Impact of Artificial Intelligence Technology on Carbon Emission Intensity of Energy Consumption in China and Examination of Spatial Effects

Dexu Wang[1], Fuli Wang[2], Yurong Cheng[3], Jun Zeng[2*]

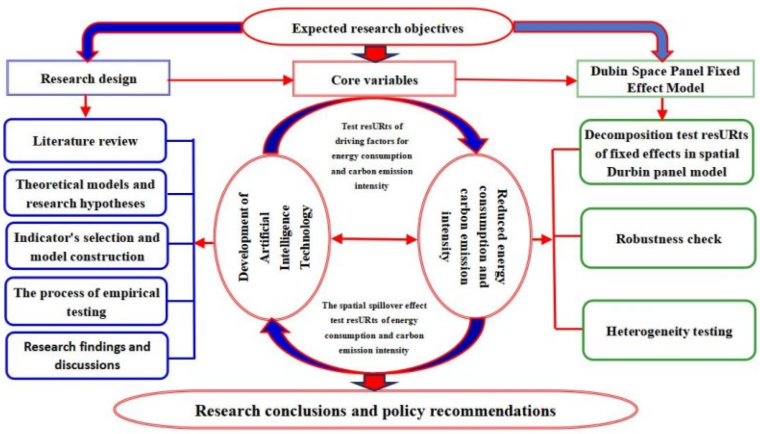
1.Hengqin Campus - Faculty of Science and Technology, University of Macau, Zhuhai, Guangdong Province, Macau SAR, 519000

2.Shandong Vocational and Technical University of International Studies, Rizhao, Shandong 276826, China

3.Qufu Normal University-Rizhao Campus, Rizhao, Shandong, 276826, China

*Corresponding author: zj916sy@163.com

Graphical Abstract



Abstract: This paper investigates the impact of artificial intelligence technology on energy consumption carbon emission intensity and its spatial effect in Chinese provinces. By analyzing the 2012-2021 data of 30 provinces and cities in China, this paper constructs a spatial Durbin panel model to test the direct and indirect effects of the application of AI technology on energy consumption and carbon emission intensity. The results show that artificial intelligence innovation development index, digital finance index, and the environmental regulation intensity reduce the provincial energy consumption carbon emission intensity, while Per capita GDP level, urbanization

rate, and industrial energy consumption intensity significantly increase the energy consumption carbon emission intensity. In addition, industrial structure upgrading and industrial technological progress, as mediating variables, have a significant inhibiting effect on carbon emission intensity. The study concludes that the application of AI technology can effectively reduce provincial carbon emission intensity by optimizing energy consumption and carbon emission scenarios, thus promoting the goal of green and low-carbon development in China.

Keywords: artificial intelligence technology, energy consumption and carbon emission intensity, spatial Dubin model, industrial structure upgrading, industrial technological progress

1. Introduction and literature review

Global climate change has become the most urgent environmental topic facing mankind, and a series of problems, such as the frequent occurrence of extreme weather events, sea level rise and ecosystem imbalance, are seriously threatening the living environment of mankind as well as the state of economic development. In order to cope with climate change, governments around the world have taken strong measures to strengthen energy conservation and emission reduction, and strive to reduce greenhouse gas emissions in order to realize green and low-carbon development. In this environment, China, as the world's largest energy consumer and energy-consuming carbon emitter, plays a key role in global climate governance. With rapid economic development, China's energy consumption and energy-consuming carbon emissions continue to grow, putting enormous pressure on the environment and ecosystem. In recent years, the Chinese government has attached great importance to energy conservation and emission reduction, and has actively promoted energy restructuring and technological innovation, with a view to reducing carbon emissions while realizing economic growth. However, the traditional means of energy saving and emission reduction are gradually showing their limitations in the face of complex and changing energy demand and production methods. Artificial Intelligence is a branch of the computer science discipline, and the concept was first proposed by John McCarthy at a summer seminar at Dartmouth College in the United States in 1956 (McCarthy, 1956). Accompanied by the generation of three cutting-edge technologies, namely space technology, energy technology and artificial intelligence in the 1970s and gene technology, nanotechnology and artificial intelligence in the 21st century, it is only in the last three decades that these cutting-edge technologies have begun to be widely used in many disciplines, among which AI has gradually become a separate branch and an independent system in both theory and practice. AI is the use of computers to simulate the human thinking process and intelligent behavior, such as learning, reasoning, thinking, planning and other means of applying artificial intelligence to the production process of energy consumption as well as targeted emission reduction areas to formulate a differentiated development policy, thereby promoting the sustainable reduction of provincial energy consumption and carbon emission intensity. According to the statistics provided by the statistics department of the Chinese government, China's total energy consumption will be 5.72 billion tons of standard coal by the end of 2023, and although China's energy consumption and carbon emission intensity has been lower than 0.5 tons per 10,000 yuan, the energy consumption and carbon emission intensity is still higher than the global average level (Mao, 2021). Therefore, in this case, it is important and urgent to study the impact of AI technology on provincial energy consumption and carbon emission intensity and test the spatial effect.

In the summer of 1956, the young American scientists McCarthy, Minsky, Rochester, and Shennong etc., first proposed the concept of artificial intelligence in an academic discussion, and the discipline of artificial intelligence was formally created in 1956, and the scientists have already used artificial intelligence in automobiles, trains, airplanes, and radio equipment, and they have also applied AI They have also applied AI to mimic the functions of body organs, creating artificial organs containing billions of nerve cells. Since then, AI terminology has become popular, with AI being selected as one of the top ten buzzwords in Chinese media in December 2017 (Kong and Zhang, 2018), and AI-related projects being included in the legislative planning on March 4, 2019 (Gan and Guo, 2020); and on September 25, 2021, in order to promote the healthy development of AI, the National New-Generation Artificial Intelligence Governance Professional Committee released the Code of Ethics for the New Generation of Artificial Intelligence (Jiang and Xue, 2022); and in April 2023, the U.S. Science Times introduced five leading technologies that will profoundly change the field of healthcare, namely; wearables and apps, AI and machine learning, telemedicine, robotics, and 3D printing (Yao and Jin, 2023). So far, AI is gradually becoming a mature technology. In the field of energy consumption and carbon emissions, AI technology shows great potential to reduce energy consumption and carbon emissions through optimizing industrial processes (Ding et al., 2018), smart buildings and smart homes (Gao et al., 2022; Farahzadi and Kioumarsi, 2023), and other applications (Hu et al., 2023; Shi et al., 2023). In the area of industrial intelligence, AI technologies promote green transformation of industries by enhancing production efficiency and optimizing resource allocation (Wei et al., 2021; Chenet al., 2024). In the field of policy formulation and regulation, the application of AI technology helps to monitor and evaluate energy consumption and carbon emissions more accurately, providing a scientific basis for policy formulation (Chai et al., 2024; Zhou rt al., 2024). In addition, the impact of AI technology on the socioeconomic structure promotes sustainable economic development by creating new employment opportunities and promoting industrial upgrading (Huang and Chen, 2024; Kusiak, 2024). In recent years, overseas scholars have increasingly applied artificial intelligence (AI) technology in the analysis of energy consumption and carbon emissions (Jia et al., 2021; Choi et al, 2013), and AI has gradually become an important means of energy conservation and emission reduction.

