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Impact of Industrial Intelligence on China's Urban Land Green Utilization Efficiency

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Abstract: Against the backdrop of the fourth technological revolution, industrial intelligence (INDI) represented by industrial robots has rapidly developed. This evolution provides favorable opportunities for precise decision-making in pollution control and achieving China's "dual carbon" goals. Previous studies have mainly discussed the economic effects of INDI from the perspective of the labor market. This study shifts its focus to examining the impact of INDI on the land green utilization efficiency (LGUE) in cities. Using the panel data of Chinese cities spanning 2009–2021, this study empirically tests the effect and transmission mechanism of INDI on LGUE. We find that urban INDI significantly enhances LGUE. In terms of its transmission mechanism, INDI drives improvements in urban LGUE through technological progress, energy structure optimization, and industrial structure upgrading. Urban infrastructure construction and financial agglomeration level can further strengthen the positive impact of INDI on LGUE. In addition, the improvement in LGUE due to INDI is more significant in non-resource-based and large-sized cities than resource-based and small and medium-sized cities. Therefore, each region should enhance the integration of intelligent technology with traditional industrial manufacturing. Doing so is essential to establish comprehensive assessment indicators that balance environmental protection and economic growth, strengthen regional information infrastructure construction, ensure steady financial flow, and support green development initiatives across regions.

Keywords: industrial intelligence; land green utilization efficiency; technological innovation; industrial structure upgrading; energy structure optimization

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1. Introduction

With the continuous acceleration of urbanization in China, non-agricultural construction land, such as urban industrial and residential areas, has been expanding disorderly. As of 2020, the built-up area of Chinese cities increased to 61,000 km^2, an increase of over 20,000 km^2 compared with 2010. Over 75% of urban land remains at a medium to low-efficiency level [1]. This inefficient land use leads to high resource consumption, pollutant emissions, and carbon emissions [2,3], which contradicts China's strategy of promoting green and sustainable development. Land is a fundamental resource that supports economic and social development. During new industrialization and urbanization, demand for land is strong, with newly added construction land constrained by natural conditions and planning regulations. As land is the basic material carrier for human production, life, and socio-economic activities, its green utilization efficiency represents the comprehensive mapping of the input and output systems of production factors centered on land in urban space under certain technological conditions. Despite pursuing economic benefits, land green utilization efficiency (LGUE) emphasizes the environmental impact of land use, with key features being efficiency and greenization [4]. Improving LGUE is crucial for alleviating land resource constraints, reducing supply-demand contradictions, and promoting high-level ecological environment protection in a coordinated manner. In the context of green development, relying solely on expanding land resource investment to achieve economic development in China is unsustainable. Thus, enhancing urban LGUE has become an urgent priority.

Since technological progress is often deemed a powerful tool to resolve environmental challenges, it is considered a potential solution for enhancing LGUE. Among various technological innovations, industrial intelligence (INDI) has recently emerged as a significant advancement closely related to manufacturing, demonstrating great potential. Breakthroughs in information and communication technologies, biology, new materials, and new energy are integrating with advanced manufacturing technologies, forming a trend of industrial intelligence. Major developed countries have implemented strategies focusing on intelligent manufacturing to gain a competitive edge in the global manufacturing industry. China is also transforming and upgrading its intelligent manufacturing capabilities, with the supply capacity of intelligent equipment and supporting technologies continuously improving. According to the World Robotics Report released by the International Federation of Robotics (IFR) in 2021, 517,385 industrial robots were installed globally, a 31% increase from 2020, setting a new historical high. Of these, 74% of newly installed robots are in Asia, with China ranking first, showing a strong growth rate of 51%.

The development of INDI is believed to have great potential in addressing two basic problems: decreasing returns of production factors and scarce resource bottlenecks in economic development driven by factors. However, what is less recognized is the potential of INDI in reducing pollutant emissions and improving green production efficiency. Most relevant literature on INDI focuses on its labor market outcomes, its impact on industrial structure, its trajectory and technological progress, as well as the embedding of INDI in the global value chain [5–8]. Only limited studies examine the impacts of INDI from the perspective of environmental economics, with attention only on its impact on certain environmental pollutants [9]. Its potential on green efficiency, especially on the sphere of land utilization, however, remains underexplored.

