aims to effectively identify the impact of AI development on urban energy efficiency. First of all, the Hausman test was conducted in this paper, and the results showed that the *p*-value is 0.000, which rejects the null hypothesis. It means that the fixed effect of the benchmark regression model in this paper is better than the random effect, so the fixed effect should be selected for analysis. And according to the theoretical mechanism and research hypothesis, the following benchmark regression model is set:

$$EE_{it} = \beta_0 + \beta_1\, AI_{it} + \gamma C_{it} + \mu_i + \lambda_t + \xi_{it} \quad (1)$$

where i denotes the city and t denotes the year. The explanatory variable EE_{it} stands for the energy utilization efficiency of city-i in period-t, and the core explanatory variable AI_{it} is the level of AI development of city-i in period-t. The most relevant coefficient in this study is the AI_{it}-estimated coefficient β_1, which reflects the degree of the impact of AI development on the city's energy utilization efficiency. If the estimated coefficient $\beta_1 > 0$, it indicates that AI development in a prefecture-level city has a promoting impact on the improvement of urban energy efficiency; if the estimated coefficient $\beta_1 < 0$, it indicates that AI development has an inhibiting impact on the improvement of urban energy efficiency. Meanwhile, to increase the reliability of the empirical results, this paper controlled as much as possible for other elements C_{it} that may affect the city's energy efficiency, primarily including the degree of development of the economy, industrial structure, science and technology expenditures of the prefecture-level city, advanced industrial structure, and foreign direct investment. Moreover, to exclude the potential interference of unobservable and time-varying factors for a prefecture-level city on the regression results, this paper added city-fixed effects μ_i and year-fixed effects λ_t, with ξ_{it} as a random error term.

4.2. Variable Selection and Data Sources

4.2.1. Explained Variable: Urban Energy Efficiency

Regarding the measurement method of urban energy efficiency, this study referred to the measurement methods of Shi, Li, and Feng et al., and measured the total-factor energy efficiency and green total-factor energy efficiency from the perspectives of energy constraints and energy and environmental constraints, respectively [36,37]. The input and output variables were set as follows: labor, capital, and energy were selected as inputs, which were measured by the number of employees per year, total fixed asset investment for society as a whole, and the electricity consumption of the whole society, respectively. The expected output was the gross regional product, and the emissions of industrial sulfur dioxide, industrial wastewater, and industrial smog (dust) were taken as the non-desired outputs that were all measured by using the SBM–Malmquist–Luen–Berger index method—the Berger index method was used for the measurement.

4.2.2. Core Explanatory Variable: AI

As mentioned above, although most studies have been conducted to measure AI indicators in different fields, there is currently no unified measurement methodology or measurement system for AI development indicators in academia [38]. Therefore, this paper primarily started from the below four industrial dimensions: research and experimental development, software and information technology services industry, the internet and related services, the manufacturing industry for computers and other electronic equipment. The main categories, including the optimization of AI algorithms and the development and application of electronic technology products and software are used as judgment criteria. After screening, this paper selected the number of AI enterprises in each prefecture-level city as a proxy variable to measure the development of AI from 2006 to 2019.

4.2.3. Control Variables

The control variables selected here are specifically as follows (Table 1): the economic development level (*GDP*), which is expressed as the GDP of prefecture-level cities (please note that due to the consideration of factors such as city size, the GDP per capita normalization is not used in here); industrial structure (*HHI*), measured by the ratio of the increase in tertiary industry to GDP; prefectural-level city science and technology expenditure (*SCS*) is expressed using the ratio of prefectural-level city science and technology expenditure to local government general budget revenues; the advanced industrial structure (*ISS*), measured as the sum of primary industry value added to GDP, the sum of two times the secondary industry value added to GDP, and three times the tertiary industry value added to GDP; foreign direct investment (*FDI*), expressed as the ratio of the actual utilization of foreign investment to GDP. And the control variables in this paper are referenced from the literature selection methods of Deng and Xiao and Zhao and Li et al. [36–43].

Table 1. Description of Control Variables.

Variables	Measurement	Properties
GDP	the GDP of prefecture-level cities	+
HHI	the ratio of the increase in tertiary industry to GDP	−
SCS	the ratio of prefectural-level city science and technology expenditure to local government general budget revenues	+
ISS	the sum of primary industry value added to GDP, the sum of two times the secondary industry value added to GDP, and three times the tertiary industry value added to GDP	+
FDI	the ratio of actual utilization of foreign investment to GDP.	−

4.2.4. Mechanism Variables

This paper measures the green technology innovation index (*Green*) as the total number of green patent applications per 10,000 people, and explores the impact of the development of AI on urban energy efficiency from the perspective of green technology innovation. Regarding the measurement indicators for the digital economy, this study mainly referred to the research methodology of Zhang and Jiao to construct a comprehensive development indicator system for the digital economy in Chinese cities in terms of five aspects [39]: the internet penetration rate, number of internet-related practitioners, internet-related outputs, number of mobile internet users, and the inclusive development of digital finance (Table 2). The sources of these indicators are available in the "Statistical Yearbook of China's Cities". Among them, China's digital financial welfare index was jointly created by the Peking University Digital Finance Research Center and the Ant Gold Service Research Institute (2020), which standardizes and downsizes the data of the above five indicators through the principal component analysis method to obtain a digital economic development index (*Digital*).

