THE IMPACT OF INDUSTRIAL INTELLIGENCE ON URBAN ECOLOGICAL RESILIENCE IN CHINA: EVIDENCE FROM THE PERSPECTIVE OF ENERGY CONSUMPTION INTENSITY AND ENERGY UTILIZATION EFFICIENCY

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Abstract. Industrial Intelligence (ININ), as a new engine driving high-quality urban development, holds great potential for enhancing urban ecological resilience through optimizing energy systems. This study explores how ININ impacts Resource-Based Cities Ecological Resilience (RBCER) in China by examining energy consumption intensity and energy utilization efficiency as key mechanisms. The results indicate that ININ significantly enhances RBCER, a robust conclusion across various sensitivity tests. The mechanism analysis reveals that ININ strengthens RBCER by reducing energy consumption intensity and improving energy utilization efficiency as distinct pathways. The spatial effect analysis demonstrates that ININ's impact on RBCER exhibits significant regional spillovers across China. The heterogeneity analysis shows that ININ's enhancement effect on ecological resilience appears more pronounced in eastern and western cities and in mature and regenerative Chinese RBCs. This study enriches the theoretical understanding of how ININ enhances urban ecological resilience through energy-related pathways while providing practical implications for Chinese RBCs pursuing sustainable development through industrial transformation.

Keywords: *environmental sustainability, resource efficiency, technological innovation, urban metabolism, green development*

Introduction

At the critical stage of China's transition to high-quality development, resource-based cities (RBCs), as strategic bases for national energy resources, face unique transformation challenges (He et al., 2017). As important pillars in China's industrialization process, these cities promote regional economic development while simultaneously bearing multiple pressures such as resource depletion, environmental pollution, and economic structural homogeneity. With the deepening advancement of green and low-carbon development concepts, RBCs are often constrained by the "carbon curse" arising from resource dependence, making enhancement of their ecological resilience particularly difficult. Against this background, how to resolve the development dilemmas of RBCs and strengthen their ecological resilience has become an important issue of common concern to academia and policy makers.

Urban ecological resilience, defined as the capacity of urban systems to coordinate, resist, and recover from external ecological risks, has become an important indicator for measuring sustainable urban development (Holling, 1973; Adger, 2000). Holling (1973) first introduced the concept of resilience into social-ecological system research, defining it as the ability of a system to maintain core functions while withstanding external disturbances. With the advancement of ecological civilization construction, theoretical and practical research on urban ecological resilience has continuously deepened, evolving from early qualitative studies focusing on development mechanisms, pathways, and influencing factors (Meerow, 2016; Wang et al., 2018) to the

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construction of comprehensive measurement methods and evaluation systems (Liu et al., 2020). For resource-based cities, their ecological resilience not only relates to their own sustainable transformation but also directly affects national ecological security and regional coordinated development (Wang et al., 2024), bearing strategic significance.

In the context of a new round of technological revolution and industrial transformation, industrial technological revolution represented by artificial intelligence, big data, and industrial internet is rapidly emerging globally, with major countries around the world promoting technological change and industrial upgrading through industrial intelligence. In late 2012, General Electric in the United States first proposed the concept of "Industrial Internet," and in 2013, Germany officially launched the "Industry 4.0" strategy, aiming to achieve intelligent transformation of industrial and overall national economic systems through the construction of "smart factories," widely regarded as the "Fourth Industrial Revolution" in human history. Industrial Intelligence (ININ), as the core driving force of this revolution, is fundamentally reshaping global industrial patterns and production modes through the integration of deep learning algorithms, big data analysis, and cloud computing technologies.

To seize this historic opportunity, China has successively issued policy documents such as "Made in China 2025," "Intelligent Manufacturing Development Plan (2016-2020)," and "The 14th Five-Year Plan for Intelligent Manufacturing Development." The report of the 20th National Congress of the Communist Party of China also clearly proposed to promote high-end, intelligent, and green development of manufacturing, making a major strategic deployment to advance new industrialization. Under the guidance of these policies, intelligent technologies represented by industrial robots have been widely applied in China, with market scale continuously expanding. According to data from the International Federation of Robotics (IFR), as of 2023, China's industrial robot shipments accounted for 44% of the global total, establishing a leading position worldwide. ININ has become an important driving force in reshaping the development model and resilience mechanisms of resource-based cities, showing enormous potential in their transformation and upgrading.

Since the Industrial Revolution, the birth and application of new technologies have had profound impacts on ecological systems. Abundant empirical research indicates that there exists a complex interaction between ININ and urban ecological environments. On one hand, ININ reduces environmental degradation (BalSalobre-Lorente et al., 2018), improves energy efficiency (Lantz and Feng, 2006), and promotes sustainable manufacturing practices (Bag et al., 2022) by optimizing production processes and enhancing resource allocation efficiency. Empirical research by Forslid et al. (2018) confirms that artificial intelligence applications significantly improve industrial standardization levels, reduce resource intensity per unit output, and enhance local environmental quality. On the other hand, ININ may trigger rebound effects in certain scenarios, leading to increased total energy consumption (Grant et al., 2016). With technological advancement, the ecological impact of ININ has expanded from basic automation to complex intelligent system collaborative optimization (Tang et al., 2019; Zhou et al., 2022), gradually penetrating urban infrastructure, energy management, and environmental monitoring systems (Franco et al., 2021), while also introducing new cybersecurity risks that require careful consideration (Tharewal et al., 2022). Moreover, scholars have found that ININ can reduce energy consumption intensity, optimize resource allocation, minimize supply-demand mismatches (Chui, 2018; Yu et al., 2022), and simultaneously enhance energy utilization efficiency through technological

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progress and process optimization (Du and Lin, 2022; Yin and Zeng, 2023). These studies indicate that the impact mechanisms of ININ on ecological systems are complex and multifaceted, requiring careful analysis in the context of specific city types and development stages. Therefore, systematically exploring the interactive relationship between ININ and Resource-Based Cities Ecological Resilience (RBCER) has important theoretical and practical significance for understanding urban economic development patterns and enhancing urban risk resistance capacity.