This paper aims to bridge the gap by exploring the impact of INDI on LGUE. Improving urban LGUE requires emphasizing economic benefits while focusing on the environmental impact of land use, aiming to achieve both efficiency and greenness [1,10]. To explore effective ways to improve LGUE in urban areas, the academic community has conducted extensive discussions on the correlation between effective markets and proactive governments. However, existing research mostly focuses on industrial agglomeration, land finance, environmental policies, and the digital economy [4,11–13], often ignoring the impact of INDI on LGUE in cities. Exploring the impact of INDI on urban LGUE is essential for promoting sustainable urban development and implementing innovation-driven green development. This study aims to theoretically clarify the mechanism by which INDI development affects urban LGUE. We construct INDI indicators at the urban level in China across three dimensions: intelligent conditions, intelligent innovation, and intelligent application. We use the entropy method to scientifically calculate the INDI development index at the urban level. Panel econometric models are then employed to empirically test the impact of INDI development on urban LGUE.

This study makes three main marginal contributions. First, it explores the path to improving LGUE from the perspective of urban INDI, finding that INDI can improve LGUE by enhancing technological innovation (TI), optimizing energy structure (ES), and promoting industrial structure upgrading (ISU). Second, in terms of indicator construction, this study developed a measurement system for INDI indicators at the urban level. Most existing literature measures INDI using regional robot data or world input–output table data. This study delves deeper into urban-level research on AI measures. It adds indicators such as new digital infrastructure and the number of intelligent enterprise patents to comprehensively measure the level of INDI, enriching the research on INDI measurement. Third, this study tests the moderating effect of urban infrastructure construction (IC) and financial agglomeration (FA) on the impact of INDI on LGUE as well as the heterogeneous effects generated by urban resources and scale. This provides guidance for promoting INDI construction and effectively improving urban LGUE in various regions.

2. Literature Review

2.1. Intention, Measurement, and Influencing Factors of LGUE

The key to curbing the disorderly expansion of urban land and achieving green and sustainable development lies in improving the green economic efficiency of unit land. With new requirements for the construction of an ecological civilization system, more scholars are focusing on urban LGUE research. Urban LGUE refers to the green economic efficiency of a unit of land, mapping the input and output levels of various resources in the city onto the land. It is specifically manifested as the ratio of labor, land, capital, and other production factors to the comprehensive output of economic, social, and environmental negative externalities [1,14]. Existing literature extensively discusses urban LGUE, with related research divided into two main aspects:

First is the measurement, evaluation, and evolution of the LGUE. Research subjects include provinces, cities, and industries, providing a wide range of insights into urbanization issues [15–17]. Methodologically, the study of LGUE has evolved from single indicator descriptions to multi-indicator construction, parametric methods, and non-parametric methods [18–20]. Measuring urban LGUE involves economic, social, and ecological indicators, so data envelopment analysis (DEA) models are effective for handling the complex relationships between these factors. The goal of LGUE is to maximize land use and expected output while minimizing unexpected output under the coupling effect of ecological, economic, and social systems [1]. Under the concept of green development, scholars increasingly emphasize reducing unexpected outputs in economic activities. True LGUE considers these unexpected outputs [21]. Some scholars consider the "three wastes" of industrial production as unexpected outputs [22], whereas others use urban population and SO_2 as unexpected outputs to measure urban LGUE [23]. In the context of carbon peaking and carbon neutrality, some scholars use CO_2 as an unexpected output to measure urban LGUE [24]. Searchinger et al. [25] propose a carbon benefits index, which measures how the output of land contributes to the greenhouse gas emissions reduction, to proxy the efficiency of land use. Incorporating unexpected outputs into the efficiency measurement index system makes urban land efficiency more realistic and effective. The main measurement method is to incorporate the SBM model of unexpected outputs into the traditional DEA model [26].

Second is an analysis of the driving factors for the LGUE in urban areas. The factors affecting urban LGUE can be divided into internal resources and the external environment. Internal resources include transportation facilities, industrial structure, and natural resources, which stem from the inherent development conditions of a single city or the competitive advantages formed collectively by multiple cities [20,27,28]. The external environment encompasses urban form, land transfer, land finance, and policy pilots. These factors arise from the development concepts or institutional arrangements of government entities [29,30]. However, few studies have focused on the relationship between INDI and urban LGUE.