Table 2. Indicator system for comprehensive development of digital economy in Chinese cities.

Primary Indicators	Secondary Indicators	Measurement	Properties
Digital Economy Development Index	Internet penetration rate	Number of internet users per 100 people	+
	Amount of internet-related employees	Percentage of computer services and software employees	+
	Internet-related outputs	Total amount of telecommunications operations per person	+
	Amount of mobile internet users	Number of mobile phone subscribers per 100 people	+
	Universal development of digital finance	China digital finance index	+

4.2.5. Descriptive Statistics

By constructing the panel data of 282 prefecture-level cities in China from 2006 to 2019, this paper studies the impact of AI development on urban energy efficiency and forms 3948 city–year data observations. The data sources are the "China Urban Statistics Yearbook", the "China Energy Statistics Yearbook", the "China Environmental Statistics Yearbook", the EPS database, the Wind information database, the statistical bulletins of each local-level city, and three "National Smart City Trial Lists" released by the Ministry of Housing and Construction. Table 3 provides descriptive statistical results for the variables used herein. The results showed that the maximum value of the AI development index was 16.99, the minimum value was 0.001, and the standard deviation was 0.915, indicating that considerable differences in AI development levels exist between locations, as does significant heterogeneity in the performance of other control variables.

Table 3. Descriptive statistical characteristics of main variables.

Types	Variables	Interruption	Obs	Mean	Std. Dev	Min	Max
Explained variable	*EE*	Urban energy efficiency	3948	0.370	0.063	0.162	1.007
Core explanatory variable	*AI*	The development of AI	3897	0.250	0.915	0.001	16.99
Control variables	*GDP*	Level of economic development	3920	2.068	3.064	0.052	38.16
	HHI	Industrial structure	3948	0.427	0.063	0.333	0.835
	SCS	Expenditure on science and technology	3948	0.812	3.032	0.000	55.50
	ISS	Advanced industrial structure	3948	2.262	0.144	1.831	2.832
	FDI	Foreign direct investment	3906	0.018	0.019	0.000	0.212
Mechanism variables	*Green*	Green technology innovation	3829	1.085	2.792	0.003	49.98
	Digital	Digital economic development index	3942	0.080	0.085	0.001	0.865

5. Empirical Analysis

5.1. Baseline Regression

This paper introduced a two-way fixed-effects model to evaluate the impact of AI development on urban energy efficiency and the baseline regression results are shown in Table 4. From the regression results in columns (1) to (6) of Table 4, it can be seen that with the stepwise addition of control variables, the estimated coefficient of AI is 0.018, which is greater than 0 and is significant at the 1% significance level. Hypothesis 1 was verified. It indicated that AI development has a significant positive effect on improving urban energy efficiency. From the performance of the control variables, the estimated coefficient of industrial optimization (*HHI*) is -0.127, which is inversely proportional to urban energy efficiency, indicating that the excessively concentrated development layout will reduce urban energy efficiency, which is in line with the current economic development status of the country. The possible reason is that a highly concentrated industrial layout will deepen the degree of monopolization in industry to a certain extent, which will in turn increase the unbalanced distribution of resources in the market, resulting in the mismatch and waste of resources, and lowering the efficiency of urban energy utilization [40]. In addition, since tertiary industry is mainly dominated by the service industry, its energy consumption is lower than that of secondary industry. However, with the increase in the proportion of the tertiary industry and the total urban economic aggregate, the total energy consumption also increases correspondingly, resulting in a decrease in energy efficiency. Therefore, controling the market position of competitors in each industry, stimulating their motivation to improve and innovate, and reducing the negative impacts of the uneven distribution of resources between industries are key concerns in the process of coordinating economic growth and environmental development in China [41].

Table 4. Benchmark regression results.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	EE	*EE*	*EE*	*EE*	*EE*	*EE*
AI	0.038 ***	0.018 ***	0.019 ***	0.018 ***	0.018 ***	0.018 ***
	(47.78)	(14.00)	(14.54)	(11.33)	(11.36)	(11.25)
GDP		0.012 ***	0.012 ***	0.012 ***	0.012 ***	0.012 ***
		(18.37)	(18.74)	(16.73)	(16.69)	(16.23)
HHI			−0.130 ***	−0.128 ***	−0.127 ***	−0.127 ***
			(−6.77)	(−6.63)	(−6.52)	(−6.52)
SCS				0.001 *	0.001 *	0.001 **
				(1.75)	(1.75)	(1.96)
ISS					0.012	0.013
					(0.94)	(0.95)
FDI						−0.153 ***
						(−3.79)
ons	0.361 ***	0.340 ***	0.395 ***	0.395 ***	0.366 ***	0.369 ***
	(714.57)	(276.46)	(47.81)	(47.75)	(11.59)	(11.62)
Year	Yes	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes	Yes
N	3897	3869	3869	3869	3869	3841
R^2	0.806	0.823	0.825	0.825	0.825	0.826
F	2283.3	1407.1	965.1	725.0	580.2	482.6

Note: Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, respectively.