Based on the above analysis, this study focuses on the impact of ININ on RBCER, raising three core questions: How does ININ affect RBCER? Through what mechanisms does ININ influence RBCER? Are there heterogeneous characteristics in this impact across different types of resource-based cities? In response to these questions, we propose the following hypotheses: Hypothesis 1: ININ has a positive impact on RBCER. ININ helps enhance cities' capacity to respond to ecological pressures by improving production efficiency, optimizing resource utilization, and reducing pollution emissions. In resource-based cities, ININ may alleviate the structural contradictions between traditional resource development and ecological protection, promote industrial transformation, upgrading, and diversification, thereby enhancing urban ecological resilience. Hypothesis 2: ININ enhances RBCER through the dual mechanisms of reducing energy consumption intensity and improving energy utilization efficiency. On one hand, ININ reduces energy consumption per unit output through optimizing production processes, precise control, and reducing resource waste; on the other hand, it improves energy conversion efficiency and the proportion of clean energy utilization through technological innovation and optimization of production factors. These two mechanisms work synergistically to significantly reduce ecological environmental pressure on resource-based cities and enhance their ability to withstand external ecological shocks. This study explores the influence mechanisms of ININ on RBCER, not only expanding relevant theoretical research but also providing empirical support and policy references for the green transformation of resource-based cities. The research results are expected to help resource-based cities achieve high-quality development under dual carbon goals and promote positive interactions between economic society and the natural environment.

Materials and methods

Models

First, to empirically test the effect of ININ on RBCER, the panel data model is constructed in this paper:

$$RBCER_{it} = \alpha_0 + \beta_1 ININ_{it} + \sum_{n=1}^{4} \theta_n Z_{nit} + \mu_n + v_t + \varepsilon_{it} \quad \text{(Eq.1)}$$

In this formulation, the indices i and t denote different resource-based cities and the respective years. $RBCER_{it}$ measures the ecological resilience of city i, while $ININ_{it}$ quantifies the level of ININ in city i. μ_n、v_t represent regional and temporal fixed effects, respectively. Z_{nit} encompasses a collection of control variables. The term ε_{it} is the stochastic error component, and α、β are the coefficients estimated for the variables involved.

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Second, this study utilizes a mediation effect model to delve deeper into how ININ affects RBCER (Chen and Lee, 2020). It examines the role of Energy consumption intensity (ECI) and Energy Utilization Efficiency (EUE) as mediators in the relationship between ININ and RBCER:

$$M_{it} = \alpha_0 + \beta_1 ININ_{it} + \sum_{n=1}^{4} \theta_n Z_{nit} + \mu_n + v_t + \varepsilon_{it} \tag{Eq.2}$$

where M_{it} denotes mediators ECI and EUE. β_1 reflects the impact of ININ on M. A significant coefficient indicates that the transformation to ININ influences RBCER through the mediating variables ECI and EUE. The rest is the same as in *Equation 1*.

Third, acknowledging that regional interactions are interconnected and influenced by proximate areas through interaction effects, this study expands on *Equation 1* by employing a spatial econometric model to examine the spatial spillover effects of ININ. The model configuration is detailed below:

$$RBCER_{it} = \alpha_0 + \beta_0 RBCER_{it-1} + \rho_1 \sum_{i=1}^{N} WRBCER_{it} + \rho_2 \sum_{i=1}^{N} WRBCER_{it-1} + \beta_1 ININ_{it} + \rho_3 \sum_{i=1}^{N} WININ_{it} + \sum_{n=1}^{4} \theta_n Z_{nit} + \tau \sum_{i=1}^{N} WZ_{nit} + \mu_n + v_t + \varepsilon_{it} \tag{Eq.3}$$

In the specified model, the terms ρ_1, ρ_2, ρ_3, and τ are the spatial lag effects of the respective variables. This study utilizes multiple spatial weighting matrices to conduct Moran's I index calculations and derive regression outcomes for the spatial panel model, ensuring these matrices are normalized before use. All other details follow as per *Equation 1*.

Variable selection

Explained variable

Adhering to the principles of data availability, comprehensiveness, and comparability and incorporating the essence of urban ecological resilience, this study references findings from earlier research (Meerow, 2016; Martin, 2012; Wu et al., 2020) to develop an RBCER evaluation framework based on resistance, adaptation, and recovery capabilities. This framework encompasses indicators that assess a city's ecological resistance (reflecting vulnerability and sensitivity to shocks), ecological adaptation (indicative of how a city adjusts to disturbances), and ecological recovery (measuring the speed and degree of recovery after disruptions). Due to varying indicator units, this paper standardizes each metric and calculates the ecological resilience levels of cities using the entropy-weighted Topsis method. The indicator system for the level of RBCER is detailed in *Table 1*.