2.2. Research on INDI

Research related to INDI focuses on its economic effects and the relationship between INDI, labor structure, and labor remuneration [31,32]. There are two views on the economic effects of INDI. The first view suggests that INDI promotes economic growth [33]. Chen et al. [34] found that INDI can mitigate the adverse effects of population aging on economic growth by enhancing automation, return on capital, and total factor productivity. Graetz and Michaels [35], using industry panel data from 1993 to 2007, concluded that INDI promotes economic growth by improving labor productivity and value added. Chen and Qin [36] found that AI has generally promoted inclusive growth within industries and narrowed the income gap among workers from different social classes, using national industry dimension data from 2000 to 2009. In addition, Lv et al. [37] examined the impact of INDI on Chinese enterprises' participation in the global value chain using detailed micro-enterprise data. The results showed that INDI promotes Chinese enterprises' participation in the global value chain. Liu and Pan [38] confirmed the promoting effect of INDI on global value chain participation from an industry perspective.

The second viewpoint suggests a "Solow paradox" in INDI, where excessive industrial automation may reduce productivity [39]. Acemoglu and Restrepo [40], using IFR industrial robot data, analyzed INDI's impact on the U.S. labor market and concluded that INDI significantly reduces employment and labor costs. Li et al. [41], using micro-enterprise data from China, found that the employment effect of robots varies significantly among different industries. Sun and Hou [42] analyzed INDI's impact on the labor force employment structure, predicting a polarization trend in China's employment structure due to INDI. Other studies, such as David and Olsen [43], found that automation, mainly replacing low-skilled workers with machines, exacerbates labor income inequality.

Few scholars have paid attention to the environmental effects of INDI. Within this limited body of literature, distinct patterns emerge between developed and developing countries. Evidence from developed countries generally supports the positive impact of industrial intelligence on the environment, including regional green innovation [44], energy efficiency [45], and pollution management [46]. However, there is disagreement regarding whether this positive effect is present in developing countries. Some studies validate the environmental benefits of INDI in the Chinese context [47], but other scholars argue that developing countries face challenges in obtaining ecological and environmental benefits from INDI due to technological barriers, skill gaps, and institutional weaknesses. For instance, Fan et al. [48] find that the impact of technology on carbon emissions varies with different levels of development. Zhang et al. [49] show that the digital economy increases carbon emissions. Yang and Liu [50] find that industrial intelligence has no significant impact on city green total factor productivity, and the positive effect is only evident in cities with strong environmental regulations.

In summary, despite considerable research on the economic effects of INDI, there is little empirical evidence demonstrating INDI's environmental effects, particularly on LGUE. Moreover, the findings in developing countries like China are mixed. Does INDI development help improve LGUE in cities? This study aims to provide an in-depth understanding of INDI's impact mechanism and empirical evidence for improving LGUE.

3. Research Hypotheses

3.1. Direct Impact of INDI on the Urban LGUE

Improving LGUE in cities is challenging due to limited space and non-renewable land. Schumpeter's endogenous growth theory suggests that technological innovation drives economic growth and reshapes economic and social structures. New production factors, technologies, and management methods (such as data analytics, hydrogen energy, CNC machine tools, and virtual platforms) improve LGUE by reducing reliance on labor, energy, and resources in land use activities, improving production factor conversion rates, and reducing resource wastage and pollutant emissions. For instance, digital technologies such as cloud computing can be applied to the industrial data service platforms, which will enable the precision and efficiency of energy and environmental management. Intelligent logistics can integrate and streamline various aspects of business operations, such as transportation, storage, packaging, and loading and unloading. Furthermore, utilizing the Internet, big data, and cloud computing, companies can quickly acquire global market information, reduce search costs, and tackle information asymmetry, facilitating international trade and FDI.

INDI introduces these technologies, attracting talent and capital, which lowers recruitment costs and boosts investment returns in land use. This enhances production factor conversion rates and investment returns in land use activities [51]. INDI fosters clustering of talent, capital, and industries, which lowers costs related to recruitment, investment, research collaboration, and transportation. This clustering promotes industrial cooperation, enhances infrastructure sharing, and facilitates the reuse of intermediate products, thereby improving land use efficiency and reducing pollution emissions [52]. As INDI clusters in cities reach saturation, it disperses resources to surrounding areas, creating spatial spillovers that impact LGUE in those regions [53].