Considering that the research topic of this paper is related to the Environmental Kuznets Curve (EKC), this paper further explored whether there is a similar U-shaped relationship between energy efficiency and income as measured by the disposable income of urban residents in prefecture-level cities. The results showed that there is a U-shaped relationship between income and energy efficiency with an extreme point of 0.2927628, and the coefficients of both the primary and squared terms are significant at the 1% level of significance. They suggest that energy efficiency begins to decrease as income increases and increases with income level when it reaches 29,276.28 yuan. The underlying logic is consistent with the inverted U-shaped relationship between environmental degradation and economic growth predicted by the EKC concept. When the energy efficiency decreases with increasing income levels, the corresponding cost of energy consumption rises, which may further lead to problems of the over-exploitation of energy resources and increased environmental pollution, and thus the environmental situation initially deteriorates with increasing income levels. However, as income levels rise further, people begin to pay more attention to energy efficiency and environmental protection, so utilization efficiency also begins to increase, which brings about an improvement in environmental conditions.

At the same time, this paper takes into account the nonlinearities of income and introduces them into the model in the form of quadratic terms. The results (Table 5) show that the impact of AI on urban energy efficiency remains significant after accounting for income. This suggests that the development of AI can be effective in improving urban energy efficiency, regardless of changes in income levels. The reason for this may be that higher revenues mean that companies have more money available to invest in R&D and the implementation of AI technologies. This includes purchasing and upgrading high-performance computing equipment, developing more advanced algorithms, etc., in order to reduce the cost of energy consumption and further promote the improvement of energy utilization efficiency. However, it is important to note that while higher incomes can provide more financial support for the application of AI in energy efficiency, this does not mean that the higher the income, the greater the impact of AI on energy efficiency. This is because the application and development of AI technology is also affected by other factors, such as the level of technology, policy support, and market demand. Therefore, a combination of factors needs to be considered to fully assess the impact of income on AI in terms of energy use efficiency.

Table 5. Benchmark regression results: introducing the nonlinearity of income.

Variables	(1)	(2)	(3)	(4)
	EE	*EE*	*EE*	*EE*
AI	0.007 ***	0.012 ***	0.009 ***	0.013 ***
	(4.33)	(7.27)	(5.60)	(8.54)
Salary	−0.038	−0.007	0.122 **	−0.342 ***
	(−1.32)	(−0.32)	(2.43)	(−6.22)
Salary2	0.350 ***	0.149 ***	0.267 ***	0.584 ***
	(6.79)	(3.88)	(3.86)	(9.85)
Cons	0.500 ***	0.465 ***	0.477 ***	0.365 ***
	(34.61)	(17.93)	(32.83)	(11.26)
Controls	Yes	Yes	Yes	Yes
Year	No	No	Yes	Yes
City	No	Yes	No	Yes
N	3841	3841	3841	3841
R^2	0.526	0.820	0.541	0.832
F	531.7	513.6	492.5	393.1

Note: Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, respectively.

5.2. Robustness Check

5.2.1. Substitution of the Explained Variable

Since China's "14th Five-Year Plan" has adopted the reduction in energy consumption per unit of *GDP* by 13.5% as one of the main constraints on economic and social development, this study took energy intensity, which denotes the energy consumption per unit of *GDP*, as a proxy variable for the explained variable of urban energy efficiency. The regression results are shown in column (1) of Table 6; the estimated coefficients of the explanatory variables were significantly negative, indicating that AI development had a significantly inhibitory effect on urban energy intensity and improved urban energy utilization efficiency by reducing energy consumption per unit of power generation, which verifies the robustness of the baseline regression results.

Table 6. Robustness test results.

Variables	(1)	(2)	(3)	(4)
AI	−0.013 **	0.063 ***	0.037 ***	0.032 ***
	(−1.97)	(2.70)	(18.26)	(11.80)
Cons	1.340 ***	0.882 ***	0.972 ***	1.061 ***
	(4.09)	(8.28)	(13.11)	(14.77)
Controls	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
N	3841	2466	3563	3841
R^2	0.384	0.847	0.827	0.806
F	13.76	143.2	376.6	373.4

Note: Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, respectively.

5.2.2. Substitution of the Explanatory Variable

Referring to the digital economy measurement method of Zhao et al. [42], this study takes the digital transformation index (*DI*) as the proxy variable of the number of artificial intelligence enterprises (*AI*) for benchmark regression, and the results are shown in column (2) of Table 6. The transformation to digitalization has a positive effect on the energy efficiency of the city at a remarkable level of 5%, which indicates that urban digital transformation contributes to urban energy efficiency. This result further demonstrates the positive effect of AI development on urban energy efficiency and validates the robustness of the baseline regression results by promoting the digital transformation of firms to reduce the cost of energy utilization in order to achieve environmental sustainability goals.

5.2.3. Lagged One-Period Regression Processing

As an emerging field of scientific and technological development in China, AI can improve urban energy efficiency through green technology innovation, efficient allocation of market resources, and the optimization of the energy structure combined with ecological protection [25]. Since the above influence mechanisms work during a certain period, there may be a time lag affecting the increase in urban energy efficiency by AI development [43]. Therefore, the core interpretation variable, namely AI development, was delayed by one period and regression processing was performed to eliminate the influence of the current period. The regression results are shown in column (3) of Table 6. The results show that the estimated coefficient of the lagged one-period interpretation variable is consistent with the baseline regression results and remains significantly positive, which verifies that the results are robust.

5.2.4. Shrinkage Treatment

This study referred to the practice of Deng and Xiao of eliminating the effects of extreme outliers, in which the explanatory variables and all the continuous variables were shrunk to extreme outliers at the upper and lower 1% mark, and the regression estimation was re-conducted [43]. The results in column (4) of Table 6 showed that the development of artificial intelligence has a significant positive effect on urban energy efficiency at a significance level of 1%, which is basically consistent with the baseline regression results.

