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Can industrial intelligence break the carbon curse of natural resources in the context of Post-Covid-19 period? Fresh evidence from China

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ABSTRACT

During the Post-Covid-19 era, the industrial industry is progressing towards technological innovation and intelligence. Industrial intelligence is anticipated to emerge as a significant determinant of carbon emissions. Additionally, the carbon curse of natural resources has impeded the region's progress towards green development. To address these challenges, industrial intelligence has emerged as a pivotal approach for achieving carbon emission reduction and mitigating the carbon curse. Based on panel data collected from 282 cities in China from 2006 to 2019, this study first investigate the validity of the carbon curse phenomenon of natural resources. Additionally, it explores the heterogeneity of this phenomenon. Furthermore, the study examines the nonlinear influence of natural resource dependence on carbon emission intensity in various stages of industrial intelligence development (namely, low, medium, and high stages) using a threshold effect model. The results show that: (1) Natural resource dependence can significantly promote carbon emission intensity. This conclusion remains robust even after employing endogenous treatment and conducting a series of rigorous tests. (2) Heterogeneity analysis reveals that the carbon curse phenomenon of natural resources exhibits significant variations due to urban resource endowment, policy development stage, and regional characteristics. (3) The threshold effect model demonstrates that if the level of industrial intelligence is below 0.022, it exacerbates the carbon curse of natural resources. When the industrial intelligence level is within the range of [0.022, 0.944], it has a mitigating effect on the carbon curse of natural resources. When the industrial intelligence level surpasses 0.944, the carbon curse of natural resources can be broken.

1. Introduction

Owing to the outbreak of the Newcastle pneumonia pandemic and the consequent imposition of trade restrictions, global energy demand witnessed a substantial decline of 4.5% in 2020, thus marking the most notable reduction since 1945. Furthermore, global carbon dioxide emissions fell by 6% during the same period, representing the most substantial decrease observed in the past 75 years. As the global economy gradually recovers and embargo measures are lifted, CO_2 emissions are likely to increase again (Sun et al., 2021). Natural resources, which serve as crucial inputs in production activities, possess both favorable and unfavorable impacts on economic development and the ecological environment (Wang et al., 2021). Consequently, the carbon curse associated with natural resources has become a subject of academic inquiry. Friedrichs and Inderwildi (2013) first proposed the concept of the carbon curse of natural resources, arguing that a country's fossil fuel endowment largely drives its carbon emission intensity. Countries or regions rich in natural resources are more likely to develop natural resource dependence (Wu et al., 2018). And the carbon curse is mainly manifested by the fact that countries or regions with high natural resource dependence tend to have higher carbon emission intensity (Chiroleu-Assouline et al., 2020).

The existence of the carbon curse runs counter to the main theme of carbon neutrality in today's world and becomes an obstacle to net-zero emissions, so how to effectively break the carbon curse of natural resources has become a key issue in carbon control. Che and Wang (2022) demonstrate that environmental regulation can effectively mitigate the rise in carbon intensity resulting from natural resource dependence. Notably, environmental regulation serves as a vital approach to reducing carbon emissions (Pei et al., 2019; Yang et al., 2020). However,

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imposing mandatory environmental regulation not only imposes production pressure on enterprises but also has the potential to prompt local businesses to form collusive alliances in order to counterbalance the external costs associated with environmental regulation through the scale effect. This phenomenon, in turn, exacerbates the "resource curse" effect (Jiang and Lu, 2023).

To fundamentally break the carbon curse of natural resources, it is imperative for enterprises to strengthen technological innovation and encourage the modernization and transformation of energy-intensive sectors. However, few studies have been conducted to address the alleviation of the carbon curse of natural resources from a market-oriented standpoint. Carbon emissions primarily stem from production activities within the industrial sector (Zahoor et al., 2022). Developing industrial intelligence is an important direction to alleviate the carbon curse. Industrial intelligence is the process of artificial intelligence penetration and application in various fields (Preuveneers and Ilie-Zudor E, 2017), which can facilitate technological innovation (Chen and Liu, 2022), enhance productivity, and optimize resource allocation efficiency (Qian et al., 2022). It is not only conducive to industrial transformation and upgrading but also encourages the transition of other sectors towards intelligence. Nonetheless, it is crucial to acknowledge that industrial intelligence itself presents energy consumption challenges. Thus, further exploration is warranted to determine whether industrial intelligence can effectively break the carbon curse of natural resources within the context of market factors.

China's abundant natural resources and its chosen path of development offer an intriguing context for investigating these concerns. With its resource-rich profile, China has experienced substantial carbon emission issues due to its reliance on a resource-driven economic growth model, resulting in its position as the world's largest carbon emitter. According to the report *Global Energy Review: CO_2 Emissions in 2021* released by International Energy Agency (IEA), China's annual carbon emissions in 2020 reached 9.894 billion tons, accounting for 30.9 percent of global emissions. To veer away from a carbon-intensive economic trajectory, China must urgently transition its development approach from resource-driven to innovation-driven. Remarkably, China has emerged as the global leader in industrial intelligent transformation. According to the "World Robotics 2021" report released by the International Federation of Robotics (IFR), China witnessed a remarkable progression from just over 2000 industrial robots in 2002 to becoming the largest industrial robot market by 2020. China serves as an exemplary case study on this subject, and its developmental experience holds valuable lessons for other developing countries reliant on natural resources.

Using a study sample of 282 cities in China, we first employ a two-way fixed effect model and a dynamic panel model to verify whether the carbon curse of natural resources exists in China. Furthermore, it aims to elucidate the variations in the carbon curse effect of natural resources concerning urban resource endowments, policy development stages, and regional differences. On this basis, we use the robot industry data of IFR, the total employed population data of China from WORLD KLEMS, and the micro-data of population sampling survey to measure industrial intelligence. And we use the threshold effect model to investigate the nonlinear influence of natural resource dependence on carbon emissions across different levels of industrial intelligence. The findings indicate natural resource dependence has different effects on carbon emission intensity within each stage of industrial intelligence. Understanding the heterogeneity of the carbon curse in various regions and policy development stages, along with exploring effective strategies to overcome the carbon curse of natural resources from a market-oriented perspective, are pivotal in breaking the carbon curse and advancing the goal of carbon neutrality.

The study's marginal contributions are as follows: Firstly, we explore ways to break the carbon curse of natural resources from the perspective of market factors, while existing literature primarily focuses on institutional factors. By integrating natural resource dependence, industrial intelligence, and carbon emission intensity within the same framework, we explore the nonlinear influence of natural resource dependence on carbon emission intensity across varying levels of industrial intelligence. Secondly, we elucidate the internal mechanism and realization path of the carbon curse of natural resources in different stages of industrial intelligence and present fresh insights for promoting energy conservation and carbon reduction in resource-dependent areas. Thirdly, we provide empirical evidence showcasing the heterogeneity of the carbon curse of natural resources across different regions and policy development stages. Prior research has often overlooked this heterogeneity, resulting in limited conclusions. To address this gap, we analyze the heterogeneity of the carbon curse across different policy development stages and regions, investigate its underlying causes, and offer valuable references for carbon control in diverse regions and stages of development.