On the other hand, INDI speeds up the replacement of manual labor with machines, reducing pollution from manual processes and easing reliance on labor in land use. This alleviates inefficiencies due to labor shortages. Furthermore, INDI fosters new technologies and concepts, preventing wastage of land resources caused by improper design and planning in urban land use. Advanced surveying technologies enabled by INDI allow for accurate land development planning, promoting rational and efficient use of land. INDI considers urban above-ground and underground spaces, functional integration, and applies innovative technologies across various aspects of land management. By employing advanced technologies, it minimizes excessive land development while maximizing commercial and civil functions, thereby conserving land resources effectively. This study posits that higher levels of INDI benefit urban LGUE, supporting H1: INDI effectively enhances urban LGUE.

3.2. Indirect Impact of INDI on the Urban LGUE

Grossman and Krueger [54] creatively analyzed how scale effects can hinder environmental improvements, highlighting the pivotal roles of technological advancements and structural changes in controlling pollution. INDI, which combines new-generation information technology with advanced manufacturing, represents a key driver of China's economic growth. Therefore, this study adopts Grossman and Krueger's [54] decomposition approach to explore the environmental impacts of economic activities. It examines the interaction between INDI development and LGUE through the lenses of technological effects (technological progress) and structural effects (energy optimization and industrial upgrading).

3.2.1. Mediating Role of TI

The adoption of intelligent devices requires highly skilled talent. Therefore, aside from replacing low-skilled labor with intelligent devices, enterprises must also provide business training or integrate high-quality talent to foster technological innovation (TI). INDI reduces information transmission costs among enterprises, enhances regional connectivity, and facilitates knowledge exchange among local enterprises on advanced production and green emission reduction technologies. This expands the public knowledge base and stimulates TI across supply chains. Porter's innovation theory highlights TI as a primary driver of economic growth. Research has shown that TI not only enhances production capacity but also significantly reduces pollutant emissions. Green TI, in particular, lowers energy consumption, promotes efficient use of clean energy, and improves both economic and environmental outcomes in land-based production activities, thereby improving LGUE [4,55]. Thus, INDI contributes to improving LGUE through its impact on TI.

3.2.2. Mediating Effect of ES

The use of intelligent technology has accelerated the integration of knowledge elements into enterprise production processes, increased the substitution of virtual for physical elements, and optimized the structural configuration of production factors. This reduces enterprises' reliance on traditional high-pollution energy sources like coal to some extent. Furthermore, intelligent energy storage devices can stabilize the supply of renewable energy, encouraging greater adoption of clean energy in enterprises [39]. Additionally, AI applications in renewable energy, smart grids, and energy trading enhance management efficiency and lower clean energy costs, expanding clean energy options for urban production and living. In summary, optimizing urban ES and mitigating energy use constraints reduce pollution emissions from urban production and living, thereby enhancing LGUE. Therefore, INDI promotes urban LGUE improvement through ES optimization.

3.2.3. Mediating Effect of ISU

INDI leverages its intelligence and automation to replace procedural labor and relies on high-end talent to enhance enterprise production efficiency. Empowered by INDI, the primary industry progresses toward secondary and tertiary sectors, transforming the industrial structure from low to high level. INDI development establishes an intelligent factor allocation system guided by AI decision-making, mitigating market information incompleteness and asymmetry. This optimizes resource allocation and promotes rational industrial structure development. Additionally, INDI-induced product innovations alter consumer demand, leading to supply-side adjustments that increase production scales for innovative products and promote industrial structure upgrading (ISU). Product upgrades also spur innovation in related products and processes, enhancing inter-industry coordination. The growth of emerging industries often entails advanced production technologies and stringent environmental standards. Consequently, high-polluting and energy-intensive enterprises exit the market, leading to more efficient use of production factors and reduced reliance on land resources [13]. This dual approach promotes output growth and pollution reduction within the land use system, thereby enhancing LGUE. Therefore, INDI improves LGUE through ISU. Based on this, we propose H2: INDI enhances urban LGUE by advancing TI, optimizing ES, and promoting ISU.