For the research on the impact of AI technology on the carbon emission intensity of energy consumption, according to the literature on China Knowledge Network, it is known that the research on AI in developed countries began in the early 1960s (Marvin, 1961; House and Rado, 1964); while the research on AI by Chinese scholars began in the late 1970s (Chen, 1979; Huang , 1979). Artificial intelligence (AI) is an inevitable trend in the development of computers and their applications. Along with the continuous development of "machine learning", statistics, information theory and cybernetics have been gradually integrated into computer applications. The application of AI technology to control China's energy consumption and carbon emission intensity only began in the 1920s, and the management of energy consumption and carbon emission by AI is a process that requires long-term efforts. It is essential to reduce carbon emission by monitoring and managing energy consumption and carbon emission in the production process, which is conducive to strengthening sustainable development, and thus contributing to the enhancement of the environment and the brand image (Xue et al., 2022); the impact on energy consumption and carbon emissions is strengthened through the use of robots in China's industrial production process, and in China's energy applications, the impact of reducing energy consumption and promoting energy consumption and carbon emission intensity is realized through the promotion of smart grids and smart building systems (Tan et al., 2023; Yampolskiy, 2013); the impact of AI on regional carbon emissions is mainly realized through the mechanism identification and rebound effect, that is, mainly through the improvement of energy consumption and carbon emission intensity. realize, that is, mainly through the improvement of energy efficiency to indirectly promote energy consumption carbon emission reduction, but also through industrial structure adjustment and marketization level enhancement to promote the reduction of regional carbon emission intensity (Sun and Yang, 2024; Hertwich and Peters, 2009); in fact, the impact of AI on the intensity of energy consumption carbon emission is not carried out individually, and the AI can only be combined with other elements to jointly promote the intensity of energy consumption carbon emission Reduction. Usually, AI can promote the reduction of energy consumption and carbon emission intensity by promoting industrial structure adjustment, industrial agglomeration and energy consumption and carbon emission efficiency improvement. Therefore, the reduction of carbon emission intensity by AI is a complex process (Liu et al., 2022; Ye and Zhang, 2024).

Although developed countries as well as other developing countries also study the impact of AI on carbon emissions from energy consumption, the perspectives as well as specific contents of the studies are very different from those of Chinese scholars. Indian scholars used two artificial intelligence (AI) techniques, Adaptive Network-based Fuzzy Inference System (ANFIS) and Multi-Gene Genetic Programming (MGGP), to simulate the capture of CO_2 emissions from a coal-fired power plant in India and facilitated the reduction of carbon emission intensity by using the AI techniques in 75 similar plants (Sharma et al., 2019); Canadian scholars tracked and communicated the impacts of energy-consuming carbon emissions by tracking and communicating the environmental impacts of ML, developing and utilizing a tool for energy consumption carbon impacts, and exploring effective ways to reduce the intensity of energy consumption carbon emissions by utilizing the machine learning function of AI, which received relatively satisfactory results (Luccioni et al., 2020); American scholar Smith, in his published book " Nearly Nuclear: A Mismanaged Energy Transition" pointed out that AI technology can significantly improve the operational efficiency of the energy system and reduce energy waste and carbon emissions by optimizing power scheduling and energy management (Smith, 2021); scholars in Turkey studied the impact of AI on energy consumption and carbon emissions, and concluded that AI is an effective tool to reduce energy consumption and carbon emissions by using the AI control Decision Tree (DT) algorithm for training to promote the minimization of carbon emissions through central intelligent control, which can reduce carbon emissions by 21%, thus promoting the reduction of carbon emission intensity (Kezban et al., 2022); French scholars believe that Artificial Intelligence is an effective tool to reduce the intensity of carbon emissions from energy consumption, and make full use of Machine Learning (ML) modeling to control the intensity of carbon emissions from energy consumption. Through the carbon emission optimization management, especially the use of multiple model control has a good carbon control effect. It can be seen that artificial intelligence has become an effective tool for energy consumption carbon emissions (PaUR et al., 2023).

It is obvious from the above literature review that artificial intelligence (AI) technology has become an effective means to control and reduce the intensity of carbon emissions. The research on AI technology in developed countries is earlier than that in China, due to the privatization of social system, the research on AI on energy consumption and carbon emission in developed countries is mostly limited to the micro level, which makes the scope and effect of AI on the control of energy consumption and carbon emission relatively small; China's research on the impact of AI on the intensity of carbon emission is different from that of developed countries as well as other developing countries. China's research on the impact of AI on carbon emission intensity is different from that of developed countries and other developing countries in that China's research on AI's control of energy consumption and carbon emission intensity focuses more on the macro level, pursuing a large-scale and comprehensive reduction of energy consumption and carbon emission intensity, which is the result of the Chinese government's issuance of the "dual-carbon" target and related support policies. According to the results of this paper's review of the research literature, high-intelligence and full-scope control of energy consumption and carbon emissions has become an inevitable trend for future development. Artificial intelligence can make full use of learning models, scientific and rational planning and design, rational arrangement of energy consumption and other effective means to minimize the intensity of energy consumption and carbon emissions by adjusting the industrial structure, production efficiency, and promoting technological advances to promote the sustainable development of China's energy consumption.

2 Materials and Methods

2.1 Data sources and research ideas

In order to examine the impact of AI technology on energy consumption and carbon emissions in Chinese provinces and its spatial effects, this paper selects 30 Chinese provinces (including municipalities and autonomous regions) as the research object, and based on the influencing factors of the intensity of energy consumption and carbon emissions in Chinese provinces as well as the drivers of the intensity of carbon emissions selected by the existing domestic and international studies, an explanatory variable of the AI index is selected in terms of AI-driver related factors and five control variables such as digital finance index, per capita GDP level, urbanization level, environmental regulation intensity and industrial energy consumption intensity to study the degree of influence of the combination of explanatory variables and control variables on the energy consumption and carbon emission intensity of China's provincial regions. Using statistical information from the China Bureau of Statistics as well as the Statistical Yearbook, Bulletin of Ecological and Environmental Conditions, Energy Statistical Yearbook, and Urban Statistical Yearbook of each province and region, we collected and organized the basic data and information of the research object by measuring the energy consumption and carbon emission intensities of each province and region in China, as well as by calculating the individual indicators for which there is no specific data. In order to facilitate the measurement of the impact of AI on the carbon emission intensity of China's provinces and regions, the China Artificial Intelligence Innovation and Development Index released by the China Electronics Information Industry Development Research Institute (CIEIDI) at the Fifth World Sonic Conference to be held in Hefei, Anhui Province, in 2022, which is referred to as the Hefei Index, was chosen. Since the data of this index ends in 2021, the data period of this paper is also chosen. Therefore, the data period of this paper is also chosen as the 10-year basic data during 2012-2021.