2. Literature review and theoretical mechanisms

2.1. Impact of natural resource dependence on carbon emission intensity

Natural resources serve as the fundamental basis for material production. Regions with high resource endowments can swiftly amass material wealth through resource extraction activities in the short term. However, excessive reliance on natural resources frequently gives rise to heightened environmental challenges (Auty, 2007). Regions exhibiting substantial natural resource dependence often characterized by a single rigid industrial structure and insufficient development of strategic new industries. Consequently, numerous industries within these regions tend to be associated with high pollution levels and elevated emission intensity (Feng et al., 2017). Natural resource dependence frequently exerts a detrimental influence on environmental sustainability (L.S. Liu et al., 2023). Regarding carbon emissions, a minority of scholars argue that natural resources contribute to carbon emission reduction. Balsalobre-Lorente et al., 2018 contend that nations endowed with abundant natural resources often adopt energy-efficient technologies, thereby facilitating carbon emission reduction. Nevertheless, the prevailing consensus among scholars suggests that countries with ample natural resources tend to fall victim to resource dependence, resulting in heightened carbon emission intensity. Wang et al. (2019) found that resource abundance hampers carbon emission efficiency using a panel Tobit model. Chiroleu-Assouline et al. (2020) examined 29 countries as the study population and found that nations endowed with substantial natural resources face an elevated risk of carbon emissions. Moreover, they observed that when natural resource abundance surpasses a specific threshold, it stimulates carbon dioxide emission intensity.

Carbon emissions are susceptible to the natural resource curse for several reasons. Firstly, regions reliant on resources often develop economic structures centered around energy, mineral resources, and other industries inherently associated with higher pollution levels (Yang et al., 2018). The extraction process of natural resources, such as energy and mineral, frequently results in the release of by-products like associated gas or coal-bed methane, which are often burned into the air, contributing significantly to regional carbon dioxide emissions (Friedrichs and Inderwildi, 2013). Secondly, resource-dependent regions exhibit limited motivation for innovation and lower energy use efficiency. As these regions face fewer constraints on resource availability for economic development and have lesser demands for technological innovation, the overall regional motivation to innovate remains low (Aljarallah, 2020; Shaheen et al., 2022). This leads to the displacement of highly skilled labor, a lower overall level of human capital, weakened innovation capacity, and ultimately reduced energy use efficiency, resulting in lower carbon emission efficiency (Y.B. Liu et al., 2023). Thirdly, resource-dependent regions exhibit suboptimal resource allocation efficiency. Dominated by resource-based industries and their associated sectors, these regions often lack diversity and encounter weaker incentives for improving resource efficiency (Meng and Zhang, 2020). The

concentration of resources in these industries diverts substantial social resources, including technology, capital, and talent, away from other innovative industries, exacerbating the crowding out effect.

In summary, natural resource dependence can not only directly affect carbon emission intensity, but also promote carbon emission by reducing energy use efficiency and resource allocation efficiency.

2.2. Natural resource dependence, industrial intelligence and carbon emission intensity

Natural resource dependence contributes to carbon intensity in both direct and indirect ways, while industrial intelligence can help promote technological innovation and productivity improvements. So, can industrial intelligence break this "dilemma" and alleviate the carbon curse of natural resources?

Industrial intelligence can affect the carbon curse of natural resources by influencing natural resource use efficiency. It facilitates a decrease in the usage of fossil fuels and alleviates the carbon curse of natural resources to a certain extent under the condition of equal production. The advantages of industrial intelligence are reflected in collecting a large amount of real-time data in production and life through empirical learning. This data-driven approach allows for precise monitoring and predicting carbon footprints, aiding governments and enterprises in making informed decisions regarding carbon reduction strategies, reducing energy consumption and usage costs (Yu et al., 2023). Specifically, on the one hand, industrial intelligence not only helps to change the production mode of enterprises, optimize their production patterns, and prompt the transformation of their production processes to intelligence (Li et al., 2022). Additionally, it enables quantitatively analysis and continuous optimization of energy-intensive production links, leading to improved energy utilization efficiency (X. Xie et al., 2021). It also contributes to the development of low-carbon energy technologies, effectively reducing carbon emission intensity (Li and Huang, 2023). On the other hand, industrial intelligence helps to realize green lifestyles. For example, in urban electricity consumption, it can use smart grids to automatically adjust power distribution settings to reduce energy waste (Xue et al., 2022; Pan et al., 2023). In transportation, it utilizes data simulations to optimize energy consumption and traffic travel plans, considering factors such as intersection passage efficiency and vehicle queues, ultimately resulting in reduced urban carbon emissions (Xue and Zhang, 2017).

Industrial intelligence can also alleviate the carbon curse of natural resources by improving resource factor allocation efficiency. Industrial intelligence can not only help enterprises make production decisions but also monitor the whole process of production management, alleviate the problem of resource mismatch, and improve enterprise production efficiency (Gan et al., 2023). Through the collection and analysis of vast consumer data, industrial intelligence empowers enterprises to understand consumer preferences, swiftly respond to market demands, and make optimal production decisions (Tang and Chi, 2022). It can help enterprises allocate capital, talent, technology, and other resources to where they are most needed, improving resource factor allocation efficiency and reducing resource waste. Within the enterprise production process, industrial intelligence relies on digital technologies such as big data and the internet to connect and dynamically analyze extensive data from the production and management domains. This facilitates the seamless integration of production and management resources within the enterprise (Huang and Li, 2017), leading to improved allocation of various production factors and a reduction in unnecessary energy consumption (Wang et al., 2023), thus improving carbon emissions efficiency. Additionally, industrial intelligence can also assist in production, not only for efficient and batch processing of simple work tasks but also for supporting complex work tasks. In addition, it may influence the structural configuration of the workforce and complement regional green innovation talent resources (Gan et al., 2023).

Industrial intelligence can alleviate the carbon curse of natural resources by improving natural resource use efficiency and resource factor allocation efficiency. However, industrial intelligence itself may also lead to additional electricity consumption and higher energy intensity, exacerbating the carbon curse of natural resources. Research has indicated that energy usage by industrial robots has become a significant component of overall energy consumption in industrial processes, accounting for approximately 8% of the total energy consumed by manufacturing companies (Brossog et al., 2015). The early development of AI technologies relied on data centers and machine learning systems, and training AI language processing systems will consume large amounts of energy (Strubell et al., 2019), resulting in large carbon emissions (Henderson et al., 2020). Based on the aforementioned analysis, it becomes apparent that when industrial intelligence is at a nascent stage of development, the advancements in natural resource utilization and resource factor allocation efficiency are insufficient to counterbalance the energy consumption it generates. Consequently, industrial intelligence exacerbates the carbon curse associated with natural resources during this phase. However, as industrial intelligence progresses, it gradually enhances natural resource utilization and resource factor allocation efficiency, thereby offsetting its own energy consumption. At this stage, industrial intelligence can help alleviate the carbon curse of natural resources. When industrial intelligence reaches a certain high level, its efficiency of natural resource utilization and resource factor allocation is very strong, which means that industrial intelligence can break the carbon curse of natural resources.

According to the above analysis, this paper contends that inadequate levels of industrial intelligence exacerbate the carbon curse associated with natural resources. However, as industrial intelligence advances, the impact of natural resource dependence on carbon emission intensity gradually diminishes. Ultimately, when industrial intelligence reaches a certain threshold, it has the potential to break the carbon curse of natural resources.

3. Methods and data

3.1. Methods

3.1.1. Baseline regression model setting

This study investigates how natural resource dependence affects carbon emission intensity using urban panel data, which is characterized by a wider N and shorter T in the data structure of this paper. To avoid the omission of characteristic variables that do not change over time for individuals and the influence of time trends on the dependent variable, this paper tries to establish a two-way fixed effect model. Meanwhile, the results of the Hausman test and F-test also indicate that a two-way fixed effect model should be used for regression. The model structure is shown as follows:

$$CEI_{i,t} = \alpha_0 + \beta_1 NRE_{i,t} + \beta X_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t} \quad (1)$$

Where $CEI_{i,t}$ in model (1) denotes the carbon emission intensity of city i in period t, $NRE_{i,t}$ denotes the natural resource dependence level of city i in period t, and β_1 represents the influence coefficient. $X_{i,t}$ denotes a series of control variables. μ_i denotes urban fixed effects, ν_t denotes time fixed effects, and $\varepsilon_{i,t}$ denotes random disturbance terms.