Core explanatory variable

The measurement approaches for ININ levels primarily fall into two categories: first, utilizing single indicators such as robot density, robot penetration, or the number of AI patent applications or grants (Dekle, 2020; Graetz and Michaels, 2018); second, constructing indicator systems and employing comprehensive evaluation methods (Xie et al., 2021; Luo et al., 2024). We adopt the first approach as it avoids data availability issues and mitigates endogeneity problems (Liu et al., 2020). As key carriers of ININ, industrial robots function as critical data producers and key executors of intelligent

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decisions, establishing a bridge between data and physical production. Their quantity can significantly reflect the development status of regional ININ (Dekle, 2020), and their prevalence and application level have become significant indicators of ININ advancement (Li et al., 2022). It is worth noting that while basic industrial robots primarily execute pre-programmed tasks and lack decision-making capabilities, with the development of Industry 4.0, an increasing number of industrial robots are being integrated with AI technologies, thereby acquiring varying degrees of intelligent decision-making abilities.

Table 1. *Indicator system for the level of resource-based cities ecological resilience (RBCER)*

Target level	System level	Indicator level	Indicator properties	Weight
UER	Ecological resistance	Industrial wastewater discharge (tons)	-	0.019
		Industrial SO_2 emissions (tons)	-	0.017
		Industrial fume emissions (tons)	-	0.005
		Ratio of fiscal environmental protection expenditure (%)	+	0.170
	Ecological adaptation	Ratio of value added in the secondary sector to value added in the tertiary sector (%)	-	0.006
		Non-hazardous treatment of domestic waste (%)	+	0.025
		Centralized sewage treatment plant rate (%)	+	0.032
		Urban economic density (%)	+	0.445
	Ecological recovery	Greening coverage of built-up areas (%)	+	0.016
		Parkland per capita (hectares)	+	0.085
		Green space ratio in built-up areas (%)	+	0.021
		Depth of green equity development (%)	+	0.157

Following Acemoglu and Restrepo (2020), we measure ININ by matching the IFR database with national economic industry classifications, then calculate city-level robot penetration rates using the formula:

$$ININ_{it} = \sum_{j=1}^{j} \frac{Emp_{ijt}}{Emp_{it}} \cdot \frac{Rob_{jt}}{Emp_{jt}} \quad \text{(Eq.4)}$$

where $ININ_{it}$ represents the robot installation density in city *i* during year *t*; Rob_{jt} denotes robots installed in industry *j*; Emp_{jt} indicates employment in industry *j*; Emp_{it} represents total employment in city *i*; and Emp_{ijt} measures employment in industry *j* within city *i*.

Mediating variable

This study employs Energy Consumption Intensity (ECI) and Energy Utilization Efficiency (EUE) as mechanism variables to examine the relationship between ININ and urban ecological resilience. For ECI measurement, because of the unavailability of

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city-level energy consumption data in China, following Yue et al. (2020) and Zhang et al. (2023), we first obtain provincial energy consumption data from the China Energy Statistical Yearbook and convert all energy types to standard coal equivalent units. We then use nighttime luminosity data to allocate provincial energy consumption to cities based on the established correlation between nighttime light intensity and energy consumption (Kiran Chand et al., 2009). The nighttime light intensity is an effective proxy as brighter nighttime illumination typically indicates higher economic development and, correspondingly, greater energy consumption. We further incorporate city-level natural gas consumption directly from the "China Urban Construction Statistical Yearbook" and electricity consumption from the "China City Statistical Yearbook", municipal statistical yearbooks, and official bulletins to ensure consistent and reliable measurements across all resource-based cities in our sample. We use the logarithm of this integrated energy consumption intensity measurement in our empirical analysis to normalize the distribution and mitigate potential heteroscedasticity.

For EUE measurement, we adopt the analytical framework of Zhang and Chen (2022), and Meng and Qu (2022), constructing a comprehensive efficiency evaluation system incorporating multiple inputs and outputs. The system encompasses three primary input factors—labor, capital, and energy—while considering both desirable and undesirable outputs (regional GDP) (industrial pollutants including sulfur dioxide, smoke and dust, and effluent emissions). The efficiency measurement employs Tone's (2001) super-efficiency (Slack-Based Measure) SBM model with undesirable outputs, utilizing the SBM-Malmquist-Luenberger index methodology to quantify energy utilization efficiency across prefecture-level cities. This sophisticated approach enables a nuanced energy efficiency assessment while accounting for economic productivity and environmental externalities.

Control variables

To avoid omitted variables, this paper refers to Bristow and Healy (2018), and Wang (2024) select the level of infrastructure, the degree of financial development, the level of urbanization, the level of government intervention, and the population density as the control variables. Among them, infrastructure level (IL), expressed as per capita paved road area; financial development level (FL), expressed as the ratio of bank deposit and loan balances to regional GDP to characterize the level of financial development in the city; urbanization level (UL), measured as the proportion of the resident urban population to the total resident population; government intervention level (GL), expressed as the proportion of the local finance general budget expenditure to regional GDP Population Density (PD), measured by the ratio of the total population to the administrative area at the end of the year in each city. The statistical attributes of these primary variables are detailed in *Table 2*.

Data source

This study utilizes annual data from 2011 to 2020 for 111 RBCs in China, guided by the classifications and definitions provided in the "National Plan for the Sustainable Development of Resource-Based Cities (2013-2020)" published by the State Council's Development and Reform Commission in December 2013. This selection was made with considerations for data continuity and accessibility. The data sources include the

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"China City Statistical Yearbook", "China Regional Statistics Yearbook", "China Urban Construction Statistical Yearbook", and annual reports from the city governments.