3.3. Moderation Role of IC and FA

The development of INDI heavily relies significantly on local infrastructure, particularly information, energy, and transportation systems. Information infrastructure such as data centers, 5G networks, and the Internet of Things are foundational for INDI and its technological applications. These infrastructures are highly dependent on electricity consumption, shaping INDI's development around energy usage [11]. Adequate transportation infrastructure fosters a conducive market environment for INDI development. Generally, more comprehensive infrastructure supports local capacity for factor absorption, enhances resource allocation efficiency, and drives overall socio-economic development. Thus, high levels of infrastructure can enhance INDI's role in improving urban LGUE, indicating a positive moderation effect.

Financial agglomeration (FA) is a result of developed finance. As financial systems mature, they foster relevant talents and institutions, leading to FA. Initially, regions leverage their advantages to attract and gather production factors such as capital, talent, and technology from surrounding areas, expanding the financial market and generating economies of scale. At the same time, auxiliary industries related to finance emerge, clustering into financial hubs that mitigate funding shortages for INDI development. In addition, FA facilitates knowledge exchange, enabling cities to acquire funds for advanced technologies catalyzed by INDI, thereby further enhancing LGUE in urban settings. Therefore, FA exerts a positive moderation effect. Based on this analysis, H3 proposes that IC and FA amplify INDI's enhancing effect on urban LGUE.

4. Research Design

4.1. Benchmark Model

Our empirical research aims to effectively identify the impact of INDI on urban LGUE. Following the common practice investigating the effects of INDI [44,50,56], we adopt a two-way fixed effects model to test H1:

$$\mathrm{LGUE}_{it} = \alpha_0 + \alpha_1 \mathrm{INDI}_{\mathrm{it}} + \alpha_2 \mathbf{Control}_{it} + \mu_i + \gamma_{\mathrm{t}} + \varepsilon_{it} \quad (1)$$

where i represents the city, and t represents the year. $LGUE_{it}$ represents the LGUE of city i in period t, and the core explanatory variable $INDI_{it}$ is the level of INDI of city i in period t. The primary focus of this study is the estimated coefficient a_1 of $INDI_{it}$, which characterizes the impact of changes in INDI on urban LGUE. If the estimated coefficient a_1 is greater than 0, it indicates that the development of INDI at the urban level has improved LGUE. $\boldsymbol{Control_{it}}$ denotes a vector of covariates that may influence urban LGUE, including economic development level, population density, foreign direct investment, degree of openness, technology expenditure, and environmental regulation intensity. To eliminate the interference of the time-invariant city-level characteristics and time-varying factors that serve as common shocks, we incorporate urban fixed effects μ and year fixed effects λ into the model.

Based on the nature of the panel two-way fixed effects model, our identification assumption is that, conditional on control variables, confounding factors affecting the causal relationship between INDI and LGUE are accounted for by time and city fixed effects. Thus, any factor that could undermine our identification must simultaneously meet the following conditions: (1) be city specific and time variant; (2) not be predominantly absorbed by the aforementioned socio-economic control variables; and (3) influence both LGUE and INDI concurrently. In general, the two-way fixed effects model provides a robust framework for identifying the relationship between INDI and LGUE by imposing stringent conditions on the potential remaining confounders.

4.2. Variable Definitions

INDI involves the use of intelligent technologies such as AI, big data, and the Internet of Things to achieve the intelligent development of traditional industries like production, warehousing, and services. Based on Luo et al. [56], we develop an INDI measurement index system from three dimensions as indicated by Table 1, namely, intelligence conditions, intelligence innovation, and intelligence application, and measure the INDI index using the entropy method. For details on the procedure for constructing the INDI index, please refer to Appendix A.

Table 1. Integrated indicator system of INDI assessment.

Indicator	Measurement	Property
Intelligence conditions	New digital infrastructure	+
	Intelligent professional talents	+
Intelligent innovation	The number of patents related to intelligent enterprises	+
Intelligent applications	Information collection	+
	Industrial robot penetration	+

Note: + denotes positive.

(1) The intelligent conditions are represented by two indicators: new digital infrastructure and intelligent professional talents. New digital infrastructure plays a crucial role in unifying data resources and providing reliable support for technologies like 5G, AI research and development, and cloud computing, which are prerequisites for achieving INDI. This study measures new digital infrastructure using the operating revenue of listed companies in computer and communication equipment manufacturing, as well as information transmission, software, and IT services. Intelligent professionals are measured by the number of employees in the information transmission, computer services, and software industries, providing necessary talent support for intelligent innovation, the adoption of intelligent technology, and the acceptance of intelligent products or services within the industry.