5.3. Heterogeneity Analysis

5.3.1. Analysis of Regional Heterogeneity

Considering the differences between different regions in terms of economic development, technological level, demographic structure, and degree of openness, AI development produces different implementation effects on urban energy efficiency [44]. This study divided the urban sample into eastern, central and western regions to conduct group regression, and the results are shown in columns (1) to (3) of Table 7. The regression results show that, in the eastern and central regions, the improvement in urban energy efficiency due to the development of artificial intelligence is at a remarkable level of 1%, which may be caused by the following reasons. First, the eastern and central regions usually have higher levels of economic development and scientific technology innovation, which provides a favorable environment for the development of AI. The industrial structure of these regions is mainly capital- and technology-intensive, and many high-tech enterprises, R&D centers, and innovation platforms gather there, which promotes the integration and upgrading of related industries. In contrast, the western region lags behind in the development level of artificial intelligence due to the limitations of the geographic environment and financial support. Moreover, the complex terrain in the western region, the high cost of infrastructure construction, and the lack of funds make the promotion and application of AI technology in the region subject to certain constraints. Therefore, the improvement of urban energy efficiency in the western region has not been significantly affected by AI technology.

Table 7. Analysis of regional heterogeneity.

Variables	**East**	**Central**	**West**
	(1)	**(2)**	**(3)**
AI	0.020 *** (7.97)	0.017 *** (5.32)	0.004 (1.61)

Table 7. *Cont.*

Variables	East	Central	West
	(1)	(2)	(3)
GDP	0.016 ***	0.015 ***	0.012 ***
	(11.64)	(14.69)	(12.28)
HHI	−0.398 ***	−0.084 ***	−0.010
	(−6.27)	(−5.37)	(−0.65)
SCS	−0.001	−0.010 ***	−0.014 ***
	(−0.93)	(−11.33)	(−6.68)
ISS	−0.004	0.024 **	0.022 *
	(−0.10)	(2.38)	(1.74)
FDI	0.042	0.040	−0.450 ***
	(0.51)	(1.23)	(−6.31)
Cons	0.522 ***	0.319 ***	0.293 ***
	(6.08)	(13.59)	(9.63)
Year	Yes	Yes	Yes
City	Yes	Yes	Yes
N	1400	1346	1095
R^2	0.830	0.830	0.763
F	199.4	108.7	53.86

Note: Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, respectively.

5.3.2. Analysis of Human Capital Heterogeneity

In this study, referring to the method of Deng and Xiao, the ratio of urban university students enrolled in urban higher education institutions to permanent urban residents was used to measure the level of urban human capital [43]. Divided into two groups of high and low human capital levels by their mean values, the regression results are shown in columns (1) to (2) of Table 8. This reveals that, in areas with low human capital levels, the development of AI has not significantly increased energy efficiency. In fact, it has somewhat decreased the city's energy efficiency. There are some possible reasons, as follows. In areas with lower levels of human capital, there is a lack of absorption and digestion capacity and comprehensive management mode in the relevant production sectors, which cannot fully and reasonably allocate effective resources, thus reducing energy utilization efficiency [45]. In addition, these regions may lack a well-developed education and training system, resulting in a relatively low-skill level of the workforce, which is difficult to adapt to the development needs of AI technology. In the meantime, high-quality talent tends to have a higher demand for environmentally friendly capital, and factors such as salary, corporate culture, and local talent policies affect the inflow of talent and innovation motivation of core R&D personnel in the region.

Table 8. Heterogeneity analysis of other factors.

Variables	Human Capital		Financial Independence		Government Intervention	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.019 **	−0.001	0.019 **	0.004	0.018 **	0.020 *
	(2.53)	(−0.21)	(2.16)	(0.37)	(2.17)	(1.85)
Cons	0.308 *	0.338 ***	0.440 ***	0.331 ***	0.380 **	0.361 ***
	(1.92)	(9.20)	(2.26)	(8.34)	(9.11)	(2.51)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes	Yes
N	1092	2711	1118	2704	1984	1802
R^2	0.804	0.903	0.812	0.826	0.916	0.796
F	16.26	10.95	22.54	11.31	15.81	7.387

Note: Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, respectively.

5.3.3. Analysis of Financial Independence Heterogeneity

In local economic development, the financial self-sufficiency rate is usually used as an essential indicator to evaluate the financial independence and financial support ability of a local government. This study took the ratio of local fiscal revenue to total funds as the measurement basis and divided the mean value into two high and low groups for regression analysis [43]; the outcomes are displayed in columns (3) to (4) of Table 8. The impact of AI development on urban energy efficiency was positive at the 5% significance level in regions with higher fiscal independence, whereas the improvement in energy efficiency due to AI development was not significant in regions with lower fiscal independence. From the perspective of technology R&D infrastructure construction, the relevant government departments in regions with higher financial independence have sufficient expenditures to support the R&D and improvement of AI technology and encourage relevant enterprises to innovate. This helps establish an atmosphere that is conducive to the advancement of scientific and technological innovation, which stimulates economic growth of the industrial upstream and downstream, which has certain spillover effects and "demonstration effects" [33]. In regions with low fiscal independence, governments may face a shortage of funds to invest sufficient resources in the R&D and promotion of AI technologies. The industrial structure of these regions may be relatively unitary and dominated by traditional industries. So, there may be relatively little demand for and application of AI technology, resulting in AI development that is out of step with market demand, and thus hinders the efficient use of local energy.