In order to use empirical research methods to test the impact of driving factors on the carbon emission intensity of energy consumption in China's provinces, the basic idea framework of this paper's research is determined according to the research objectives as well as the research design. This idea framework reflects both the main content of this paper's research and the basic methodology of the paper's research, and the structure of the basic idea framework of this paper's research is shown in Figure 1.

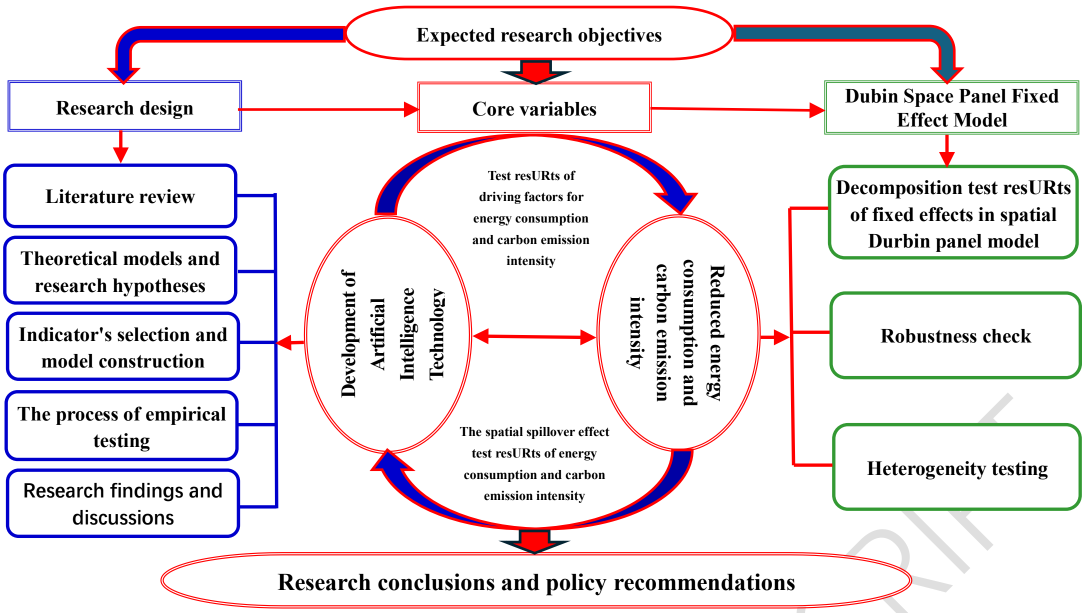


Fig 1. The research idea diagram of this paper

2.2 Theoretical Model and Research Hypotheses

Artificial intelligence is a new control technology that has gradually emerged with economic development and technological progress and has gradually played an increasingly important role in controlling the intensity of energy consumption and carbon emissions in China's provinces. It mainly makes full use of the strength of computers to calculate and process data, and through reasonable planning of the control plan for the intensity of energy consumption and carbon emissions, makes full use of different resources, optimizes and modifies control strategies, and selects efficient paths and plans to achieve effective control of the intensity of energy consumption and carbon emissions in provinces. According to the research design explanatory variables AI innovation development index as the explanatory variables and digital finance index, per capita GDP level, urbanization rate, environmental regulation intensity and industrial energy consumption intensity five control variables of the research design. The AI development index uses the "Hefei Index" issued by the China Academy of Electronic Information Industry Development, which is expressed as AIDI; the digital finance index among the control variables uses the "Peking University Digital Financial Inclusion Index 2022", which is expressed as DFI; the GDP per capita level uses the GDP of each province issued by the National Bureau of Statistics (NBS), which is the same as the GDP of each province at the end of the same period, using PGL to calculate; urbanization rate using the statistical indicator data of each province released by the National Bureau of Statistics, using UR to indicate; environmental regulation intensity reflects the ratio of environmental regulation costs to the total output value of the environmentally polluted region, and this paper draws on the methodology of scholars such as Zhang Can (Zhang et al., 2024) to use the proportion of industrial pollution control investment in the secondary industry of each province and region is used to measure the intensity of environmental regulation, which is expressed by ERI; the industrial energy consumption intensity is the amount of energy consumed per unit of gross domestic product (GDP), which reflects the efficiency of energy utilization and the level of economic activities, and this indicator is expressed by IECI. According to the control mechanism of variables of selected combinations of drivers of energy consumption and carbon emission intensity in Chinese provinces, by analyzing the process of combinations of variables on carbon emission intensity in Chinese provinces, the theoretical model of the influence of drivers on carbon emission intensity in provinces is constructed as shown in Fig. 2.

Fig 2. Theoretical Model of the Impact of AI technology on Carbon Emission Intensity from Energy Consumption