3.1.2. Threshold effect model setting

The baseline regression model (1) portrays a simple linear relationship between natural resource dependence and carbon emission intensity. However, since the effect is not invariant in the theoretical analysis, it is influenced by industrial intelligence. Therefore, we further construct a threshold effect model based on the baseline model (1) to investigate the nonlinear effects of natural resource dependence on carbon emission intensity under different levels of industrial intelligence. The main idea of the threshold effect model is to determine the threshold value conditional on the minimization of the sum of squared

residuals and construct the segmentation function from it. The threshold effect model can identify the effects of key variables on the explanatory variables at different threshold intervals and therefore fits well with the research needs of this paper. The model structure is shown as follows:

$$CEI_{i,t} = \alpha_0 + \beta_1 NRE_{i,t}(INTE_{i,t} <= \gamma_1) + \beta_2 NRE_{i,t}(\gamma_1 < INTE_{i,t} <= \gamma_2) + \beta_3 NRE_{i,t}(INTE_{i,t} > \gamma_2) + \beta X_{i,t} + \mu_i + \nu_t + \varepsilon_{i,t}$$

where the threshold variable is industrial intelligence (*INTE*), and γ_1 and γ_2 are the first and second thresholds, respectively. β_1, β_2 and β_3 denote the impact coefficients of natural resource dependence on carbon emission intensity at different levels of industrial intelligence, respectively. Here, a double-threshold model is used as an example. In the empirical evidence, the number of thresholds of the model is determined by testing the significance level of each estimated threshold value according to the sample data.

3.2. Variable selection

3.2.1. Explained variables

Carbon emission intensity (*CEI*). Referring to Wu (2021), we use carbon emission intensity, i.e., the ratio of carbon emissions to real GDP, as a proxy variable for *CEI*. The specific calculation formula is as follows:

$$CEI_{i,t} = \frac{TEC_{i,t}}{GDP_{i,t}}$$

Where $CEI_{i,t}$ denotes carbon emission intensity, reflecting the pattern of urban economic development. $GDP_{i,t}$ denotes the real regional GDP, $TEC_{i,t}$ denotes the total carbon emissions. We refer to Wu and Guo (2016) and sum up the carbon emissions from direct energy (raw coal, liquefied petroleum gas, and natural gas) consumption and carbon emissions from electricity consumption. Among them, carbon emission from direct energy consumption = energy consumption × coal discount factor × carbon emission factor, energy consumption is statistical data, coal discount factor and carbon emission factor are taken from 2006 IPCC guidelines, carbon emission from electric energy consumption is calculated using the baseline emission factor of each regional grid and urban electric energy consumption.

To understand the temporal evolution trend and pattern of *CEI*, the kernel density estimation diagram (Fig. 1) is engraved in this paper. From the movement of the peaks, the highest value of *CEI* gradually moves to the left, indicating a decreasing trend of *CEI*; from the shape, the width of the kernel density curve becomes smaller, indicating that the absolute difference between cities with higher and lower *CEI* appears to be narrowing; from the fluctuation of the trailing on both sides of the curve, there is an obvious right trailing phenomenon, and the distribution extension gradually becomes narrower, indicating the existence of cities with very high *CEI*.

3.2.2. Core explanatory variables

Natural resource dependence (*NRD*). Common indicators used to measure *NRD* are the share of natural resource rents in GDP (Destek et al., 2022), the share of mining output (Che and Wang, 2022), and the share of people employed in mining (Y.C. Xie et al., 2021; Li et al., 2023). While the first two indicators are typically employed in national-level or provincial-level studies due to data availability challenges at the city level. Therefore, we refer to Li et al. (2023) to measure the degree of *NRD* of cities from an employment perspective using the proportion of mining workers to total employment. The reason for this choice is that China's mining industry mainly includes energy mining (such as coal mining and washing, oil and gas mining, etc.), metal mining and non-metal mining. And this indicator can better reflect the extent to which a city's employment structure is tilted toward resource-based industries.

We fit a scatter plot between *NRD* and *CEI* (Fig. 2) and tentatively determine that *NRD* promotes *CEI*. However, it is important to note that this initial analysis provides only a preliminary depiction of the variable relationship. To establish more robust research findings, it is crucial to comprehensively consider the effects of various other factors and incorporate them into a unified analytical framework for rigorous empirical testing.

3.2.3. Threshold variables

Industrial intelligence (*INTE*). We refer to Acemoglu and Restrepo (2020) to construct a measure of industrial intelligence using the Bartik instrumental variable "robot penetration" at the regional level in the United States. The robotics data are obtained from IFR, a database that has been providing industry-specific robotics data for China since 2006. To address concerns regarding endogeneity between robotics applications and the job market, we adopt the methodology employed by Chen et al. (2022). Specifically, the employment variable uses data from the initial year, 2005, in measuring the number of employed people, and this data is calculated from the microdata of the 1% population sample survey in 2005. The formula is as follows:

$$INTE_{i,t} = \sum_{j \in I} \frac{l_{i,j,2005}}{l_{i,2005}} \frac{robots_{j,t}}{tep_{j,2005}}$$

where $INTE_{i,t}$ denotes the level of industrial intelligence. $l_{i,j,2005}$ denotes the number of people employed in industry j in prefecture-level city i in 2005, and $l_{i,2005}$ denotes the total number of people employed in prefecture-level city i in 2005. $tep_{j,2005}$ denotes the total number of people employed in industry j nationwide in 2005, with data from the WORLD KLEMS database. $robots_{j,t}$ measures the amount of industrial robots used by industry j at time t at the national level. Based on China's

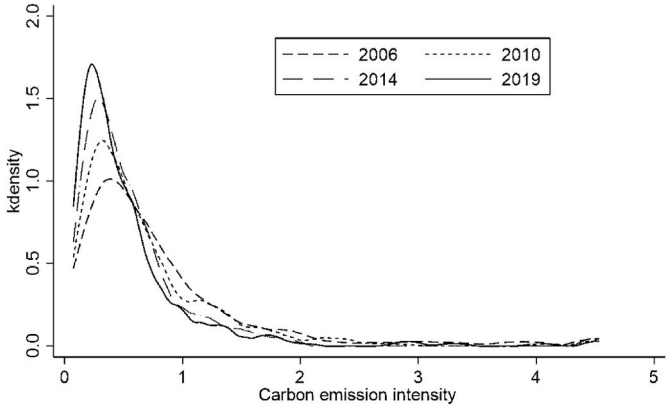


Fig. 1. Kernel density estimation diagram.

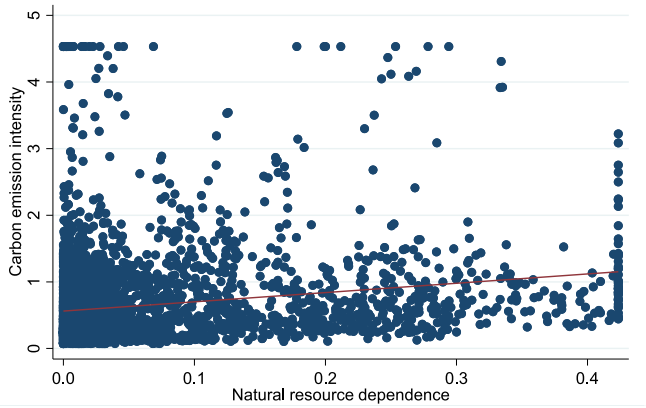


Fig. 2. Scatter fitting graph of *NRD* and *CEI*.

industry classification and IFR's industry classification of robot operation, we classify industrial robot operation by 18 industries. These industries include automobile manufacturing and other transportation equipment manufacturing, plastic products and chemical industry, metal products industry, equipment manufacturing, food and beverage manufacturing, metal smelting, electronic products manufacturing, non-metallic mineral products industry, wood processing industry, textile industry, paper and printing industry, other manufacturing, mining, education and research, agriculture, public utilities, construction, and service industries.