Table 2. *Descriptive statistics*

Variables	Obs.	Mean	Std. Dev	Min	Max
RBCER	1110	0.116	0.014	0.04	0.182
ININ	1110	2.233	1.878	0.098	11.289
ECI	1110	-0.263	0.479	-1.643	1.188
EUE	1110	0.299	0.113	0.133	1.177
FL	1110	17.041	7.888	1.37	60.07
IL	1110	16.941	0.703	15.079	19.015
UL	1110	53.81	13.822	21.399	99.728
GL	1110	0.225	0.107	0.044	0.741
PD	1110	5.377	0.973	0.683	6.983

Data processing and statistical analysis

All data processing and econometric analyses in this study were performed using Stata 18.0. Spatial visualization, including maps illustrating the spatial distribution of RBCER, was conducted using ArcGIS 10.8. The statistical methods applied in this study include panel fixed-effects regression analysis, instrumental variable (IV) method, mediating effect analysis, and spatial econometric models (specifically Spatial Autoregressive Models).

Empirical research and discussion

Spatiotemporal change of RBCER

Temporal variation of RBCER

The "National Plan for the Sustainable Development of Resource-Based Cities (2013-2020)" analysis stratifies RBCs into growth, mature, recessive, and regenerative stages based on their developmental phases. During the decade from 2011 to 2020, disparities in carbon emission efficiency were observed among cities at these different stages. Specifically, the average RBCER values for cities in the growth, mature, recessive, and re-generative stages were 0.112, 0.115, 0.118, and 0.119, respectively, which demonstrates a ranking sequence where recession cities exhibit higher efficiency than regenerative cities, followed by mature and, finally, growth cities. Moreover, their distribution is visually represented in *Figure 1*.

Spatial variation of RBCER

In this study, ArcGIS 10.8 software is employed to categorize the ecological resilience levels across a sample of 111 resource-based cities, illustrating the disparities. A visual map is then used to depict the spatial variation of RBCER, as demonstrated in *Figure 2*.

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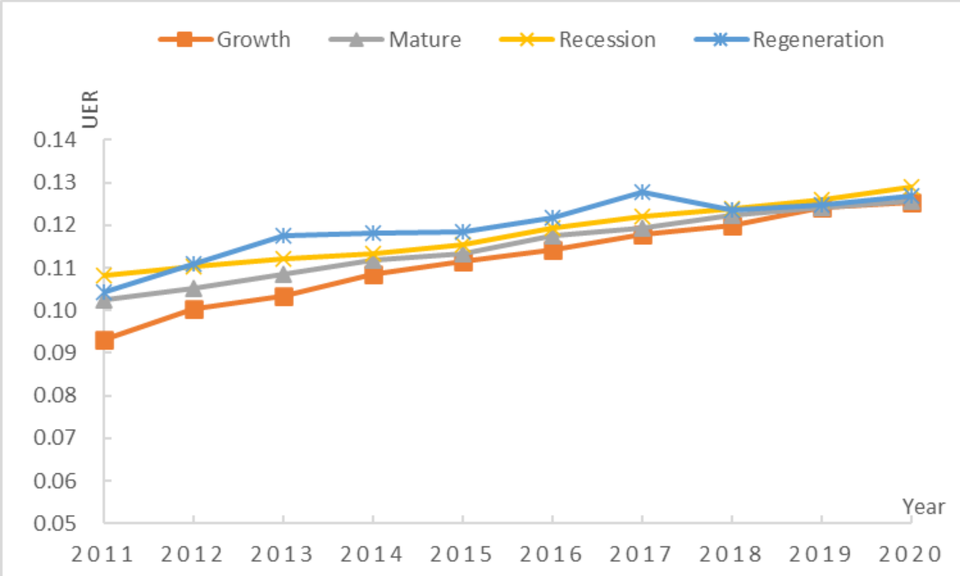

Figure 1. *Temporal variation of resource-based cities ecological resilience (RBCER)*

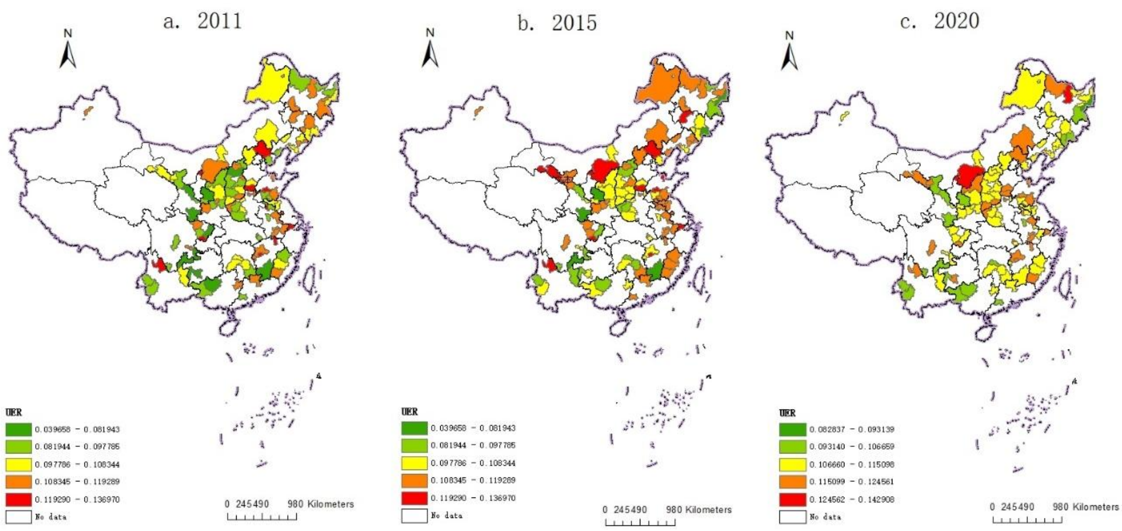

Figure 2. *Spatial variation of resource-based cities ecological resilience (RBCER)*