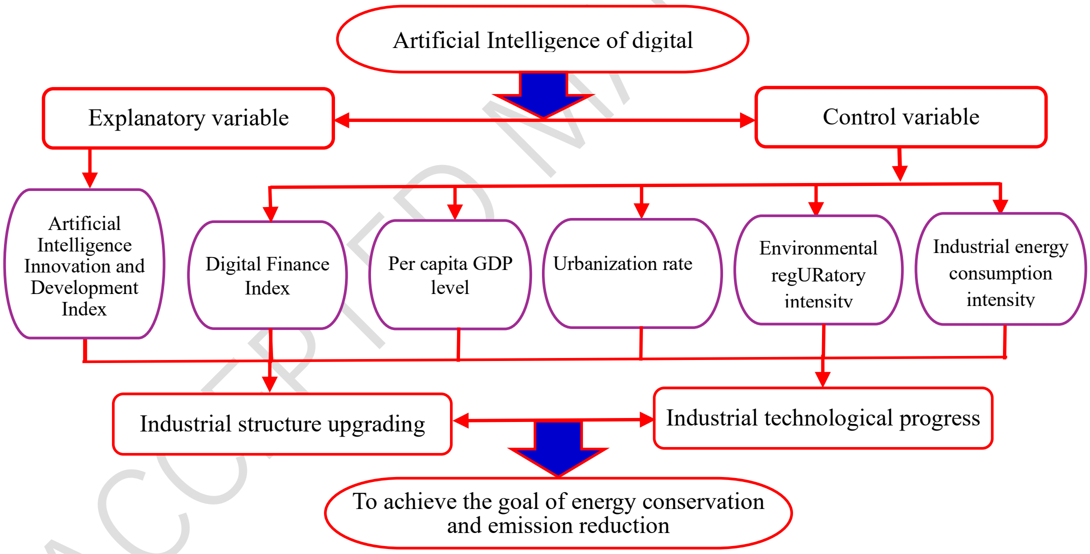


Figure 2 shows the impact of artificial intelligence technology and its control variables on the intensity of energy consumption and carbon emissions in China's provincial areas. According to the practice of artificial intelligence in the control of energy consumption and carbon emission intensity and its effect, artificial intelligence technology has an obvious inhibiting effect on the intensity of energy consumption and carbon emissions through optimizing the energy consumption and carbon emission plan, energy saving and emission reduction, and improving the efficiency of energy consumption and emission, etc., and the impact of artificial intelligence on the carbon emission intensity has obvious heterogeneous characteristics. intensity of artificial intelligence has obvious heterogeneity characteristics, managers can achieve effective control of energy saving and emission reduction through the regional differences in the control of carbon emissions by artificial intelligence, to achieve the purpose of reducing the intensity of energy consumption and carbon emissions. Therefore, according to the above theoretical analysis, the first research hypothesis can be made on the impact of artificial intelligence on energy consumption carbon emission intensity. Research hypothesis, H_1 : Artificial intelligence has an obvious inhibitory effect on energy consumption carbon emission intensity. The impact of artificial intelligence technology on urban energy consumption carbon emissions includes two parts: direct impact and indirect impact. The direct impact is produced directly through the role of explanatory variables as well as control variables, and the indirect impact mainly works through mediating variables. According to the current situation of China's economic development, in the process of China's AI affecting carbon emission intensity, industrial development mainly plays a role in China's urban industrial energy consumption carbon emission intensity through the two intermediary variables of industrial structure upgrading and technological progress. Therefore, this paper puts forward the second research hypothesis, H_2 : industrial structure upgrading and technological progress are the intermediary variables of AI's impact on urban energy consumption and carbon emission intensity; there is an obvious spatial spillover effect in the process of AI's impact on urban energy consumption and carbon emission intensity, and this spatial spillover effect is mainly manifested in the following characteristics: technological spillover effect, industrial correlation effect, and resource sharing effect, and so on. This spatial spillover effect is mainly characterized by the technology spillover effect, industrial association effect and resource sharing effect. Therefore, AI technology can realize energy saving and emission reduction by promoting resource integration, and reduce urban energy consumption and carbon emission intensity through industrial structure adjustment and green technology progress. Therefore, this paper proposes the third research hypothesis, H_3 : there is an obvious spatial spillover effect in the suppression of urban energy consumption and carbon emission intensity by AI technology.

2.3 Construction of the spatial Durbin model

2.3.1 Construction of a spatial relative rights model

In order to test the spatial spillover effect of AI technology on the existence of urban energy consumption and carbon emission intensity, this paper proposes the Durbin spatial model on the basis of the spatial model, which is selected on the basis of comprehensive analysis: spatial adjacency matrix, economic weight matrix and spatial economic and geographic weight matrix. The spatial adjacency matrix is a matrix reflecting the relationship between neighboring cities, which is 1 for neighboring cities and 0 for non-neighboring cities; the economic weight matrix reflects the relationship between the economic development level of two cities, which is expressed as the inverse of the difference in the GDP size between two cities; and the spatial economic and geographic weight matrix is the weighted average of the spatial adjacency matrix and the economic weight matrix. If W_1 is used to denote the spatial adjacency matrix, W_2 is used to denote the economic weight matrix, and W_3 is used to denote the spatial economic-geographical weight matrix, the three matrices can be expressed as follows:

$$W_1 = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \vdots & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}; W_2 = \left(GDP_j - GDP_i\right)^{-1}; W_3 = \xi \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \vdots & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} + (1-\xi)W_2 \quad (1)$$

In the above equation, ξ is the W_3 the weighting coefficient, which, according to the weighting theory of space, is generally chosen as: $\xi = 0.4$, making the value of W_3 the value of is skewed in favor of W_2. In order to test the spillover effect of the influence of AI and its control variables on the carbon emission intensity of urban energy consumption in China, Moran′ s I index is introduced, and the spatial test results of Moran′ s I index are utilized to judge the status of the influence of the independent variable on the dependent variable. Moran′ s I method is a statistical test that was proposed and started to be used in 1950, and according to the theory of Moran′ s I, when the Moran′ s I value range in the interval of [-1,1], Moran's I > 0 indicates positive spatial correlation, and the larger the value of Moran′ s I, the more significant the spatial correlation; Moran's I < 0 indicates negative spatial correlation, and the smaller the value of Moran′ s I, the larger the spatial difference, and when Moran's I = 0, the spatial stochasticity is observed. Moran′ s I is calculated as follows formula is as follows:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \cdot \left(x_i - \bar{x}\right) \cdot \left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\left(x_j - \bar{x}\right)^2 \cdot \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \quad (2)$$

According to statistical theory and methodology, the standard statistic Z indicator is generally used to test the significance level of the indicator, and the standard statistic of Moran′ s I is used to calculate the Z value using the following model, and the specific measurement model is as follows:

$$Z = \frac{I - E(I)}{\sqrt{Var(I)}} \quad (3)$$

In order to improve the effectiveness of the spatial test of variables, this paper introduces the spatial statistic of C, denoted as Geary′ s C. This metric is often referred to as the Irish Neighbor to Neighbor Ratio, and the formula for the calculation of this spatial statistic can be expressed as follows:

$$C=\frac{(n-1)\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}\cdot(x_i-x_j)^2}{2\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}\cdot\sum_{i=1}^{n}(x_i-\bar{x})^2}=\frac{(n-1)\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}\cdot(x_i-x_j)^2}{2nS^2\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}} \quad (4)$$

In Eq:w_{ij} is the relative weight of the variance of the variable x, n is the number of variables, and S is the standard deviation of the variable x. The domain of values of this indicator can be expressed as Geary′ s C∈ [0,2], when Geary′ s C=1 indicates no spatial autocorrelation. When Geary′ s C<1 indicates positive spatial autocorrelation, and when Geary′ s C>1 indicates having negative spatial autocorrelation. According to the theory and methodology of statistics, the formula for calculating the standard statistic of Geary′ s C index is expressed as follows:

$$C^*=\frac{C-1}{\sqrt{Var[C]}}=(C-1)\cdot\left[\left((2W_2+W_3)\cdot(n-1)-4W_1^2\right)\cdot\left(2(n+1)\cdot W_1^2\right)^{-1}\right]^{-1/2} \quad (5)$$

In the formula: $W_1=\sum_{i=1}^{m}\sum_{j=1}^{n}w_{ij}$, $W_2=\frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n}(w_{ij}+w_{ji})^2$, $W_3=\sum_{i=1}^{m}\left(\sum_{j=1}^{n}w_{ij}+w_{ji}\right)^2$. According to the original assumption, the formula for the value of p can be expressed as follows:

$$p=erfc\left(\frac{|C-E[C]|}{\sqrt{2Var[C]}}\right) \quad (6)$$

Since the carbon emission intensity of urban energy consumption in Chinese provinces is affected by many factors, this paper focuses on how the selection of independent variables affects the dependent variables. Since the spatial Durbin model constructed in this paper has different forms, the study draws on Han Xiuyan (Han and Cao, 2022) the form of the spatial Durbin model, and the following spatial Durbin model expression is obtained after correction:

$$Y_{it}=\rho\sum_{t=1}^{n}W_{it}\cdot Y_{it}+\alpha_i X_{it}+\sum_{t=1}^{n}\beta_1\cdot W_{it}\cdot X_{it}+\mu_i+\theta_t+\varepsilon_{it} \quad (7)$$