To understand the development trend of *INTE*, we drew a spatial distribution map of the level of *INTE* with ArcGIS software (Fig. 3). Fig. 3a–d show the spatial distribution of *INTE* in 2006, 2010, 2014 and 2019, respectively. From the time point of view, the level of *INTE* is on a continuous upward trend, and the highest distribution range of industrial intelligence in 2006 is 0.0084–0.0175, while the highest distribution range of industrial intelligence in 2019 has reached 0.4528–1.8108. From the regional point of view, the level of *INTE* is ladder-like, with significant layer effect. Overall, the spatial distribution can be categorized into three tiers. The first tier comprises the eastern coastal region, characterized by the highest level of industrial intelligence. The second tier consists of the central and northeastern regions, which exhibit the second highest level of industrial intelligence. The western region falls into the third tier, representing the area with the lowest level of industrial intelligence.

3.2.4. Control variables

The control variables selected contain the main factors that affect carbon emissions, which are: First is infrastructure level (lninfr), measured as the logarithm of total urban postal and telecommunications operations. Second is financial development (fina), which is measured using the ratio of loan balance of financial institutions to urban GDP at the end of the year. Third, population density (lnpopu), we collected WorldPop global-wide 1 km resolution population raster data, aggregated the China-wide data to obtain urban panel data, and logged them. The fourth is natural population growth rate (npgr), which is measured in this paper as the ratio of the natural increase in population to the average population over the same period. Fifth is the degree of openness to the outside world (open), which is measured in this paper by the share of actual foreign capital used in the city in the year to the regional GDP.

3.3. Sample selection and data description

Considering the data availability and completeness of the selected variables, this paper excludes the cities with serious missing data, and finally selects 282 cities in China from 2006 to 2019 as the research object. The sample of this paper does not include the Tibet Autonomous Region, and cities with serious missing data, such as Turpan, Shigatse, Linzhi, Hami, Haidong, Sansha, Danzhou, Bijie, Shannan, and Tongren, are also excluded. Data are obtained from *China Energy Statistical Yearbook*, *China City Statistical Yearbook*, IFR database, WORLD KLEMS database, 1% Population Sample Survey Microdata, WorldPop dataset, and provincial and municipal statistical yearbooks.

To eliminate the influence of sample outliers on the regression results, we performed the 99% and 1% quantile tailing process for all variables. Additionally, we interpolated some missing values using the interpolation method and the mean method to obtain unbalanced panel data after preliminary processing. The descriptive statistics of the main study variables are shown in Table 1.

4. Results and discussion

4.1. Impact of natural resource dependence on carbon emissions

Table 2 reports baseline regression results of the impact of *NRD* on *CEI*, with each column of the regression controlling for city and year fixed effects. Among them, column (1) is the regression result

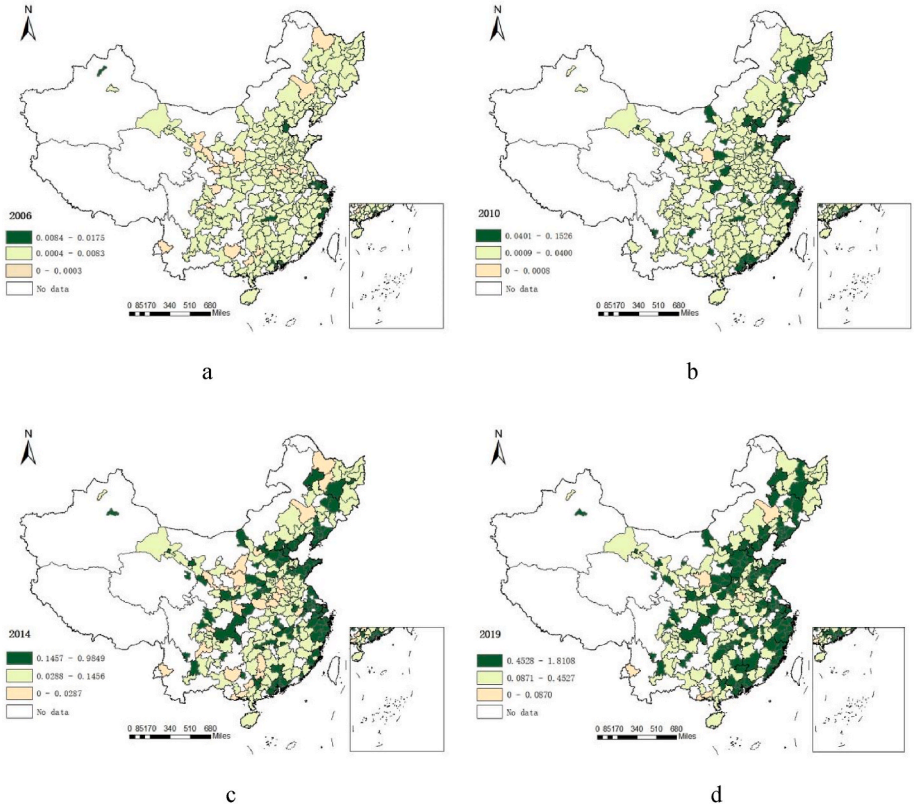


Fig. 3. Spatial distribution of industrial intelligence level.

Table 1
Descriptive statistics of variables.

Variable	Obs	Mean	Std	Min	Max
CEI	3948	0.637	0.662	0.074	4.533
NRD	4018	0.053	0.089	0	0.424
INTE	3962	0.182	0.325	0.0003	1.811
lninfr	3997	10.303	1.194	8.000	13.992
Fina	3998	0.885	0.518	0.270	3.045
lnpopu	3990	6.934	0.699	5.354	8.829
Npgr	4004	5.818	5.031	−7.200	20.480
Open	4008	0.018	0.019	0	0.199

Table 2
Baseline regression results.

	(1)	(2)	(3)	(4)
NRD	1.805***	1.886***	0.495*	0.556**
	(0.565)	(0.553)	(0.272)	(0.271)
l_CEI			0.673***	0.667***
			(0.074)	(0.076)
lninfr		0.029		0.001
		(0.023)		(0.009)
fina		−0.034		0.019
		(0.059)		(0.025)
lnpopu		−0.777***		−0.238**
		(0.263)		(0.106)
npgr		0.003		0.0007
		(0.002)		(0.0009)
open		−0.551		−0.289
		(0.611)		(0.248)
Constant	0.720***	5.803***	0.263***	1.878**
	(0.039)	(1.759)	(0.055)	(0.735)
City fixed effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Observations	3947	3929	3665	3648
R^2	0.191	0.206	0.576	0.574

Note: ***, **, and * denote 1%, 5%, and 10% significance levels, respectively, with robust standard errors in parentheses. Same below.

considering only the univariate of *NRD*, and the regression coefficient is positive at the 1% significance level; column (2) is the regression result adding control variables to column (1), and the effect coefficient of *NRD* on *CEI* is 1.886 with a significance level of 1%. The above results indicate that *NRD* significantly exacerbates *CEI*. It is not only because large amounts of carbon dioxide are released in the process of extracting natural resources such as energy and mineral resources, but also probably because *NRD* tends to result in lower sectoral energy use efficiency and resource allocation efficiency.