5.3.4. Analysis of Government Intervention Heterogeneity

As different local governments have different degrees of supervision and intervention in environmental protection, this paper measures the level of government intervention using the ratio of general budget revenue from local taxes to *GDP*, and divides its mean value into high and low groups for regression [43]. The outcomes are listed in columns (5) to (6) of Table 8. In locations where government intervention is more intense than in areas where it is less intense, AI development has a greater impact on enhancing urban energy efficiency. This may be attributed to the following reasons. The relevant government departments often have stronger supervision and enforcement on enterprise resource input and utilization, and stricter requirements on the implementation of pollutant discharge standards. Therefore, this tends to prompt enterprise R&D departments to accelerate the optimization of the energy production and consumption system, freeing the traditional labor force from complicated and trivial processes [34], so as to reduce the costs of labor and increase the effectiveness of resource allocation. On the other hand, in areas where government intervention is lower, the relevant enterprises may have insufficient motivation to invest in the R&D of AI green technologies due to the lack of corresponding incentives, penalties, and supervision [46], which may prevent AI technologies from being integrated with traditional industries to some extent; thus, affecting the improvement of urban energy efficiency.

5.4. Analysis of Impact Mechanisms

To make the research more comprehensive, this paper attempts to explore the internal logic of AI development on the improvement of urban energy efficiency. So, it utilizes the mediated-effect test model to examine the mechanism of AI development on urban energy efficiency from the perspectives of green technology innovation and the digital economy, respectively. In accordance with the logical theory of the mediation effect test and Equation (1), the mediation effect test models (2) and (3) are set as follows:

$$Mediantor_{it} = \rho_0 + \rho_1\, AI_{it} + \rho_2\, C_{it} + \mu_i + \lambda_t + \xi_{it} \tag{2}$$

$$EE_{it} = \eta_0 + \eta_1\, AI_{it} + \eta_2\, Mediantor_{it} + \eta_3\, C_{it} + \mu_i + \lambda_t + \xi_{it} \tag{3}$$

where i denotes the city, t denotes the year, $Mediantor_{it}$ is the mediating variable that represents green technology innovation and the development index of the digital economy, respectively. The impact of AI development on the mediating variable was examined using Model (2), and Model (3) was further used to test the mediating effect of the mediating variable on the process of AI development affecting the city's energy efficiency. The remaining control variables are the same as in the previous study, and the two-way fixed-effects model was introduced into the regression process to ensure the robustness of the regression results.

5.4.1. Green Technology Innovation

Referring to the methods of Zhang and Liu, this paper utilized the number of green patent applications per 10,000 people as an indicator to measure the level of green technology innovation, so as to further explore the impact mechanism of AI development on urban energy efficiency [47]. The regression results are displayed in column (1) of Table 9 and column (1) of Table 10, indicating that AI development can increase urban energy efficiency by promoting green technology innovation. This is due to the fact that AI technology in the field of energy management can effectively enhance the energy utilization mode of traditional industries and lessen the intensity of energy consumption by improving production efficiency, which not only pursues economic benefits but also emphasizes environmental and ecological effects at the same time [48]. In addition, based on the R&D and promotion of green technologies, enterprises in the industry can learn from each other so as to generate a horizontal technology spillover effect and lessen the communication and transaction costs to prompt the transformation of achievements in each region [49]. At the same time, according to the theory of system optimization and the theory of sustainable development, artificial intelligence technology plays an important role in promoting green and low-carbon development. The urban energy system is a complex network, including multiple subsystems such as electricity, heat, and gas. AI can globally optimize the entire energy system through big data analysis and optimization algorithms to improve energy use efficiency. And AI can also help realize the intelligent deployment of renewable energy by promoting the application of clean energy, so as to realize the transformation from traditional energy with high pollution levels and high energy consumption to clean and low-carbon energy.

Table 9. Mechanism test results I.

Variables	**(1)**	**(2)**
	Green	***Digital***
AI	0.921 ***	0.017 ***
	(15.67)	(8.34)
Cons	11.884 ***	0.155 ***
	(9.84)	(3.69)
Controls	Yes	Yes
Year	Yes	Yes
City	Yes	Yes
N	3756	3841
R^2	0.875	0.830
F	970.8	141.2

Note: Robust standard errors in parentheses: *** $p < 0.01$.

Table 10. Mechanism test results II.

Variables	**(1)**	**(2)**
	EE	***EE***
AI	0.026 ***	0.018 ***
	(17.25)	(11.49)
Green	0.002 ***	
	(3.55)	

Table 10. *Cont.*

Variables	**(1)**	**(2)**
	EE	***EE***
Digital		−0.031 **
		(−2.42)
Cons	1.001 ***	0.374 ***
	(14.10)	(11.75)
Controls	Yes	Yes
Year	Yes	Yes
City	Yes	Yes
N	3756	3841
R^2	0.819	0.826
F	370.1	415.1

Note: Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, respectively.