The above equation is the general equation for the spatial Durbin model. In the equation:Y_{it} is the dependent variable, also known as the explanatory variable, and the right-hand side of the equation isY_{it} is called the lag term;X_{it} is the driver term, andW_{it} is the spatial weights.ρ， α 和β are the equation's coefficients to be determined, theμ_i are the individual fixed effects, theθ_t are time fixed effects, andε_{it} is the error perturbation term, which cannot be directly used in the correlation test of variables. According to the actual situation of China's provincial energy consumption and carbon emission intensity control, five control variables, namely, artificial intelligence innovation development index (AIDI), digital finance index (DFI), Per capita GDP level (PGL), urbanization rate (UR), environmental regulation intensity (ERI) and industrial energy consumption intensity (IECI) are selected, and substituting the variables into Durbin's spatial lag model yields the following test Equation:

$$\begin{aligned}CEI_{it} = \rho W \cdot CEI_{it-1} + \alpha_1 AIDI_{it} + \alpha_2 DFI_{it} + \alpha_3 PGL_{it} + \alpha_4 UR_{it} + \alpha_5 ERI_{it} + \\ \alpha_6 IECI_{it} + \beta_1 W_{it} \cdot AIDI + \beta_2 W_{it} DFI_{it} + \beta_3 W_{it} \cdot PGL_{it} + \beta_4 W_{it} \cdot UR_{it} + \\ \beta_5 W_{it} \cdot ERI_{it} + \beta_6 W_{it} \cdot IECI_{it} + \varepsilon_{it}\end{aligned} \tag{8}$$

The indirect impact of AI on urban energy consumption and carbon emission intensity is mainly realized through mediating variables, and this paper chooses two mediating variables, industrial structure upgrading (ISU) and industrial technology progress (ITP), and the indirect impact model of the mediating variables is as follows:

$$\begin{cases} ISU_{it} = \rho W \cdot CEI_{it-1} + \alpha_1 DFI_{it} + \alpha_2 PGL_{it} + \alpha_3 UR_{it} + \alpha_4 ERI_{it} + \\ \quad \alpha_5 IECI_{it} + \beta_1 W_{it} DFI_{it} + \beta_2 W_{it} \cdot PGL_{it} + \beta_3 W_{it} \cdot UR_{it} + \\ \quad \beta_4 W_{it} \cdot ERI_{it} + \beta_5 W_{it} \cdot IECI_{it} + \varepsilon_{it} \\ ITP_{it} = \rho W \cdot CEI_{it-1} + \alpha_1 DFI_{it} + \alpha_2 PGL_{it} + \alpha_3 UR_{it} + \alpha_4 ERI_{it} + \\ \quad \alpha_5 IECI_{it} + \beta_1 W_{it} DFI_{it} + \beta_2 W_{it} \cdot PGL_{it} + \beta_3 W_{it} \cdot UR_{it} + \\ \quad \beta_4 W_{it} \cdot ERI_{it} + \beta_5 W_{it} \cdot IECI_{it} + \varepsilon_{it} \end{cases} \tag{9}$$

The mediator variable has a direct impact on the carbon emission intensity of urban energy consumption in Chinese provinces, and it also reflects the indirect impact of the driving factors on the carbon emission intensity of urban energy consumption in Chinese provinces. The mechanism of the intermediary factors is shown in Figure 1, and the influence of the intermediary factors on the carbon emission intensity of urban energy consumption in the provinces is determined by empirical tests, and making full use of the intermediary indicators to reduce the carbon emission intensity of urban energy consumption is an effective way to save energy and reduce emissions.

3. Analysis of findings

3.1 Measurement of carbon emission intensity of energy consumption in China's provincial areas

The basic data used in this paper come from the national and provincial Statistical Yearbook, Energy Statistical Yearbook, and Environmental Status Bulletin. In order to calculate China's provincial energy consumption and carbon emission intensity, the Kaya model is extended to obtain the relevant variables, and on the basis of estimating the scale of energy consumption and carbon emission in each province, the estimated scale of energy consumption and carbon emission in each province is used to calculate the scale of energy consumption and carbon emission in each province, together with the scale of the GDP in each province. emission intensity of each province and region based on the estimated energy consumption and carbon emission scale of each province and region and the GDP scale of each province and region:

(1) Carbon emissions from energy consumption$E(CO_2)_t$ Estimation. Since carbon emissions from energy consumption will eventually be transformed into CO_2 , what people call carbon emissions is actually CO_2 emissions. Carbon emissions in China's new urbanization are mainly embodied in energy consumption emissions, including carbon emissions from production and operation energy consumption and carbon emissions from residents' production and consumption energy. In order to measure the scale of carbon emissions generated by energy consumption in China's new urbanization, we draw on the measurement method of carbon emissions from energy consumption recommended in the 2016 IPCC Guidelines for National Greenhouse Gas Inventories, and select eight forms of energy, including coal, coke, crude oil, fuel oil, gasoline, kerosene, diesel, and natural gas, based on the statistical classification of energy sources in the China Energy Statistical Yearbook. If we use $E(C)$ to denote the scale of carbon emissions from energy consumption in China's urbanization, useSCC_{it} to denote the size of carbon emissions from energy consumption in urbanization in China, and use$i$ the energy standard coal conversion factor in theCEF_{it} denotes the standard coal conversion coefficient of the first$i$ energy carbon emission coefficient, then the formula for measuring the scale of carbon emission from energy consumption in urbanization construction can be expressed as follows:

$$E(C)_t = \sum_{i=1}^{m}(EC_t \times SCC_t \times CEF_t) \tag{10}$$

In the above equation:$i = 1，2, \cdots, m$; $t = 1,2, \cdots，n$. Carbon emissions from urban energy consumption will eventually be converted into CO_2 , and excessive CO_2 emissions will produce a greenhouse gas effect, and this greenhouse gas effect will pose a serious threat to the human living environment and affect the health of residents. According to the molecular structure of CO_2 , the molecular weight of carbon dioxide is 44, of which the molecular weight of elemental carbon is 12. If we use the term$E(CO_2)_t$ to express the per capita CO_2 emissions, there are:

$$E(CO_2)_t = E(C)_t \times (44/12) \tag{11}$$

Based on the reference coefficients of various energy sources converted to standard coal in the appendix of the 2016 China Energy Statistics Yearbook, and the carbon emission coefficients of the 2006 IPCC Guidelines for National Greenhouse Gas Emission Inventories, the parameters in the model were determined as detailed in Table 1.