The empirical results of the static panel model have shown that *NRD* significantly exacerbates *CEI*, however, the results do not take into account the inertia of *CEI*. If the dynamic lag effect of *CEI* is considered, is the contribution of *NRD* to carbon intensity still significant? We further use the dynamic panel model for analysis, where column (3) is based on column (1) with the addition of the first-order lag term of *CEI* and column (4) adds control variables to column (3). Both results show that the natural resource-dependent carbon curse phenomenon still exists. In addition, the first-order lag term of *CEI* is significantly positive at the 1% level, indicating that there is a dynamic continuum of *CEI*, i.e., the previous period's *CEI* has a significant positive effect on the current period's *CEI*.

4.2. Endogeneity treatment and robustness test

To further test the validity of the effect of *NRD* on *CEI*, we use the instrumental variables approach for endogeneity and robustness tests in the following ways.

4.2.1. Instrumental variables method

There are many factors affecting *CEI*, and there may be the problem of omitted variables. The instrumental variables approach is an important method to overcome endogeneity, so we try to mitigate the endogeneity problem through the instrumental variables approach to ensure the reliability of the empirical results. Column (1) of Table 3 reports the results of the instrumental variables method test, which yields conclusions consistent with the previous paper, justifying the rationality of the baseline model and the validity of the conclusions. The results of the weak instrumental variables show that the F-value of the Cragg-Donald test of the instrumental variables with respect to the endogenous explanatory variables is 2971.00, which is greater than the threshold value of 16.38 at the 10% bias level of the Stock-Yogo weak instrumental variables. Consequently, it can be concluded that the instrumental variables used in this study are suitably selected, and there is no indication of weak instrumental variables present.

4.2.2. Changing the way the explained variable is measured

Referring to Shan et al. (2022), we change the measurement of *CEI* to total CO_2 emissions with data from the China Carbon Accounting Database (CEADs). As can be seen from column (2) of Table 3, the significance of the effect of *NRD* on *CEI* does not change substantially after changing the measurement of the explanatory variables compared to the results of the base regression, reflecting the robustness of the study findings.

4.2.3. Controlling for joint province and time fixed effects

Considering that there are still some time-varying unobservable factors at the provincial level that may have an impact on *CEI*, we also control the time trend term of province and year crossing on the basis of controlling city and time-fixed effects. As can be seen from column (3) of Table 3, the regression coefficient of *NRD* on *CEI* is significantly positive at the 1% level, indicating the robustness of the regression results in this paper.

4.2.4. Adding control variables

In addition to the above control variables, environmental regulation and industrial structure may also affect *CEI*. To ensure the robustness of the estimation, we further control for environmental regulation and industrial structure.

Among them, the measurement of environmental regulation is based on the methodology proposed by Dong et al. (2022). This approach incorporates five key indicators: industrial sulfur dioxide removal, industrial soot removal, domestic wastewater treatment rate, domestic waste harmless treatment rate, and general industrial solid waste comprehensive utilization rate. The comprehensive index of environmental regulation is constructed using the entropy value method. Industrial structure is measured using the share of secondary sector GDP to tertiary sector GDP. Column (4) of Table 3 shows that the carbon curse of natural resources still exists.

4.2.5. Shorten the sample time span

To identify whether the carbon curse effect of natural resources varies with the length of the sample, we perform a robustness test by varying the regression time interval. We re-run the regression by changing the time span of the panel to 2008–2017, and the regression results are presented in column (5) of Table 3. Changing the time span of the panel data slightly changes the magnitude and significance, but the coefficient sign of the core explanatory variables remains the same, indicating that the baseline regression results are robust.

4.3. Heterogeneity analysis

4.3.1. Based on heterogeneity analysis of urban resource endowment

Considering that the differences in resource endowments of individual cities also affect the carbon curse effect of natural resources, we divide the urban sample into resource-based cities and non-resource-based cities based on the *National Sustainable Development Plan for*

Table 3
Endogeneity treatment and robustness test results.

	Instrumental variables method	Substitution of explanatory variables	Controlling for joint province and time fixed effects	Adding control variables	Shorten the sample time span
	(1)	(2)	(3)	(4)	(5)
NRD	2.444***	1.079**	1.807***	1.544***	1.886***
	(0.303)	(0.418)	(0.611)	(0.568)	(0.553)
Constant		−8.080**	8.029***	5.239***	5.803***
		(3.789)	(2.573)	(1.855)	(1.759)
Control variables	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes
Province × Year	No	No	Yes	No	No
Observations	3648	3929	3929	3583	3929
R^2	0.190	0.113	0.345	0.210	0.206

Resource-based Cities (2013–2020) issued by the Chinese government. The Chinese government defines a resource-based city as a city with mining and processing of natural resources such as minerals in the region as the leading industry, and the planning scope includes 126 prefecture-level resource-based city administrative regions, and 113 prefecture-level resource-based city administrative regions are included in the sample of this paper. The regression results are shown in Table 4.

Columns (1) and (2) demonstrate the effect of *NRD* on *CEI* in resource-based cities. We can see that the effect of *NRD* on *CEI* is significantly positive with or without the inclusion of control variables, which indicates the existence of the carbon curse of natural resources in resource-based cities. Columns (3) and (4) demonstrate the effect of *NRD* on *CEI* in non-resource-based cities, which is not significant with or without the inclusion of control variables. The findings suggest that resource-based cities are more likely to follow a carbon-intensive path compared to non-resource-based cities. It may be because resource-based cities are relatively rich in resource endowments, which easily form an economic structure with energy and mineral resources as the leading industries, thus leading to a more pronounced carbon curse of natural resources.

4.3.2. Based on policy development stage heterogeneity analysis

We further consider the impact of policy development stages on the carbon curse of natural resources. Based on the three strategic plans implemented by the Chinese government, the sample is divided into three time periods: the 11th *Five-Year Plan* (2006–2010), the 12th *Five-Year Plan* (2011–2015), and the 13th *Five-Year Plan period* (2016–2019). The reason for the delineation is mainly because different strategic development stages affect the direction of economic growth, industrial layout, and environmental regulation intensity of whole country, and the demand for natural resources and the tolerance of carbon emissions are different. Based on this, the regressions are divided into time samples separately.

From the regression results in Table 5, the effect of *NRD* on *CEI* is significantly positive in the years 2006–2010 and 2011–2015. During the 11th *and* 12th *Five-Year Plans*, there is a clear phenomenon of carbon curse of natural resources in China. It reflects that although some environmental policies were introduced in the 11th *and* 12th *Five-Year Plans*, Chinese cities were more concerned with the growth of the total economic volume and not enough with the improvement of the quality of the economy during this period. In 2016–2019, there is no significant impact of *NRD* on *CEI*. It may be due to the fact that the dual control of energy intensity and total energy consumption implemented during the 13th *Five-Year Plan* period has effectively improved natural resource utilization efficiency and achieved significant results in energy conservation and emission reduction.

Table 4
Heterogeneity based on resource endowment.

	Resource-based Cities		Non-resource-based cities	
	(1)	(2)	(3)	(4)
NRD	1.646**	1.873***	0.697	0.779
	(0.661)	(0.658)	(1.273)	(1.153)
Constant	0.729***	4.133	0.745***	7.154***
	(0.090)	(2.617)	(0.031)	(2.299)
Control variables	No	Yes	No	Yes
City fixed effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Observations	1581	1567	2366	2362
R^2	0.248	0.257	0.144	0.176

Table 5
Heterogeneity based on policy development stages.