(2) Intelligent innovation is measured by the number of patents related to intelligent enterprises. We manually collect patent application data from Tianyancha, a leading business inquiry platform with information on nearly 300 million entities nationwide. Using enterprise names, we aggregate the total number of patent applications at the city level, ensuring accuracy through registration location information.

(3) Intelligent applications are measured by selecting two indicators: information collection and industrial robot penetration. Information collection is quantified by the

per capita scale of Internet broadband access users. Following the approach of Luo et al. [56], the installation volume of robots across various industries at the national level, sourced from the IFR database, is disaggregated to urban levels. The penetration rate of industrial robots is calculated using the employment share of each industry as a weighting factor.

LGUE is assessed using a super efficiency Slack-Based Measure (SBM) model, as described by Bian [55] and Zhou et al. [4]. By applying the super efficiency SBM model, we are able to assess the efficiency of urban land green utilization (LGUE) comprehensively. The inclusion of multiple indicators allows for a detailed analysis of how inputs (land, capital, labor) are converted into desirable outputs (economic, social, and ecological) while minimizing undesirable outputs (pollutant emissions). The specific indicator system for urban LGUE is detailed in Table 2. By minimizing the ratio of input excesses ("slacks") to inputs and the shortfall in desirable outputs, while considering the reduction in undesirable outputs, the super efficiency SBM model determines the efficiency score for each city. The resulting efficiency scores indicate how well each city utilizes its inputs to maximize desirable outputs and minimize undesirable ones, providing a comprehensive assessment of urban land green utilization efficiency.

Table 2. Measuring indicators of LGUE.

Indicator Type	Indicator Name	Indicator Connotation
Input	Land	Urban built-up area
	Capital	Urban fixed assets investment
	Labor	Urban employment
Desirable output	Economic output	Value added of the second and third industries
	Social output	Average salary of urban employees
	Ecological output	Green coverage rate in built-up areas
Undesirable output	Pollutant emission	Industrial wastewater discharge Industrial sulfur dioxide emissions Industrial dust emissions

Control variables include economic development (RGDP), expressed as the logarithm of urban per capita GDP; population size (POP), measured by the natural logarithm of the year-end permanent population; foreign direct investment (FDI), represented as the proportion of actual foreign investment to GDP in the current year; technology expenditure (RD), indicated by the proportion of technology expenditure to fiscal expenditure; and environmental regulation (ER), assessed by the proportion of urban environmental pollution control investment to GDP. The descriptive statistics of these variables are presented in Table 3. Our main variable of interest, LGUE, has a mean of 0.232 with a standard deviation of 0.152, indicating significant variation in how efficiently land resources are used across the sample.

Table 3. Descriptive statistics.

Variable	Obs.	Mean	SD	Min.	Max.
LGUE	3510	0.232	0.152	0.047	1.252
RGDP	3510	10.682	0.701	4.798	15.836
FDI	3510	0.039	0.043	0.001	0.798
POP	3510	7.169	0.677	4.211	9.521
RD	3510	0.034	0.018	0.006	0.088
ER	3510	0.031	0.015	0.001	0.103

4.3. Data Source

The study period spans from 2009 to 2021, covering 270 prefecture-level cities. Data on industrial robots are sourced from the International Federation of Robotics (IFR) database.

The IFR's global industrial robot database provides the total number of ISO-compliant industrial robots in over 100 countries and regions and is considered the most authoritative source for studying robot applications. City-level data, including indicators used to construct INDI and LGUE, as well as control and mechanism variables, are obtained from the China Urban Statistical Yearbook and the National Intellectual Property Patent Database.

5. Empirical Results

5.1. Benchmark Regression Results

This study uses model (1) to test the impact of INDI on urban LGUE. Table 4 reports the benchmark regression results. Regardless of whether control variables are included in the model, the coefficients for INDI are consistently positive, and the estimated impact of INDI on LGUE is statistically significant at the 1% level. This indicates that INDI consistently enhances urban LGUE, validating H1. Specifically, based on Column (2), a one-unit increase in INDI is associated with a 0.408 increase in urban LGUE.

Table 4. Effect of INDI on LGUE.