Table 1 List of standard coal conversion factors and carbon emission factors for major fossil fuels

Fuel name	coals	coking coal	crude oil	feedstock oil	diesel	gasoline	diesel fuel	petroleum
SCC_{it}	0.7143	0.9714	1.4286	1.4286	1.4714	1.4714	1.4571	1.3300
CEF_{it}	0.7559	0.8550	0.5538	0.5857	0.5921	0.5714	0.6185	0.4483

The carbon emission intensity of energy consumption (ECI_t) is the ratio of the total amount of CO_2 emissions generated by energy consumption to the GDP of the same period, reflecting the scale of CO_2 emissions generated per unit of GDP. Based on the measurement of CO_2 emissions from energy consumption, the calculation of CO_2 emission intensity of energy consumption is obtained by utilizing the results of the measurement as well as the statistics of GDP in the China Statistical Yearbook. According to the meaning of energy consumption and carbon emission intensity and the corresponding basic data, it is confirmed that the energy consumption and carbon emission intensity in the first quarter of 2012 is the highest in China.t The formula for calculating the carbon emission intensity of energy consumption in the period is:

$$ECI_t = E\left(CO_2\right)_t \big/ GDP_t \tag{12}$$

3.2 Spatial correlation test of empirical variables

In order to test the extent to which the drivers of energy consumption and carbon emission intensity in China's provincial areas affect energy consumption and carbon emission intensity, all the test variables were normalized in the study. On this basis, spatial correlation tests were conducted on selected variables, and Moran's I and Geary's C tests were conducted on all variables to test the spatial correlation of each variable using the test models (2) and (5) determined in the study design, and the specific test results are shown in Table 2.

Table 2.Results of spatial correlation test between variables

variable	Moran's I	P	Geary's C	P
CEI	0.3217	0.0021	0.3316	0.0002
AIDI	0.3026	0.0016	0.3125	0.0001
DFI	0.3138	0.0022	0.3235	0.0012
PGL	0.2986	0.0016	0.3025	0.0001
UR	0.2757	0.0021	0.2926	0.0001
ERI	0.3016	0.0018	0.3127	0.0002
ITP	0.3126	0.0024	0.3215	0.0003

In order to test the validity of the variables and models, this paper selects the LM, LR and Hausman methods for the correlation test of spatial variables, in which the purpose of the LR and LM test methods is to test whether the variables are spatially lagged as well as and the size of the spatial error effect, and the purpose of the Hausman test is to determine whether the variables obey the fixed-effects model or the random-effects model, in order to determine the specific spatial test model. The results of the LM test, LR test and Hausman test are shown in Table 3.

Table 3 Variable lags, error effects and model selection tests

Inspection method		Coefficient	P Value
LM t-test	LM (error) test	178.418	0.001
	Robust LM(error)test	168.274	0.021

	LM (lag) test	17.265	0.012
	Robust LM (lag) test	10.417	0.009
LR Test	SDM&SAM chi2	48.326	0.002
	SDM&SEM chi2	69.472	0.001
Hausman test		16.625	0.014

According to the test results in Table 3, it can be clearly seen that the P of the LM test is significantly less than 0.05, and the P values are all significant, which proves the acceptance of the original hypothesis, i.e., there is no autocorrelation of the variables. According to the test results, the test model should be selected: spatial autocorrelation (SAR) model, spatial error (SEM) model or Durbin spatial fixed effects (SDM) model. According to the test results of LR SDM model can be degraded to SAR or SEM model, and the test results show that both of them are significant at 0.5% level, and the parameter constraints are valid and non-degenerate; according to the results of Hausman's test, due to the existence of the test probability of $0<P<0.05$, the test result is the rejection of the original hypothesis, which means that the fixed-effects model is better than the random-effects model is superior. Therefore, the spatial Durbin fixed effect model should be selected for testing. Summarizing the test results of the above three testing methods, in the process of empirical testing, it is better to choose the fixed effect model than the random effect model, so the fixed effect model should be chosen. The purpose of this paper is to empirically test the impact of AI development index and its control variables on the carbon emission intensity of urban energy consumption in China. The dependent variables in this paper are calculated and determined based on the estimation results of the scale of energy consumption and carbon emissions of Chinese provinces and regions, as well as the GDP determined by the National Bureau of Statistics as well as the statistical bureaus of each province and region, and the descriptive statistics of these basic information are shown in Table 4.

Table 4.Descriptive statistics results of all empirical test variables

variable	average value	standard deviation	minimum value	maximum values
CEI	2.06	2.01	0.08	8.32
AIDI	0.747	0.896	0.045	6.561
ISU	42.78	9.93	11.17	85.47
ITP	5.47	1.78	0.089	8.96
DFI	1.57	0.69	0.18	2.86
PGL	7.638	10.18	1.793	20.45
UR	50.26	20.56	22.56	89.27
ERI	1.511	3.273	0.102	1.862
IECI	0.979	0.556	0.212	3.964

3.3 Test results of the spatial Durbin panel model

According to the analysis results, the fixed effects can be decomposed into direct and indirect effects, and the test model (10) is applied to test the different effects based on the decomposition of effects (Yang et al., 2022). The specific test results are shown in Table 5.

Table 5 Decomposition test results for fixed effects in the spatial Durbin panel model

variant	direct effect	indirect effect	aggregate effect
AIDI	-0.5136*** (-5.0651)	-0.1787*** (-4.857)	-0.6923*** (-3.546)
DFI	-0.4627*** (-4.426)	-0.1632*** (-4.1731)	-0.6259*** (3.426)
PGL	0.3815** (2. 962)	0.2257** (2.5462)	0.6072** (2.2134)
UR	0.3616** (2.486)	0.2147** (2.2584)	0.5763** (-2.2325)
ERI	-0.3038*** (-4.1624)	-0.1684*** (-3.8061)	-0.4722*** (-3. 2826)
IECI	0.4168*** (4.3217)	0.2237*** (4.1726)	0.6405*** (3.6527)
$W \cdot CEI_{t-1}$	0.3562*** (4.3427)	0.1615*** (4.0781)	0.5177*** (2.8632)
W· AIDI	-0.5043** (4.2751)	-0.1673** (-3.8625)	-0.6716** (3.6725)
W· DFI	0.4327*** (3.6521)	0.1605*** (3.2527)	0.5932*** (-3.1742)
W· PGL	0.3685*** (3.4537)	0.2064*** (3.3256)	0.5749*** (3.1736)
W· UR	0.3464*** (2.8952)	0.1807*** (2.7628)	0.5271*** (2.5628)
W· ERI	-0.3271*** (-2.8726)	-0.1652** (-2.6736)	-0.4923*** (-2.6027)
W· IECI	0.4165*** (4.3217)	0.2243*** (4.1726)	0.6408*** (3.6527)
Rho	0.2284*** (3.6726)	0.1878*** (3.5217)	0.4162*** (3.4872)
R^2	0.4416	0.4217	0.4126
$sigma^2$	0.0784	0.0771	0.0763
$logL$	-10.1627	-54.8726	-47.8425

Note: Significance levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively, and T-statistics are in parentheses. The corresponding probabilities are all: $p<0.05$.