	2006–2010	2011–2015	2016–2019
NRD	1.421**	1.886***	0.187
	(0.720)	(0.553)	(0.320)
Constant	6.008**	5.803***	4.039**
	(2.502)	(1.759)	(1.917)
Control variables	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Observations	1405	3929	1119
R^2	0.116	0.206	0.032

4.3.3. Based on regional heterogeneity analysis

Differences in natural resource base and industrial development patterns among different regions affect the effect of *NRD* on *CEI*. We divide China into eastern, central, western, and northeastern regions by geographic location for sub-sample discussion, and the results are shown in Table 6.

Table 6
Based on regional heterogeneity.

	East region	Central region	Western region	Northeast region
NRD	1.557**	0.985*	3.643***	−0.196
	(0.597)	(0.509)	(1.031)	(0.944)
Constant	8.573***	8.874***	7.183**	2.057
	(2.097)	(2.977)	(3.044)	(7.680)
Control variables	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Observations	1186	1120	1162	461
R^2	0.251	0.160	0.211	0.398

In terms of significance level, the effect of *NRD* on *CEI* was significantly positive at the 1%, 5% and 10% levels in the western, eastern and central regions, respectively, while in the northeastern region, the effect of *NRD* on *CEI* was not significant. In terms of coefficients, the highest level of significance is found in the western region, followed by the eastern region and the central region. It may be due to the fact that the western region is relatively rich in natural resources and has the strongest dependence on natural resources. The northeastern region, on the other hand, was a traditional center of heavy industry concentration and had a heavy industry system that was highly dependent on resource consumption until 2003, but then the resource advantage gradually diminished. And in 2003, the central government made a major strategic decision to revitalize the old industrial bases in the northeast, a strategic move that accelerated the development of new industries and weakened the dependence on natural resources. Since the research sample of this paper is from 2006 to 2019, it shows that the phenomenon of natural resource carbon curse in Northeast China is not obvious, which also shows that China's strategic decisions are effective to some extent and can help enterprises in Northeast China to transform and upgrade and develop clean energy.

4.4. Threshold effect

4.4.1. Threshold effect and threshold value test

Considering that this paper first tests whether there is a threshold effect and the number of thresholds for the carbon curse effect of natural resources to judge the existence of the threshold effect, the results are shown in Table 7. The single threshold effect passed the 1% significance level test, indicating the presence of at least one threshold, and therefore, we needed to run a panel two-threshold model regression. The p-value of the F-statistic for the two-threshold effect is 0.030, which rejects the original hypothesis of "only one threshold", i.e., there are at least two thresholds, so we need to conduct a three-threshold panel model regression. The p-value of the F-statistic for the three-threshold effect is 0.503, and the original hypothesis of "only two thresholds" is accepted. After determining the existence of a threshold effect, we further constructed the likelihood ratio function of the threshold variables to test the consistency of the threshold estimates. Fig. 4 clearly shows the process of constructing the estimates of the threshold values with confidence intervals.

4.4.2. Threshold regression results

Based on the results of the F-statistic test for determining the threshold effect, we regressed with a panel double threshold model. Table 8 shows the double threshold values of 0.022 and 0.944, respectively. Table 9 shows the estimation results of the double threshold effect. When the level of *INTE* is below 0.022, the coefficient of *NRD* on *CEI* is 2.286, which is significant at the 1% level of significance, and the coefficient is increased from the baseline regression coefficient of 1.886. It indicates that when the level of *INTE* is too low, it not only fails to alleviate the carbon curse of natural resources but also intensifies it. The main reason is that industrial intelligence itself needs to consume electricity and produce carbon dioxide, and when the level of *INTE* is too low, its improvement of energy efficiency is not enough to offset the energy consumed by itself. When the level of *INTE* is in the interval [0.022, 0.944], the impact coefficient is 1.513, which is significant at the 1% level, and the coefficient is reduced compared with the baseline regression coefficient of 1.886. This indicates that when *INTE* reaches a certain level, it helps to alleviate the carbon curse of natural resources. When the level of *INTE* is greater than 0.944, the impact coefficient is −3.949, which is significant at the 1% level. This indicates that a high level of *INTE* can effectively break the carbon curse of natural resources, transforming it from a "curse" to a "blessing". The intelligent development and rational utilization of natural resources not only facilitate urban production but also contribute to enhanced carbon emission efficiency. Despite the steady improvement in China's average level of industrial intelligence over the years, reaching 0.541 in 2019 and placing it within the second threshold interval, there remains a considerable gap from the value of the second inflection point. Therefore, significant room for improvement still exists to break the carbon curse of natural resources.

Table 7
Tests for the existence of threshold effects.

	Single threshold test	Double threshold test	Three-threshold test
F-value	86.030	49.000	30.660
Bootstrap P-Value	0.000	0.030	0.503
10%, 5%, 1% key values	42.064, 47.630, 58.126	38.940, 45.471, 54.349	84.857, 98.074, 114.697

4.5. Results discussion

Based on the findings presented in the initial section of this study, *NRD* exacerbates *CEI*, thus providing support for the carbon curse hypothesis (Chiroleu-Assouline et al., 2020). In essence, reliance on natural resources leads to decreased efficiency in carbon emissions (Wang et al., 2019). Further investigation reveals that cities reliant on resource-based industries are more inclined to adopt a carbon-intensive trajectory compared to non-resource-based cities. This finding aligns with the perspective proposed by Che and Wang (2022), asserting that resource-dependent cities tend to facilitate local economic development by leveraging abundant fossil energy and mineral resources, which in turn drives the growth of energy-intensive and environmentally detrimental industries. Furthermore, our analysis considers the stage of policy development and regional variations. Notably, during the 13th *Five-Year Plan* period, the carbon curse phenomenon was relatively inconspicuous, indicating a shift in China's economic growth model from crude to more efficient and intensive practices. Conversely, this phenomenon is highly pronounced in the western region, reflecting that the western region is prone to form a relatively homogeneous industrial structure, with low innovation level, and thus the efficiency of natural resources utilization is relatively low.

Another crucial topic of discussion centers around mitigating the carbon curse of natural resources. It is widely recognized that the COVID-19 pandemic has reshaped global trends in natural resource consumption and altered consumption patterns (Zhao and Rasoulinezhad, 2023). As the global economy gradually recovers and embargoes are lifted, carbon dioxide intensity stemming from natural resource consumption may once again escalate (Sun et al., 2021). Consequently, effectively breaking the carbon curse of natural resources becomes a pivotal issue for carbon control. Che and Wang (2022) have suggested that environmental regulations can effectively mitigate the rise in carbon intensity attributable to *NRD*. Furthermore, alongside institutional factors, market dynamics play a critical role in effectively alleviating the carbon curse associated with natural resources. As industrial intelligence continues to advance, it holds the potential to alleviate, and even eliminate, the carbon curse by enhancing energy utilization efficiency and optimizing resource allocation efficiency. Thus, harnessing the empowering capabilities of industrial intelligence in the post-pandemic era is of paramount importance in breaking the carbon curse linked to natural resources, significantly contributing to the pursuit of carbon neutrality.