Utilizing the natural breakpoint classification method, this study organizes 111 resource-based cities into five distinct tiers. The maps clearly illustrate notable variations in the spatial distribution of RBCER across the study area, including evident spatial dependencies and local clustering effects. *Figure 2a* shows that in 2011, the top 20 cities in RBCER rankings were distributed among eastern, central, and western regions, with counts of 7, 8, and 5 cities, respectively. Notably, 45% of these cities were primarily located in the provinces of Shandong, Jiangxi, and Anhui. In *Figure 2b,* data from 2015 indicate an increase in the average RBCER compared to 2011, though significant disparities persisted within the region. That year, cities in the top 20 rankings for urban economic resilience were distributed 30%, 45%, and 25% across eastern, central, and western regions, respectively, with 75% clustered in Hebei

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and Shandong provinces, showcasing significant regional agglomeration. *Figure 2c* from 2020 shows that among the top 20 RBCER cities, the distribution was 5, 10, and 5 across the eastern, central, and western regions, respectively, with half of these cities concentrated in Shanxi Province, highlighting pronounced geographical clustering.

The influence of ININ on RBCER

The basic regression results

Initially, a Hausman test is performed, with results supporting using a fixed effect model for assessment. The decisive rejection of the null hypothesis by the Hausman test within the basic Model necessitates the employment of a fixed effect model for the regression analysis. All data are log-transformed to minimize multicollinearity. The primary regression findings for ININ's impact on RBCER, presented in *Table 3,* show Model (1) employing time and regional fixed effects, while Model (2) incorporates control variables into Model (1) to further explore ININ's influence on RBCER. The results reveal that the coefficients for ININ are consistently positive at a 1% significance level, suggesting a significant positive link between ININ and RBCER. This relationship can be attributed to the transformative effects of artificial intelligence in industrial processes, which enhance the RBCER. Additionally, efficiency gains from ININ reforms boost ecological adaptability, with subsequent improvements in industrial quality further enhancing urban ecological recovery capacities. Thus, ININ facilitates a dual-benefit scenario, simultaneously securing economic and environmental advantages (Li et al., 2022). Therefore, the theoretical prediction proposed in Hypotheses 1 was preliminarily verified.

Table 3. *Basic regression results*

	(1)	(2)	(3)	(4)	(5)	(6)
	RBCER	**RBCER**	**RBCER**	**RBCER**	**RBCER**	**RBCER**
ININ	0.025*** (0.008)	0.028*** (0.007)	0.024*** (0.007)	0.027*** (0.007)	0.027*** (0.007)	0.027*** (0.007)
IL		0.082*** (0.010)	0.081*** (0.010)	0.079*** (0.010)	0.079*** (0.010)	0.079*** (0.010)
FL			0.054*** (0.017)	0.042** (0.017)	0.043** (0.017)	0.042** (0.017)
UL				0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)
GL					0.034 (0.053)	0.033 (0.053)
PD						0.002 (0.012)
_cons	-39.331*** (3.697)	-30.529*** (3.745)	-21.748*** (4.675)	-14.003*** (4.822)	-13.247*** (4.971)	-13.412*** (5.072)
N	1110	1110	1110	1110	1110	1110
R^2	0.746	0.762	0.764	0.771	0.771	0.771

() Within is the standard error. *p < 0.1, **p < 0.05, ***p < 0.01

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IV estimation

To address potential issues of reverse causality and omitted variables between ININ and RBCER, this research employs appropriately designed instrumental variables to reduce endogeneity. Initially, the study adopts the U.S. level of ININ as an instrumental variable. The U.S. ININ, being a global leader, has influenced the transformation toward ININ in developing nations like China, meeting the criteria for "relevance." Furthermore, ININ levels in China do not reciprocally impact the U.S., as changes in U.S. ININ primarily affect China by driving its own ININ transformation, thus meeting the "homogeneity" criterion. The penetration rate of industrial robots in the U.S. is used as the instrumental variable, with associated regression results presented in *Table 4,* Models (1) and (2). Additionally, the paper constructs an instrumental variable using the mean robot penetration rates from the U.S., Germany, Korea, Japan, and Sweden, with findings detailed in *Table 4,* Models (3) and (4). These international robotics data were all sourced from the IFR database and World Robotics Reports published annually during the study period.

Table 4. *IV test*

	(1)	(2)	(3)	(4)
	IV1		**IV2**	
	First step ININ	**Two step RBCER**	**First step ININ**	**Two step RBCER**
IV1	1.878*** (71.18)			
IV2			2.207*** (35.03)	
ININ		0.033*** (4.37)		0.026*** (2.74)
Kleibergen-Paap rk LM Statistic	423.07		335.70	
Cragg-Donald Wald F Statistic	5066.65			1226.98
N	1110	1110	1110	1110
R^2	0.986	0.771	0.963	0.771

According to *Table 4,* the Cragg-Donald F statistics for the two instrumental variables surpass the critical threshold for the 5% level specified by Stock-Yogo, indicating that the model does not suffer from weak instrumental variables. The p-values for the Kleibergen-Paap rk LM Statistic are uniformly 0.000, leading to a rejection of the hypothesis that the model is under-identified. Furthermore, the coefficient for ININ continues to be significant, confirming the previously established positive correlation between ININ and RBCER.

Robustness test

To reinforce and validate the reliability of our estimation outcomes, this study will implement robustness checks using the methods listed below, building upon the foundation of control variables already utilized.