5.4.2. Digital Economy

From the perspective of the digital economy, the regression results are listed in column (2) of Table 9, which show that AI effectively promotes digital economic development at the 1% significance level. The possible reasons may be that with the application of artificial intelligence technology in urban energy management, scheduling, and optimization, government departments can more accurately grasp the urban energy demand and supply through real-time analysis of urban energy consumption data, so as to formulate scientific and reasonable energy distribution plans [27]. At the same time, as the development of the digital economy promotes the progress of information technology and rich data resources, the application scope of smart grids and smart transportation continues to expand [24], which provides new solutions for urban energy management and thus improves the efficiency of urban energy utilization.

However, it is worth noting that, in column (2) of Table 10, the coefficient of the variable indicator of the digital economy is yet significantly negative. This shows that the development of the digital economy instead has a negative impact on energy efficiency. Indeed, this negative impact may stem from the marginal diminishing effect of digital resources as input factors and the rebound effect of energy consumption. At the mature stage of the development of the digital economy, the diminishing marginal effect of energy savings of the digital economy is negative, and the improvement of energy utilization efficiency brought about by the application of technology has reached the maximum value, which makes it difficult to further promote the optimization of energy structure. Moreover, the development of the digital economy is often accompanied by a large amount of energy consumption, especially in data centers, cloud computing, and large-scale data processing, which requires a large amount of electricity consumption, thus increasing the overall energy consumption and may lead to a decline in energy efficiency.

Although the development of the digital economy may have a certain negative impact on energy efficiency, it does not mean that we should deny the development of the digital economy. On the contrary, we should actively seek solutions to the energy and environmental challenges posed by the digital economy and promote synergistic development of the digital economy and energy efficiency. Therefore, Hypothesis 2 is verified.

6. Further Research: Smart City Policy

With the increasingly prominent problems of global climate change and environmental pollution, balancing economic growth and ecological development is an important issue that governments around the world are focusing on. The smart city pilot policy emerged in this context, with the aim of realizing the intelligent management of urban services through the innovation and application of digital technologies such as the Internet of Things, big data, and cloud computing, so as to improve the efficiency of urban energy utilization and foster sustainable social economic development [16]. From the standpoint of diffusion theory and policy innovation, the introduction of new regulations usually starts with pilot projects. It selects representative areas to carry out intelligent system transformation, and then gradually spreads to other areas through practical tests and summary of experience [50]. The execution of the pilot policy for smart cities encourages the adoption of advanced energy management technology and equipment so as to realize the continuous monitoring and intelligent management of energy consumption. This will improve the level of intelligence and operational efficiency of urban energy management to guarantee the stability and security of the energy supply and rationally allocate energy resources [11]. At the same time, the implementation of this policy has deepened residents' understanding of AI technology in terms of the improvement of energy efficiency, and more and more people are aware of the importance and urgency of the development of AI. The formation of this social consensus also creates a favorable environment for the popularization and application of AI technology. Accordingly, Hypothesis 4 is proposed in this study.

Hypothesis 4: *The implementation of the smart city pilot policy contributes to the improvement of urban energy efficiency.*

6.1. Model Design

To promote the establishment of smart cities in an orderly manner, China has issued a series of policy documents since 2012 and has gradually launched pilot projects in three batches of pilot cities. The implementation of this policy has accelerated the development of urban information technology and digital technology, and has carried out comprehensive and systematic transformation of urban governance and public management, so it has a certain effect on AI development in the process of improving urban energy efficiency. Based on the quasi-natural experiment of the smart city pilot policy, this paper refers to the research of Guo and Zhong to set a multi-period DID model and adds a two-way fixed-effects model to examine the impact of smart cities on urban energy efficiency [51]. The model was set up as follows:

$$EE_{it} = \alpha_0 + \alpha_1\ Treat_i{\cdot}Post_t + \alpha_2\ AI_{it} + \alpha_3\ C_{it} + \mu_i + \lambda_t + \xi_{it} \tag{4}$$

In Equation (4), $Treat_i$ represents both the control group and the experimental group: the cities included in the demonstration list of smart city construction are the experimental group, and the cities not included in the demonstration list of smart city construction are the control group. $Post_t$ represents the pre-experiment and post-experiment state of affairs, and the cross-multiplication term $Treat_i{\cdot}Post_t$ represents whether the smart city pilot construction is included. C_{it} is in line with the previous section as the control variables, μ_i and λ_t stand for the city-fixed effect and year-fixed effect, respectively, and ξ_{it} is a random disturbance term.

Specifically, this study used the cross-multiplier term $Treat_i{\cdot}Post_t$ as a measure of the city smartness indicator (*did*). The term $Treat_i$ denotes the policy dummy variable, which indicates that the cities included in the pilot list of smart cities in 2012~2014 are denoted as $Treat = 1$, and vice versa are denoted as $Treat = 0$. $Post_t$ denotes the policy implementation time dummy variable. As the policy effect appears with time lag, $Post = 1$ is recorded one year after the policy implementation time and subsequent years, otherwise $Post = 0$. The coefficient estimate α_1 of the cross-multiplier term $Treat_i{\cdot}Post_t$ indicates the net effect of smart city construction on urban energy efficiency.