5. Conclusions and prospects

5.1. Conclusion

Using a sample of 282 cities in China from 2006 to 2019, this paper examines whether the carbon curse of natural resources exists in China and explores whether industrial intelligence can break the carbon curse

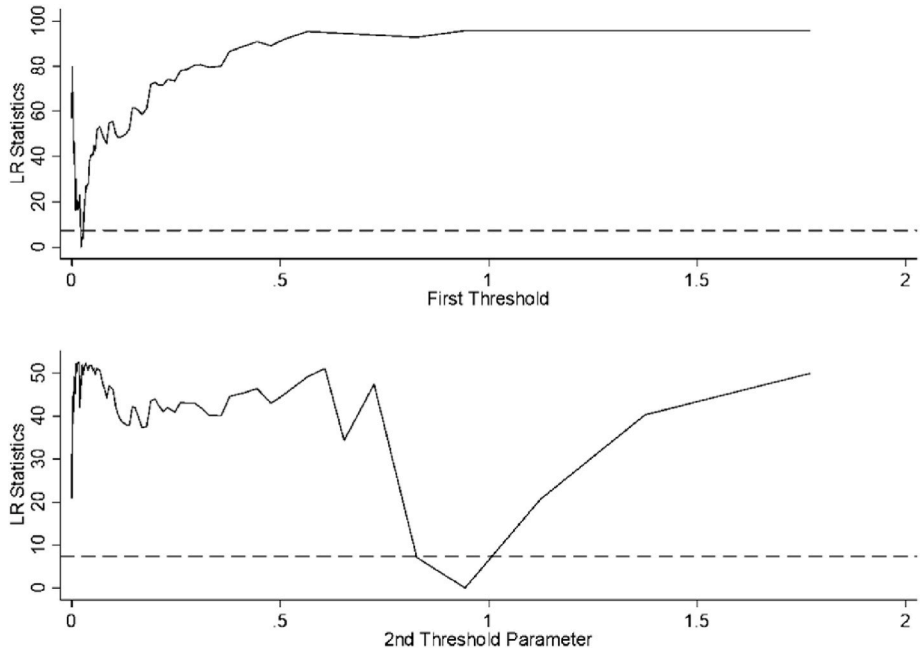


Fig. 4. Likelihood ratio function graph.

Table 8
Threshold estimation results.

Double threshold value	Lower limit of the interval	Upper limit of the interval
0.022	0.020	0.024
0.944	0.776	1.125

Table 9
Estimated results of threshold effects.

Explanatory variables	Coefficient	Standard error	P-value
lninfr	−0.030	0.016	0.066
fina	−0.079	0.059	0.182
lnpopu	−1.058	0.278	0.000
npgr	0.003	0.001	0.048
open	−0.317	0.611	0.604
$INTE \leq 0.022$	2.286	0.605	0.000
$0.022 < INTE \leq 0.944$	1.513	0.558	0.007
$INTE > 0.944$	−3.949	1.211	0.001
Constant	8.253	1.863	0.000
Observations	3705		
R^2	0.192		

of natural resources from the perspective of market factors. The findings are as follows: firstly, natural resource dependence can significantly exacerbate carbon emissions intensity. The conclusion still holds after a series of robustness tests by changing the way the explanatory variables are measured, controlling for joint province and time-fixed effects, adding control variables, and shortening the sample time span. Secondly, the carbon curse phenomenon is mainly concentrated in resource-based cities but not in non-resource-based cities; it is more obvious in the 11th and 12th Five-Year Plan periods, but not in the 13th *Five-Year Plan period*; it is more obvious in the east, central, and west but not in the northwest. Thirdly, significant variations in the carbon curse of natural resources are observed across different stages of industrial intelligence development. When the level of industrial intelligence is below 0.022, it exacerbates the carbon curse. Conversely, within the range of 0.022–0.944, industrial intelligence helps alleviate the carbon curse. When the level of industrial intelligence surpasses 0.944, it has the potential to completely break the carbon curse of natural resources.

5.2. Policy recommendations

In response to the above findings, this study makes the following policy recommendations: (1) Facilitate the advancement and adoption of new energy sources while gradually reducing reliance on conventional energy. Considering the potential rise in CO_2 intensity following the post-epidemic period, it is crucial to guide the expansion of clean and renewable energies such as wind power, photovoltaic, and hydropower. This approach will foster a shift towards cleaner and lower-carbon energy consumption, gradually transforming the existing energy consumption structure dependent on coal, oil, and other high-carbon sources. (2) Strengthen research on the fundamental principles of artificial intelligence and foster the development of industrial intelligence. It is essential to enhance the exploration and development of key artificial intelligence technologies and promote their integration into enterprise production processes. Support the transformation of traditional industries to intelligence and encourage the transformation of enterprise production methods to digitalization, refinement, and flexibility. (3) Promote differentiated environmental policy mechanisms. Taking into account the influence of resource endowment factors, urban resource endowment, and regional characteristics on the heterogeneity of the carbon curse phenomenon, it is recommended to formulate tailored regional development strategies and environmental governance policies.

5.3. Shortcomings and prospects

Although this paper explores how industrial intelligence helps alleviate the carbon curse of natural resources from the perspective of market factors based on the verification of the existence of the carbon curse of natural resources in China, there are still some shortcomings. These shortcomings can be summarized as follows: Firstly, the empirical testing section employs a single indicator to measure natural resource dependence, which imposes certain constraints on the analysis. To overcome this limitation, future research can explore the construction of a comprehensive index system to measure natural resource dependence and examine the impact of natural resource dependence on carbon emission intensity from different dimensions. Secondly, natural resources encompass diverse types such as mineral resources, fossil

energy, and forest resources, among others. Although this paper examines the differences in the carbon curse based on urban resource endowments, it fails to differentiate between various types of natural resources. Future studies should aim to conduct separate investigations for each natural resource type, enabling a more nuanced exploration of the disparities among different resource categories. By addressing these limitations in future research, a more comprehensive and nuanced understanding of the interplay between natural resource dependence, industrial intelligence, and carbon emissions can be achieved.

CRediT authorship contribution statement

Yuqiao Hou: Conceptualization, Writing - review & editing. **Rong Wang:** Writing - original draft; Methodology. **Fengfu Mao:** Writing - review & editing, Formal analysis. **Zongshun Wang:** Project administration, Supervision, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Acemoglu, D., Restrepo, P., 2020. Robots and Jobs: Evidence from US Labor Markets. J. Polit. Econ. 128 (6), 2188–2244.

Aljarallah, R.A., 2020. Natural resource dependency, institutional quality and human capital development in Gulf Countries. Heliyon 6 (7), e04290.

Auty, R.M., 2007. Natural resources, capital accumulation and the resource curse. Ecol. Econ. 61 (4), 627–634.

Balsalobre-Lorente, D., Shahbaz, M., Roubaud, D., Farhani, S., 2018. How economic growth, renewable electricity and natural resources contribute to CO_2 emissions? Energy Pol. 113, 356–367.

Brossog, M., Bornschlegl, M., Franke, J., 2015. Reducing the energy consumption of industrial robots in manufacturing systems. Int. J. Adv. Manuf. Technol. 78 (5), 1315–1328.

Che, S., Wang, J., 2022. Can environmental regulation solve the carbon curse of natural resource dependence: evidence from China. Resour. Policy 79, 103100.

Chen, F., Liu, S.T., 2022. Can artificial intelligence technology become a new engine of urban green development. Journal of Nanjing University of Finance and Economics 235 (3), 78–86.

Chen, Y.Y., Zhang, J., Zhou, Y.H., 2022. Industrial robots and spatial allocation of labor. Econ. Res. J. 57 (1), 172–188.

Chiroleu-Assouline, M., Fodha, M., Kirat, Y., 2020. Carbon curse in developed countries. Energy Econ. 90, 104829.

Destek, M.A., Aydın, S., Destek, G., 2022. Investigating an optimal resource dependency to prevent natural resource curse: evidence from countries with the curse risk. Resour. Policy 79, 102981.