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Substituting the ININ indicator. This study measures the level of ININ using the density of robot stock in China's RBCs. Robot stock density is considered an adequate measure of ININ as it directly reflects the penetration and utilization of advanced robotic technologies within the industrial sector. As displayed in Model (1) in *Table 5,* the coefficient for ININ is significantly positive at the 1% level, suggesting that the transition to ININ has positively impacted RBCER.

Table 5. *Robustness test*

	(1)	(2)	(3)	(4)	(5)
	Substituting the ININ indicator	**Addressing the bias issue**	**Shrinkaging data**	**Adding control variables**	**Adjusting the sample**
	RBCER	**RBCER**	**RBCER**	**RBCER**	**RBCER**
ININ	0.075***	0.023**	0.025***	0.027***	0.029***
	(0.018)	(0.009)	(0.007)	(0.007)	(0.008)
Control	Y	Y	Y	Y	Y
City FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
N	1110	999	1110	1110	910
R^2	0.772	0.784	0.790	0.771	0.767

Addressing the bias issue caused by lag effects. Due to the possible latency in the impact of ININ on RBCER, to address the bias issue caused by lag effects, this paper regresses using the one-period lagged ININ variable, with results shown in Model (2) of *Table 5*. The coefficient estimates are consistent with the current period regression results.

Eliminating the impact of outliers on empirical results. This article applies a 1% trimming to all continuous variables, with results shown in Model (3) of *Table 5*. It is observable that the estimated coefficient of ININ remains significantly positive, indicating that there is still a significant positive relationship between ININ and RBCER, reaffirming the robustness of the previously stated conclusions.

Adding additional control variables. Enhancing informatization can facilitate communication among regional economic entities and reduce their spatial-temporal distances, leading to more efficient production and effortless living. Building on the basic model, this study incorporates an indicator of regional informatization (Inter), defined by the number of mobile phone users per hundred individuals within the region. Model (4) from *Table 5* indicates that including this informatization variable does not affect the established positive correlation between ININ and RBCER, thus validating the study's main findings again.

Adjusting the sample. Given the substantial differences in ININ between huge and smaller resource-based cities, this study focuses on assessing how advancements in industrial informatization affect the economic resilience of smaller RBCs. It excludes cities with over 5 million residents and includes cities with fewer than 5 million, allowing for a more targeted robustness check. Model (5) results in *Table 5* confirm that ININ continues to boost RBCER significantly, reinforcing the study's central assertions.

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Heterogeneity test

Considering that other urban factors might affect how ININ influences RBCER, resulting in variable effects, this study investigates the heterogeneity of ININ's impact on RBCER across different cities. This analysis concerns two key variables: the geographical position and the development stage of the cities.

Geographical location heterogeneity test. Recognizing China's significant regional economic disparities, this study assesses the impact of ININ in RBCER across the eastern, central, and western regions. *Table 6* presents the heterogeneous effects of ININ on RBCER across different geographical regions, with Models (1), (2), and (3) representing the eastern, central, and western regions of China respectively. As detailed in *Table 6,* there is a marked variation in the effects of ININ on RBCER across these regions. In the eastern region, the regression coefficient is highly significant at the 1% level, in the western region at the 10% level, and insignificant in the central region. This variance might stem from the eastern cities pioneering industrial informatization, rapidly evolving post-integration of advanced foreign technologies. Consequently, eastern RBCs can swiftly adapt their industrial frameworks to external pressures, seeking innovative developmental paths and strategies. Conversely, the western RBCs, despite a basic initial setup of ININ, can capitalize on the resultant technological spillover and, with policy aid, fortify their local ININ implementations. This capability allows them to modify their industrial and regional growth frameworks, progressively bolstering their ecological resilience.

Table 6. *Geographical location heterogeneity test*

	(1)	(2)	(3)
	Eastern region	**Central region**	**Western region**
	RBCER	**RBCER**	**RBCER**
ININ	0.036*** (0.009)	0.009 (0.010)	0.026* (0.015)
Control	Y	Y	Y
City FE	Y	Y	Y
Year FE	Y	Y	Y
N	240	490	380
R^2	0.806	0.740	0.800

Development stage heterogeneity test. Following the framework established by the "National Sustainable Development Plan for Resource-Based Cities (2013—2020)," this analysis segregates resource-based cities into growth, mature, recession, and regenerative phases. This classification is based on official criteria evaluating resource reserves, the contribution of resource industries to local GDP, resource exploitation intensity, and alternative industry development. *Table 7* presents the differential effects of ININ on RBCER across these four distinct development stages, with Models (1), (2), (3), and (4) representing growing, mature, recession, and regenerative cities respectively. The results indicate that ININ significantly influences the RBCER in mature and regenerating stages, but its impact is negligible on RBCs in growing or recession phases. This discrepancy may stem from the smaller developmental scale and less pronounced locational benefits of the growing and recession RBCs, coupled with their relatively weak foundations in ININ, limiting its effectiveness in enhancing RBCER.

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***Table 7.** Development stage heterogeneity test*

	(1)	(2)	(3)	(4)
	Growth	**Mature**	**Recession**	**Regeneration**
	RBCER	**RBCER**	**RBCER**	**RBCER**
ININ	0.021	0.028***	0.005	0.039*
	(0.028)	(0.010)	(0.012)	(0.021)
Control	Y	Y	Y	Y
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
N	140	600	230	140
R^2	0.833	0.739	0.828	0.731

Moderating effect test

ININ demonstrates significant capacity to enhance UER through reduced industrial energy consumption and improved energy resource utilization efficiency. Following the methodological framework established by Chen and Lee (2020), we empirically examine how ININ influences UER via its effects on energy consumption intensity and energy utilization efficiency.