In Table 5, The aggregate effect is the sum of the direct effect and indirect effects, and in order to improve the test effect, the test results are retained to four decimal places. According to the test results of the direct effect, the artificial intelligence index (AIDI) has the greatest impact on the energy consumption carbon emission intensity, with an impact coefficient of -0.5136, and the environmental financial index (DFI) has the second greatest impact on the energy consumption carbon emission intensity, with an impact coefficient of -0.4627; the environmental regulation intensity (ERI) also presents a negative impact on the energy consumption carbon emission intensity, with an impact coefficient of -0.3038; Other driving factors have a positive impact on the relative energy consumption and carbon emission intensity, and the order of the impact coefficients is as follows: the intensity of industrial energy consumption has the greatest impact, with an impact coefficient of 0.4168; the ratio of Per capita GDP level and the degree of urbanization, with the corresponding impact coefficients of 0.3815 and 0.3616, respectively; the lagged terms of the carbon emission intensity are significantly positive, which indicates that the intensity of energy consumption and carbon emission of urban China has an obvious spatial spillover effect. The test result of the weighted term is in the same direction as that of the unweighted term, and its test result is slightly reduced, indicating that the spatial weight reduces the spatial intensity of spatial carbon emission intensity.

3.4 Discussion of fixed effects test results for different combinations of independent variables

In order to test the effects of different combinations of all independent variables on the carbon emission intensity of urban energy consumption in Chinese provinces, the Durbin spatial lag model is simplified without using spatial weights, and it is modified to a general lag model, and the simplified lag model can be expressed as follows:

$$ECI_{it} = \rho \cdot ECI_{it-1} + \alpha_1 AIDI_{it} + \alpha_2 DFI_{it} + \alpha_3 PGL_{it} + \alpha_4 UR_{it} + \alpha_5 ERI_{it} + \alpha_6 IECI_{it} + \varepsilon_{it} \quad (13)$$

In this state, the variables in the model above are combined in different forms, and the public terms are the test equation coefficients α and the provincial energy consumption carbon emission intensity lag termECI_{it-1} On this basis, the independent variables: *AIDI, DEI, PGL, UR, ERI* and *IECI are* added one by one to form the test equations with six different combinations of variables, and the specific test results are shown in Table 6.

Table 6.Test results of fixed effect models with different combinations of variables

variant	Model (1)	Model (2)	Models (3)	Models (4)	Models (5)	Models (6)
α	0.5152***	0.5228***	0.5435***	0.5567***	0.5651***	0.5765***
	(4.6537)	(4.5616)	(4.4163)	(4.2652)	(4.1636)	(4.0742)
ECI_{it-1}	-0.5063***	-0.5126***	-0.5218***	-0.5317***	-0.5527***	-0.5656***
	(4.4517)	(4.3416)	(4.2651)	(4.1526)	(4.0763)	(3.8965)
AIDI	-0.4984***	-0.5053***	-0.5126***	-0.5317***	-0.5425***	-0.5563***
	(-4.8625)	(-4.6536)	(-4.4526)	(-4.3652)	(-4.2651)	(-4.1657)
DFI		-0.4988***	-0.5156***	-0.5208***	-0.5258***	-0.5387***
		(-4.5628)	(-4.4672)	(-4.3761)	(-4.2167)	(-4.0862)
PGL			0.4906***	0.5083***	0.5175***	0.5237***
			(4.4851)	(4.3725)	(4.2763)	(4.1875)
UR				0.5026**	0.5085**	0.5186**
				(2 .8634)	(2 .6372)	(2.4664)
ERI					-0.4985***	-0.5076***
					(-5 .5173)	(-4.6856)
IECI						0.4976***
						(4.5482)

Note: Significant levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively, and t-statistics are in parentheses.

According to the test results in Table 6, the test results for model (1) reflectα constant, carbon emission intensity lag termECI_{it-1} and AIDI together on the energy consumption carbon emission intensity *CEI*, the impact coefficient of the explanatory variable *AIDI* is -0.4984; the test results of model (2), the main reflection of the variables: *AIDI and DFI* together on the *CEI*, the impact coefficients are: -0.5053, 0.-0.4988; the test results of model (3), the main reflection of the variables: *AIDI The test results of model (3*) mainly reflect the influence of variables: AIDI*, DFI and PGL* on *CEI*, and the influence coefficients are: -0.5126, -0.5156, 0.4906, respectively, due to the negative influence of *AIDI and DFI* on *CEI, which* makes the carbon emission intensity of energy consumption of the provincial area show a downward trend; the test results of model (4) mainly reflect the influence of variables: *AIDI, DFI, PGL and UR* on CEI, and the influence coefficients are: -0.5053, 0.-0.4988, respectively. The test results of model (4) mainly reflect the influence of variables: AIDI, DFI, PGL and UR together on *CEI*, and the influence coefficients are -0.5317, -0.5208, 0.5083, 0.5026; the test results of model (5) mainly reflect the influence of variables: *AIDI, DFI, PGL, UR and ERI* together on *CEI*, and the influence coefficients are -0.5425, -0.5258, 0.5175, 0.5085, -0.4985; the test results of model (6) reflect the impact of all drivers on the carbon emission intensity of energy consumption, and the corresponding impact coefficients are -0.5563, -0.5387, 0.5237, 0.5186, -0.5076, 0.4976, respectively, which can be seen, and the test results of model (6) are the final test results.

3.5 mediating effects test results

Although the complete elimination of fossil energy is the key to realizing the green transformation of Chinese cities, China's current share of clean energy in all energy sources is only less than 20% (Guo et al., 2020), so it is impossible to fully realize a clean energy development economy in the short term. In this case, China also has to promote the green and low-carbon transformation of Chinese cities through green technological innovation, industrial structure upgrading and improving green production efficiency, etc. In this paper, we choose the two intermediary variables of industrial structure upgrading (ISU) and industrial technological progress (ITP), and the results of intermediary impacts on carbon emissions in Chinese cities through intermediary variables are shown in Table 7.

Table 7.Results of the mediating effect test

norm	Upgrading of industrial structure		Industrial technological progress	
	ISU	*CEI*	*ITP*	*CEI*
AIDI	0.875^{***} (4.397)	-0.765^{***} (-4.218)	0.548^{***} (3.816)	-0.685^{***} (3.545)
ISU		-0.275^{***} (-4.682)		
ITP				-0.241^{***} (-4.463)

constant term	3.027***	2.145***	1.857***	1.783***
(math.)	(4.236)	(4.147)	(4.027)	(3.852)
control variable	control	control	control	control
individual effect	control	control	control	control
time effect	control	control	control	control
N	300	300	300	300
R^2	0.465	0.187	0.486	0.194

Note: *** is passing the 1% confidence test, ** is passing the 5% confidence test, * is passing the 10% confidence test, and the t-test result values are in parentheses.

From the test results in Table 7, it is obvious that the mediating effect on energy consumption and carbon emission intensity through industrial structure upgrading is -0.275, and the mediating effect on energy consumption and carbon emission intensity through technological innovation mediating effect is -0.241. It can be seen that the mediating variable promotes the reduction of energy consumption and carbon emission intensity of China's urban areas.