Dong, X.S., Wei, Y.Y., Xiao, X., 2022. How does fiscal decentralization affect green innovation? China Popul. Resour. Environ., 3286274

Feng, X.Z., Cai, B.F., Wang, M., Wang, J.N., Cao, L.B., 2017. A comparative study on CO_2 emission of resource-based cities in China. China population, resources and environment 27 (2), 5–9.

Friedrichs, J., Inderwildi, O.R., 2013. The carbon curse: are fuel rich countries doomed to high CO_2 intensities? Energy Pol. 62, 1356–1365.

Gan, J., Liu, L., Qiao, G., et al., 2023. The role of robot adoption in green innovation: evidence from China. Econ. Modell. 119, 106128.

Henderson, P., Hu, J., Romoff, J., et al., 2020. Towards the systematic reporting of the energy and carbon footprints of machine learning. J. Mach. Learn. Res. 21 (1), 10039–10081.

Huang, J.W., Li, Y.H., 2017. Green innovation and performance: the view of organizational capability and social reciprocity. J. Bus. Ethics 145 (2), 309–324.

Jiang, S.L., Lu, C.B., 2023. Study on multiple paths and threshold model of environmental regulation on carbon efficiency[J]. Journal of Technology Economics 42 (1), 117–129.

Li, H.H., Huang, Y.S., 2023. Can digital development contribute to the achievement of carbon neutrality?—an empirical analysis based on urban panel data. Journal of Xiangtan University(Philosophy and Social Sciences) 47 (1), 30–36.

Li, J., Dong, K., Wang, K., Dong, X.C., 2023. How does natural resource dependence influence carbon emissions? The role of environmental regulation. Resour. Policy 80, 103268.

Li, Y., Zhang, Y., Pan, A., Han, M.C., Veglianti, E., 2022. Carbon emission reduction effects of industrial robot applications: heterogeneity characteristics and influencing mechanisms. Technol. Soc. 70, 102034.

Liu, L.S., Saeed, M., Gioia, A., Iskandar, M., Rosario, H.-S., Zhai, S.M., 2023. Natural resources, green innovation, fintech, and sustainability: a fresh insight from BRICS. Resour. Policy 80, 103119.

Liu, Y.B., Lu, F., Xian, C.F., Ouyang, Z.Y., 2023. Urban development and resource endowments shape natural resource utilization efficiency in Chinese cities. J. Environ. Sci. 126, 806–816.

Meng, W.S., Zhang, Y., 2020. Natural resource endowment, path selection of technological progress, and green economic growth: an empirical research based on China's provincial panel data. Resour. Sci. 42 (12), 2314–2327.

Pan, M.J., Zhao, X., lv, K.J., Joanna, R.-S., et al., 2023. Internet development and carbon emission-reduction in the era of digitalization: where will resource-based cities go? Resour. Policy 81, 103345.

Pei, Y., Zhu, Y., Liu, S., et al., 2019. Environmental regulation and carbon emission: the mediation effect of technical efficiency. J. Clean. Prod. 236, 117599.

Preuveneers, D., Ilie-Zudor, E., 2017. The intelligent industry of the future: a survey on emerging trends, research challenges and opportunities in Industry 4.0. J. Ambient Intell. Smart Environ. 9 (3), 287–298.

Qian, Y., Liu, J., Shi, L., Forrest, J.Y.L., Yang, Z., 2022. Can artificial intelligence improve green economic growth? Evidence from China. Environ. Sci. Pollut. Res. 1–20.

Shaheen, F., Lodhi, M.S., Rosak-Szyrocka, J., et al., 2022. Cleaner technology and natural resource management: an environmental sustainability perspective from China. Cleanroom Technol. 4 (3), 584–606.

Shan, Y., Guan, Y., Hang, Y., Zheng, H., Li, Y.X., Guan, D.B., Li, J.S., Zhou, Y., Li, L., Hubacek, K., 2022. City-level emission peak and drivers in China. Sci. Bull. 67 (18), 1910–1920.

Strubell, E., Ganesh, A., McCallum, A., 2019. Energy and Policy Considerations for Deep Learning in NLP arXiv preprint arXiv 1906.02243.

Sun, H., Edziah, B.K., Kporsu, A.K., Sarkodie, S.A., Taghizadeh-Hesary, F., 2021. Energy efficiency: the role of technological innovation and knowledge spillover. Technol. Forecast. Soc. Change 167, 120659.

Tang, X.H., Chi, Z.M., 2022. An empirical study on industrial intelligence to improve the efficiency of industrial green development. Economist (2), 43–52.

Wang, J.L., Wang, W.L., Liu, Y., Wu, H.T., 2023. Can industrial robots reduce carbon emissions? Based on the perspective of energy rebound effect and labor factor flow in China. Technol. Soc. 72, 102208.

Wang, K., Wu, M., Sun, Y., Shi, X.P., Sun, A., Zhang, P., 2019. Resource abundance, industrial structure, and regional carbon emissions efficiency in China. Resour. Policy 60, 203–214.

Wang, R., Tan, J., Yao, S., 2021. Are natural resources a blessing or a curse for economic development? The importance of energy innovations. Resour. Policy 72, 102042.

Wu, C.X., 2021. Research on the synergistic effect of low-carbon economy in China. Journal of Management World 37 (8), 105–117.

Wu, J.X., Guo, Z.Y., 2016. Research on the convergence of carbon dioxide emissions in China: a continuous dynamic distribution approach. Statistical Research 33 (1), 54–60.

Wu, S., Li, L., Li, S., 2018. Natural resource abundance, natural resource-oriented industry dependence, and economic growth: evidence from the provincial level in China. Resour. Conserv. Recycl. 139, 163–171.

Xie, X., Li, K., Liu, Z.Q., Ai, H.S., 2021. Curse or blessing: how does natural resource dependence affect city-level economic development in China? Aust. J. Agric. Resour. Econ. 65 (2), 413–448.

Xie, Y.C., Hou, Z.M., Liu, H.J., Cao, C., Qi, J.G., 2021. The sustainability assessment of CO_2 capture, utilization and storage (CCUS) and the conversion of cropland to forestland program (CCFP) in the Water–Energy–Food (WEF) framework towards China's carbon neutrality by 2060. Environ. Earth Sci. 80 (14), 1–17.

Xue, F., Liu, J.Q., Fu, Y.M., 2022. The effect of artificial intelligence technology on carbon emissions. Sci. Technol. Prog. Policy 39 (24), 1–9.

Xue, L., Zhang, H.Y., 2017. Impact and challenge of the fourth industrial revolution to the construction of China's environmental governance system. China Population, Resources and Environment 27 (9), 1–5.

Yang, G.L., Zha, D.L., Wang, X.J., Chen, Q., 2020. Exploring the nonlinear association between environmental regulation and carbon intensity in China: the mediating effect of green technology. Ecol. Indicat. 114, 106309.

Yang, L., Wang, K.L., Geng, J.C., 2018. China's regional ecological energy efficiency and energy saving and pollution abatement potentials: an empirical analysis using epsilon-based measure model. J. Clean. Prod. 194, 300–308.

Yu, L.Z., Wang, Y., Wei, X.H., Zheng, C.Y., 2023. Towards low-carbon development: the role of industrial robots in decarbonization in Chinese cities. J. Environ. Manag. 330, 117216.

Zahoor, Z., Latif, M.I., Khan, I., Hou, F.J., 2022. Abundance of natural resources and environmental sustainability: the roles of manufacturing value-added, urbanization, and permanent cropland. Environ. Sci. Pollut. Res. 29 (54), 82365–82378.

Zhao, L.H., Rasoulinezhad, E., 2023. Role of natural resources utilization efficiency in achieving green economic recovery: evidence from BRICS countries. Resour. Policy 80, 103164.