Our empirical results, presented in Model (1) of *Table 8,* reveal a statistically significant negative coefficient for ININ at the 1% level, establishing a robust inverse relationship between ININ and energy consumption intensity. This finding suggests that the progressive implementation of industrial informatization corresponds with substantially reducing energy consumption intensity across re-source-based cities. This relationship can be attributed to optimizing production processes and energy distribution efficiency through intelligent manufacturing systems and automated production lines. The mechanism operates through dual channels: first, intelligent sensors and IoT technology enable real-time monitoring and control of energy consumption, effectively minimizing waste; second, AI algorithms optimize production scheduling and energy allocation, facilitating precise management and intelligent regulation of energy consumption.

***Table 8.** Moderating effect test*

	(2)	(4)
	ECI	**EUE**
ININ	-0.226***	0.007**
	(0.023)	(0.003)
Control	Y	Y
City FE	Y	Y
Year FE	Y	Y
N	1110	1110
R^2	0.830	0.012

Furthermore, Model (2) in *Table 8* demonstrates a statistically significant positive coefficient for ININ at the 5% level, confirming a robust positive correlation between

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ININ and energy utilization efficiency. This evidence indicates that the advancement of industrial informatization corresponds with marked improvements in energy utilization efficiency across resource-based cities. This enhancement can be attributed to the implementation of sophisticated control systems and optimization algorithms, which minimize energy conversion losses, enhance production precision and stability, and reduce energy waste from operational errors, ultimately leading to improved energy conversion efficiency. Therefore, the theoretical prediction proposed in Hypotheses 2 was verified.

Spatial spillover effect test

Spatial correlation test

Traditional panel econometric models may generate biased results by neglecting potential spatial spillover effects. To determine the existence of spatial correlations between ININ and RBCER, this paper employs the global Moran's I statistic for spatial correlation analysis. Drawing on the methodologies of Feng et al. (2019) and Li et al. (2018), the analysis is conducted using both an inverse geographical distance squared spatial weights matrix (W1) and an adjacency spatial weights matrix (W2) for RBCER. According to the results displayed in *Table 9* covering the period 2010–2020, the Moran's I values for both the explanatory and dependent variables are significantly positive at the 1% level, demonstrating a notable positive global correlation between RBCER and ININ. This substantiates the appropriateness of employing a spatial econometric model in this research context.

Table 9. *Spatial correlation test*

	W1				W2			
	RBCER	Z	ININ	Z	RBCER	Z	ININ	Z
Year	Moran' I		Moran' I		Moran' I		Moran' I	
2011	0.036***	3.552	0.063***	5.485	0.072	1.416	0.254***	4.408
2012	0.046***	4.245	0.065***	5.659	0.135**	2.426	0.258***	4.480
2013	0.028***	2.910	0.065***	5.654	0.127**	2.353	0.258***	4.474
2014	0.034***	3.391	0.063***	5.507	0.173***	3.124	0.255***	4.430
2015	0.031***	3.128	0.061***	5.402	0.138**	2.485	0.252***	4.375
2016	0.022***	2.446	0.061***	5.340	0.118***	2.157	0.249***	4.332
2017	0.043***	4.043	0.064***	5.614	0.231***	4.108	0.256***	4.451
2018	0.043***	4.055	0.059***	5.185	0.129**	2.368	0.243***	4.228
2019	0.047***	4.341	0.060***	5.322	0.181***	3.246	0.247***	4.299
2020	0.018***	2.393	0.063***	5.501	0.101**	2.138	0.253***	4.392

Spatial regression results

Following the preliminary procedures, this study subjected *Equations 3* to econometric tests, including the LM, RLM, WALD, and Hausman tests. The results indicated that all tests demonstrated significant results except the RLM-error test, which did not significantly reject the null hypothesis. Consequently, the analysis was conducted using a Spatial Autoregressive Model (SAR) with fixed effects. *Table 10* presents the effect decomposition of SAR models using two different spatial weight

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matrices, with Model (1) employing the geographic distance-based weight matrix (W1) and Model (2) employing the economic distance-based weight matrix (W2). This dual approach tests the robustness of spatial relationships under different neighborhood definitions and confirms the consistency of our findings across alternative spatial specifications.

Table 10. *The effect decomposition of dynamic spatial autoregressive model (SAR)*

	(1)	(2)
	RBCER	**RBCER**
	W1	**W2**
ININ	0.017**	0.028***
	(0.007)	(0.006)
IL	0.076***	0.076***
	(0.009)	(0.009)
FL	0.034**	0.053***
	(0.015)	(0.013)
UL	0.004***	0.004***
	(0.001)	(0.001)
GL	0.042	0.054
	(0.049)	(0.049)
PD	0.004	-0.001
	(0.011)	(0.011)
Spatial rho	0.362***	0.067**
	(0.093)	(0.029)
Log-likelihood	1134.1738	1134.1738
N	1110	1110
R^2	0.388	0.360

The empirical analysis reveals that the coefficient of the ININ is significantly positive, underscoring that the shift towards industrial informatization markedly boosts RBCER. To further explore the spatial spillover effects of ININ on RBCER, this study employs the analytical framework developed by LeSage and Pace (2009). *Table 11* presents a comprehensive decomposition of spatial effects under two different spatial weight matrices. Models (1), (2), and (3) show the direct, indirect, and total effects under W1, while Models (4), (5), and (6) present these same effects under W2. This parallel analysis allows us to assess the robustness of spatial spillover patterns across different definitions of spatial relationships, providing a nuanced understanding of how ININ impacts both local RBCER and neighboring cities' ecological resilience.