4. Discussion of findings

4.1 Discussion of the robustness of the findings

In order to test the impact of artificial intelligence on urban energy consumption and carbon emission intensity, it is necessary to carry out a robustness test on the selected variables and the constructed empirical test model. The purpose of the robustness test is to examine and evaluate the explanatory ability of the test indicators and the robustness of the test model, that is, when certain parameters are changed, the test indicators and their test results can maintain a relatively stable explanation of the process. There are many specific methods for robustness test, this paper, according to the specific research object, driver selection status and empirical test model, adopts the alternative variable method, lag test method and shorten the data period, under the conditions of fixed control variables, fixed city effect, fixed year effect, fixed city and fixed time to carry out the robustness test, and the specific test results **are** shown in **Table 8**.

Table 8 Results of robustness discussion

variant	substitution of variables act		lag test		Reduced Data Cycle Method (2015-2021)
	Replacement of the dependent variable	Sample correction method for explanatory variables	lag 1st period	lag 2st period	
AIDI	-0.484*** (-4.852)	-0.632*** (-4.158)	0.378*** (4.271)	0.367*** (3.871)	0.489*** (3.671)
control variable	yes	yes	yes	yes	yes
city effect	yes	yes	yes	yes	yes
vintage effect	yes	yes	yes	yes	yes

Urban fixed	yes	yes	yes	yes	yes
fixed time	yes	yes	yes	yes	yes
N	300	300	300	300	300
R^2	0.441	0.432	0.39	0.42	0.44

Note: Significant levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively, with t-test values in parentheses.

According to the test results in Table 8, it is obvious that the test results of the three methods do not show the phenomenon of changing sign and non-significance, which proves that the test of robustness using the three methods is effective, that is, the tested variables and the model are robust, and their test results are credible.

4.2 Discussion of Heterogeneity of Findings

Heterogeneity test is a statistical method used to test whether there is a significant difference between different samples, that is to say, to test whether there is a significant difference in the test results due to sample differences. In order to carry out the heterogeneity test, this paper distinguishes 269 cities in 30 provinces in China into two categories of high-level cities and low-level cities according to the average GDP, i.e., high-level cities refer to the cities with GDP exceeding the average GDP and there are 104 cities; while low-level cities refer to the cities with GDP lower than the average GDP and there are 165 cities; and at the same time, the cities are divided into coastal cities and inland cities according to the geographic location, and there are 35 prefectural cities in the coastal cities and inland cities. Meanwhile, according to geographical location, all cities are divided into coastal cities and inland cities, and there are 35 prefecture-level cities in coastal cities and 234 prefecture-level cities in inland cities. The results of the heterogeneity test for the two classifications are shown in Table 9.

Table 9. test results of heterogeneity in the level of AI technology development and heterogeneity in administrative divisions

variant	By average GDP per capita		By geography	
	High-level urban CEI	Low-level urban CEI	Coastal Cities CEI	CEI for Inland Cities
AIDI	-0.784^{***}	-0.513^{**}	-0.803^{***}	-0.506^{**}
	(-4.026)	(-2.475)	(-3.851)	(-2.215)
constant term	1.063^{***}	1.657^{**}	0.936^{***}	1.583^{**}
(math.)	(3842)	(2.326)	(3.264)	(2.157)
control variable	control	control	control	control
individual effect	control	control	control	control
time effect	control	control	control	control
N	1040	1650	350	2340
R^2	0.178	0.216	0.327	0.231

Note: Significant levels of 1%, 5%, and 10% are indicated by ***, **, and *, respectively, with t-test values in parentheses.

According to the test results in Table 9, it is obvious that the suppression effect of AI technology on urban energy consumption and carbon emission intensity in high-level cities is much stronger than that in low-level cities, and the suppression coefficient of AI technology on energy consumption and carbon emission intensity in high-level cities is -0.784, while the suppression coefficient in low-level cities is -0.513, and the suppression coefficient is higher than that in low-level cities by 0.271; The inhibition coefficient of AI technology in coastal cities is -0.803, while inland cities is -0.506, and its inhibition coefficient is 0.297 higher, which also shows that the economic development of China's coastal cities is much better than inland cities. From the significance of the test results, the status quo of AI technology in high-level cities and coastal cities is very high, both passing the 1% significance test; while the significance of the test results of AI technology in low-level cities as well as inland cities is relatively poor, passing only the 5% significance test.

5 .Conclusions and policy recommendations

In order to study the impact of the level of AI technology on the energy consumption and carbon emission intensity of China's provincial areas, and explore effective ways to minimize the energy consumption and carbon emission intensity of China's provincial areas. Based on the measurement of provincial energy consumption and carbon emission intensity, this paper makes full use of the statistical data of measuring provincial energy consumption and carbon emission intensity as well as provincial GDP to measure provincial energy consumption and carbon emission intensity, and on this basis, utilizes the spatial Durbin panel model, the test-determined fixed effect model, and the basic statistical data to test the impact of selected driving factors on provincial energy consumption and carbon emission intensity. It is found that: the three drivers of artificial intelligence technology index, digital finance index and the degree of environmental regulation have a negative impact on the provincial urban energy consumption and carbon emission intensity, that is, they have an inhibitory effect on the increase of urban energy consumption and carbon emission intensity, with the influence coefficients of -0.6923, -0.6259 and -0.4722, respectively; the three drivers of the per capita industrial value-added share, the urbanization rate and the intensity of industrial energy consumption have a positive impact impact on the provincial urban energy consumption and carbon emission intensity. The three driving factors of per capita industrial value added, urbanization rate and industrial energy consumption intensity have a positive effect on the energy consumption and carbon emission intensity of provincial cities, with the influence coefficients of 0.6072, 0.5763 and 0.6405 respectively; the study also found that: the upgrading of industrial institutions and industrial technological progress have an intermediate inhibitory effect on the energy consumption and carbon emission intensity of provincial cities, with the corresponding influence coefficients of -0.275 and -0.241, and the significance of the tests are all 1%. significance are 1%. Therefore, based on the above findings, this paper proposes the following policy recommendations to maximize the reduction of carbon emission intensity of energy consumption in Chinese provincial cities:

(1) Make full use of AIDI, DFI and ERI inverse inhibitory factors to maximize the inhibition of carbon emission intensity rise through energy saving and emission reduction. Since the direct and indirect effects of the three drivers are in the same direction, maximizing the inhibition of the total effect is a powerful means of reducing the carbon emission intensity of energy consumption in provincial cities.

(2) Adequately controlling the positive effects of PGL, UR and IECI on the carbon emission intensity of urban energy consumption in provincial areas. These three factors are the main factors contributing to the rise of urban energy consumption and carbon emission intensity in China's provincial areas, and by effectively controlling the positive effects of the three drivers, the reduction of carbon emission intensity will be realized along with the continuous rise of GDP.

(3) Make full use of industrial structure upgrading and industrial technology progress to improve the suppression of urban energy consumption and carbon emission intensity reduction. Since the intermediary variables have the effect of suppressing carbon emission intensity, the effective control of carbon emission intensity can be gradually realized by effectively utilizing the suppressing effect of intermediary factors, so as to play the role of reducing the carbon emission intensity of urban energy consumption.

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