6.2. Baseline Regression Analysis

This study divided them into four groups for empirical research based on whether to consider the two-way fixed-effects model, and the baseline regression results are listed in Table 11. The results show that, at the 1% significance level, the execution of the smart city pilot policy plays a positive role in the improvement of urban energy efficiency, regardless of whether the two-way fixed-effects model was considered or not. The implementation of the smart city pilot policy not only promotes the improvement of urban energy efficiency, but also has a far-reaching impact on the city's industrial structure, transportation and travel, and environmental protection. Based on the two-way fixed effects model, the estimated value of the coefficient of the interaction term (*did*) was 0.032, indicating that under certain other control variables, smart city construction promotes an average increase of 3.2% in the urban energy efficiency relative to non-pilot cities. Through intelligent management, the city is able to allocate resources more efficiently and guide enterprises to develop in the direction of high technology and high value-addedness, so as to reduce the energy consumption and pollution emissions to further realize green and sustainable development. The application of ITS also makes urban transportation smoother and reduces the energy waste and environmental pollution caused by congestion. This is essentially consistent with the examination of the benchmark regression results in the preceding section, supporting the robustness of the results and the validity of Hypothesis 4.

Table 11. Benchmark regression results for smart city pilot policy.

Variables	(1)	(2)	(3)	(4)
	EE	***EE***	***EE***	***EE***
did	0.028 ***	0.031 ***	0.026 ***	0.032 ***
	(9.34)	(8.02)	(7.87)	(7.87)
AI	0.022 ***	0.028 ***	0.022 ***	0.029 ***
	(9.21)	(9.15)	(8.97)	(9.22)
Cons	0.053 **	0.068	0.085 ***	0.880 ***
	(2.06)	(1.29)	(3.04)	(5.21)
Controls	Yes	Yes	Yes	Yes
Year	No	No	Yes	Yes
City	No	Yes	No	Yes
N	3855	3855	3855	3855
R^2	0.312	0.495	0.316	0.502
F	249.5	138.0	202.4	79.52

Note: Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, respectively.

6.3. Parallel Trend Test

In response to the treatment of endogeneity issues, this study also added all of the control variables discussed in the previous section and carried out the parallel trend test to exclude the changes in other external influencing factors and the possible impact on energy efficiency. The results are displayed in Figure 1. In the first two periods of the implementation of the pilot policy, the impact of the smart city policy on increasing urban energy utilization efficiency is not significant, but in the current period and after the implementation of the policy, the construction of smart cities plays an important role in improving urban energy efficiency, which passes the parallel trend test. This may be due to the fact that, after the adoption of the smart city pilot policy, the relevant government departments can carry out comprehensive monitoring and analysis of urban energy supply, distribution, and consumption through the system for intelligent energy management, so as to timely identify and solve the problems of resource mismatch and waste [12,13]. In addition, through the management system for intelligent transportation and other management systems, the urban planner can optimize the traffic layout and road construction [52], encourage citizens to use public transportation, cycle or walk for travel and reduce the use of private cars, so as to minimize exhaust emissions and energy consumption to improve the efficiency of urban energy use.

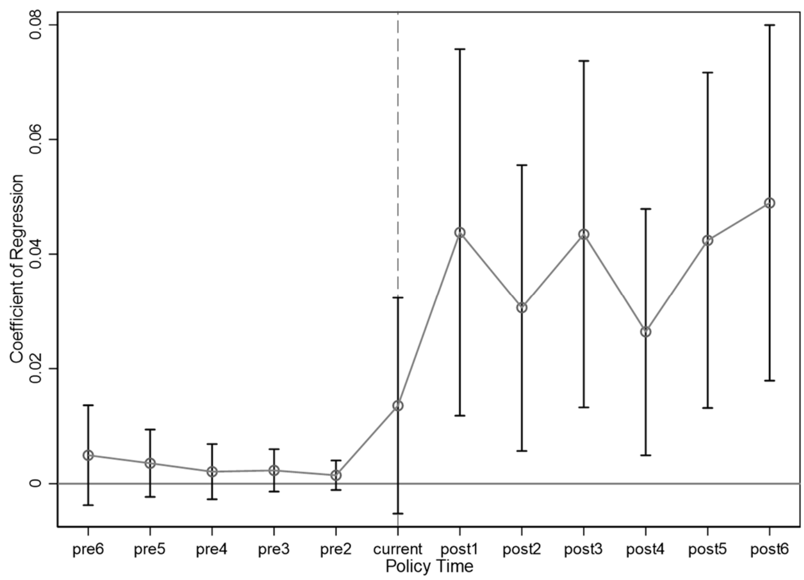

Figure 1. Parallel trend test results.

7. Conclusions and Policy Recommendations

This paper used panel data from 282 prefecture-level cities in China from 2006 to 2019 to rigorously sort out the influence mechanism and effect of AI development on urban energy efficiency. It was discovered that the development of AI has considerably accelerated the growth of green technology innovation and the digital economy, hence increasing urban energy efficiency. In terms of heterogeneity analysis, AI development had a greater impact on improving urban energy efficiency in the eastern region, where the levels of human capital, financial independence, and government intervention were higher. At the same time, this paper utilized the multi-period DID model to explore the effect of the establishment of the smart city policy on urban energy efficiency. Through the analysis of baseline regression and the two-way fixed-effects model test, it concluded that the execution of the smart city policy considerably improved urban energy efficiency. In addition, based on the treatment of the endogeneity issues, this paper also performed a parallel trend test, which showed that the pilot smart cities are more efficient in energy utilization relative to the non-pilot cities. Based on the above findings, this paper draws the following policy implications.