The evaluation of partial effects, as measured using spatial weight matrices W1 and W2, reveals that under spatial spillover influences, the direct, indirect, and total effects of ININ are all statistically significant at the 5% level. *Table 11* demonstrates that ININ fosters ecological resilience within the region and contributes to resilience enhancements in neighboring areas. An analysis using the W1 spatial weight matrix indicates that under spatial spillover dynamics, ININ exhibits a direct effect of 0.018, an indirect effect of 0.009, and a total effect of 0.027, implying that spatially driven growth

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effects represent over 30% of the total growth effects. Furthermore, using the W2 spatial weight matrix, the spatially driven growth effects account for even more than 15% of total effects, thereby underlining the substantial role of ININ's spatial spillovers in enhancing RBCER.

Table 11. *The effect decomposition for dynamic spatial autoregressive model (SAR)*

	(1)	(2)	(3)	(4)	(5)	(6)
	W1			W2		
	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
ININ	0.018** (0.007)	0.009** (0.004)	0.027*** (0.010)	0.028*** (0.006)	0.005*** (0.002)	0.033*** (0.007)
IL	0.076*** (0.009)	0.044** (0.019)	0.120*** (0.022)	0.076*** (0.009)	0.015*** (0.005)	0.091*** (0.011)
FL	0.036** (0.014)	0.019** (0.009)	0.055*** (0.021)	0.054*** (0.013)	0.011*** (0.004)	0.065*** (0.016)
UL	0.004*** (0.001)	0.002*** (0.001)	0.006*** (0.001)	0.004*** (0.001)	0.001*** (0.000)	0.005*** (0.001)
GL	0.042 (0.047)	0.023 (0.030)	0.065 (0.074)	0.053 (0.046)	0.010 (0.010)	0.064 (0.055)
PD	0.005 (0.011)	0.003 (0.007)	0.008 (0.018)	-0.001 (0.011)	-0.000 (0.002)	-0.001 (0.014)

Discussion

This study demonstrates that industrial intelligence significantly enhances ecological resilience in resource-based cities, particularly through energy-related pathways. The positive relationship between ININ and RBCER aligns with Shen and Yang (2023), who found that industrial robot deployment significantly reduced carbon emissions and particulate matter concentrations in Chinese provinces. The current research extends their work by examining resource-based cities specifically and investigating ecological resilience as a more comprehensive environmental outcome measure.

The dual energy-related mechanisms identified in this paper—reduced energy consumption intensity and improved energy utilization efficiency—offer a nuanced understanding of how industrial intelligence affects urban ecological systems. Du and Lin (2022) established a U-shaped relationship between industrial robot application and total factor productivity across Chinese provinces, while the present study specifically links industrial intelligence to ecological outcomes through energy pathways. Interestingly, these findings contrast with Luan et al. (2022), who found that robot usage exacerbated air pollution globally due to increased total energy consumption from expanded production. This divergence likely reflects China's specific policy context, where industrial upgrading is closely coupled with environmental regulations or the unique characteristics of resource-based cities compared to broader global samples.

Furthermore, the current findings extend recent research by Yu et al. (2022) and Balsalobre-Lorente et al. (2018), who confirmed that industrial robots and Industry 4.0 technologies reduce urban air pollution and promote industrial green transformation. The mechanisms identified herein are consistent with Chui's (2018) research, which shows smart grids optimize electricity consumption and promote energy efficiency.

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Similarly, Mehmood et al. (2019) and Xiang et al. (2021) noted improved energy and water efficiency through AI applications and streamlined information processes, further supporting the energy-mediated pathways observed in this study. Looking forward, Gong et al. (2025) highlight how AI enhances life cycle assessments and circular economy practices, suggesting promising directions for expanding ecological benefits in resource-based cities transitioning toward more sustainable development models.

Despite these promising results, limitations of this research include reliance on industrial robot penetration as the primary measure of industrial intelligence and the specific timeframe of the study period. Nevertheless, the findings have significant implications for theory and practice, contributing to understanding the relationship between technological advancement and ecological sustainability in resource-constrained environments. The results suggest that policymakers consider industrial intelligence not merely an economic development tool but a strategic pathway toward enhanced ecological resilience, particularly concerning energy system optimization in resource-based cities.

Conclusions

This study systematically investigates the impact of Industrial Intelligence (ININ) on resource-based city ecological resilience (RBCER) from the perspective of energy consumption and utilization, drawing on data from the Customs Trade Database and IFR industrial robot statistics. The research uncovers multiple significant findings through a comprehensive methodological framework combining dual fixed effects panel models, mediation analysis, and spatial panel model. The empirical results demonstrate that ININ has a significant positive effect on RBCER, with this finding remaining robust across various sensitivity tests, including instrumental variable analysis using robot penetration rates from developed countries. The mechanism analysis reveals that ININ enhances RBCER through two distinct pathways: reducing energy consumption intensity (ECI) and improving energy utilization efficiency (EUE). These energy-related mechanisms serve as crucial channels through which ININ contributes to urban ecological resilience. Additionally, the spatial analysis identifies significant regional spillover effects in ININ’s impact on RBCER, with direct effects being more pronounced than indirect effects. The heterogeneity analysis further indicates that ININ’s positive impact on ecological resilience is powerful in eastern and western regions and mature and regenerative resource-based cities. These findings enrich the theoretical understanding of the relationship between ININ and urban ecological resilience and provide valuable insights for resource-based cities seeking sustainable development through industrial transformation and energy system optimization.

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