7.1. Accelerate the Coordinated Development of AI and Traditional Industries

Due to the broad range of traditional industries and their different characteristics, the establishment of perfect standards for the use of AI technology is an extremely important component of the integration and development process with traditional industries. Government departments need to formulate and release relevant policies, build online detection systems for energy consumption in key energy-using units, strengthen the support of intelligent information technology equipment, and create a good atmosphere that encourages the adoption of AI technology in traditional organizations. This will lead to the greening and intelligent transformation of the upstream and downstream industrial chain, and will improve the efficiency and marginal effects of energy allocation [15]. Meanwhile, under the condition of ensuring technological safety and sustainable development, governments should encourage the shift of developmental momentum from factor-driven to innovation-driven, optimize the energy structure, and lessen energy consumption to further increase energy utilization efficiency. In addition, the government should formulate industrial development plans in conjunction with national sustainable development goals to avoid duplication of construction and waste of resources so as to further realize sustainable economic and environmental development.

7.2. Increase the Training of AI Professionals

According to the heterogeneity test results, the development of artificial intelligence has a more significant effect on improving urban energy efficiency in areas with higher levels of human capital. There are multiple factors behind this phenomenon. A high level of human capital means that the region has more talent with innovation ability and professional skills, so it is often more receptive to new technologies and models, and more willing to try digital and green transformation in the energy field, thus promoting the improvement of energy efficiency. In view of this, government departments and related enterprises should attach great importance to the introduction and training of complex energy technology talent [31]. In particular, higher education institutions can help students consolidate and apply theoretical knowledge to practical operations by establishing a cross-disciplinary curriculum. On the other hand, government departments can attract more outstanding talent to join the field of energy technology research and application by formulating more attractive policies, such as providing favorable remuneration packages, creating a good working environment and career development prospects. At the same time, government should also strengthen cooperation with universities and scientific research institutions to jointly cultivate composite talent with interdisciplinary knowledge and practical ability, so as to provide a solid talent pool for the city's green transformation and sustainable development goals.

7.3. Improve the System of Regulations and Policies

Since the role of AI in improving urban energy efficiency is more significant in areas with higher financial independence and government intervention, government departments should improve the relevant laws, regulations, and policy systems to strengthen their intervention in AI companies. Specifically, government departments should establish and improve the application standards of AI technology in the field of energy management, prompt the standardization of AI technology, so as to improve the efficiency of energy management, and then promote the improvement of urban energy efficiency. At the same time, local governments should coordinate the financial revenues and expenditures of various departments to set aside certain funds for the technological research and development of AI in the field of energy management, with the aim of ensuring the smooth implementation of relevant projects.

7.4. Promote the Construction of Smart Cities

The promotion of smart city construction is a significant way to increase urban energy efficiency [53]. Government departments should increase investment in smart city construction, focus on citizen participation and satisfaction surveys, strengthen public awareness of energy conservation and exhaust reduction, and form a smart city energy management pattern with the participation of society as a whole. In the process of smart city construction, government departments should establish a sound monitoring and evaluation mechanism to regularly assess and monitor the effectiveness of smart city construction. At the same time, considering the differences in the characteristics and needs of different pilot cities, the government should also optimize the energy management system of smart cities in a targeted manner to ensure that project implementation is consistent with strategies for sustainable urban development. It needs to set up a sound safety risk prevention and control system so that the public can enjoy the convenience of smart cities and encourage sustainable urban development that is green, intelligent, and low-carbon.

8. Limitation and Future Prospects

There may be some possible limitations in this study. First, although this paper used panel data for 282 prefecture-level cities in China from 2006 to 2019, some indicators may have some unobservable factors or omitted variables due to the limitations of data access. In this regard, this paper screened as many control variables as possible for regression analysis and used a variety of methods for robustness testing to ensure the reliability of the study's conclusions. In the future, with the continuous enrichment and improvement of data resources, the research samples and indicator system can be further expanded to reflect the mechanism of the impact of AI on urban energy efficiency more comprehensively. Second, the impact of AI on urban energy efficiency is a complex and dynamic process. While this paper provides insights from multiple perspectives, there may still be factors or mechanisms that have not yet been considered. Therefore, future research can further explore the intrinsic connection between AI and energy efficiency, and explore more potential impact paths and mechanisms to provide more comprehensive and in-depth theoretical support and practical guidance. Finally, this paper's measurement of AI and smart city construction is largely based on existing statistics, which may not fully reflect the complexity of the actual situation. However, in terms of the research direction of this paper, the statistics of the relevant data in this period may be biased due to the occurrence of force majeure emergencies such as COVID-19 from 2019 to 2022. So, the data before 2019 were intercepted in this paper to ensure the universality of the research model. Accordingly, the model also applies to the period of 2024 and beyond.

And, during COVID-19, AI may have a more complex impact on energy efficiency. For example, due to pandemic restrictions and social distancing requirements, many businesses and organizations are starting to rely more on remote working and virtual meetings, which could lead to changes in energy consumption patterns. In addition, the application of AI in key fields such as medical care, logistics, and energy distribution may also be strengthened to cope with the challenges brought about by the pandemic. Therefore, future research can further pay attention to the impact of epidemics and other emergencies on the relationship between AI and energy efficiency, so as to more comprehensively evaluate the role of AI in coping with global challenges, and provide more specific strategies and suggestions for the sustainable green, intelligent, and low-carbon development of cities.

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