	(1)	**(2)**
	LGUE	*LGUE*
INDI	0.175 ***	0.408 ***
	(0.052)	(0.109)
PGDP		−0.003 **
		(0.001)
FDI		0.001
		(0.002)
POP		0.002
		(0.002)
RD		0.003 ***
		(0.0001)
ER		0.001
		(0.002)
City FE	N	Y
Year FE	N	Y
Observations	3510	3510
R-squared	0.9	0.92

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

5.2. Robust Test

5.2.1. Instrumental Variable (IV) Method

Although the fixed-effects models in the benchmark regression help mitigate major confounders, potential endogeneity issues may still remain. First, cities with higher levels of INDI may prioritize low-carbon emission reduction, increase pollution control investment, and enhance LGUE. Conversely, cities with higher LGUE may also show greater inclination toward research and development of intelligent technologies, suggesting a bidirectional causal relationship between INDI and LGUE. Second, unobservable variables may simultaneously affect both INDI and LGUE, posing a challenge of omitted variable bias. To address endogeneity concerns and ensure robust estimation results, we employ the IV method.

Given the relatively stable labor market conditions in the United States, the application of industrial robots across various sectors may exogenously influence the Chinese labor market, thereby promoting the development of industrial robots in China. Research indicates a correlation between the penetration of industrial robots in the United States and Chinese INDI [56]. Moreover, the development of the industrial sector in the United States is less influenced by developing countries, ensuring exogeneity when using the penetration of American industrial robots as an instrument [57]. Following the practices of existing literature [58,59], Table 5 shows the two-stage regression results using IV. The first column demonstrates the relationship between the IV and INDI, and the F-statistic of the first stage regression results is 95.8, so it is considered that there is no weak instrumental variable problem, whereas the second column shows that, with the IV included, INDI continues to enhance urban LGUE. The consistently positive impacts of INDI on LGUE using the alternative specification alleviate concerns about endogeneity. However, estimates based on IV analysis reflect the local average treatment effect [60], which in this context refers to the treatment effect driven by cities with higher exposure to US industrial robots. Since our primary interest is in the average treatment effect, we focus on the results from the two-way fixed effects model.

Table 5. IV test.

	(1)	**(2)**
	INDI	*LGUE*
IV	0.007 ***	
	(0.002)	
INDI		3.968 ***
		(0.95)
Control variables	YES	YES
City FE	YES	YES
Year FE	YES	YES
Observations	3510	3510
R-squared	0.877	0.92
Kleibergen–Paap rk Wald F statistic	95.8	
Stock–Yogo weak ID test critical values (10%)	16.38	

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

5.2.2. Exclusion of Policy Interference

Within the study's scope, China has implemented several policies influencing LGUE, such as the "Broadband China" policy to enhance the digital economy and low-carbon pilot policies aimed at reducing urban carbon emissions. To mitigate potential policy effects on urban LGUE outcomes, we introduce an interaction term between urban fixed effects and time fixed effects in Model (1). This approach helps to account for time-varying policy impacts specific to each urban context. After incorporating the interaction term, the coefficient of INDI in Table 6 retains its positive direction, indicating that INDI continues to have a beneficial impact on urban LGUE despite potential policy influences.

Table 6. Robustness test.

	(1)	**(2)**	**(3)**
	Excluding policy interference *LGUE*	*Core variable lagged by one period* *LGUE*	*Remove some samples* *LGUE*
INDI	0.413 ***	0.351 ***	0.325 ***
	(0.117)	(0.122)	(0.107)
Control variables	YES	YES	YES
City FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	3510	3240	2925
R-squared	0.919	0.928	0.895

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

5.2.3. Core Variable Lagged by One Period

As a pivotal development trend of the new technological revolution and the integration of manufacturing, INDI promotes sustainable economic development and continuous improvement of LGUE through technological progress, energy optimization, and industrial structure. Given the time-lagged effects of technological progress, energy optimization, and industrial structure, the improvement in INDI may have a time lag. This study regresses the core explanatory variable of the urban INDI index by one period. Table 6 confirms that using lagged explanatory variables in the regression maintains a positive coefficient for *INDI*. This supports the robustness of the benchmark regression results.

5.2.4. Removal of Certain Samples

To address potential biases from cities with higher levels of digital economic development and policy resources—such as municipalities directly under the central government, provincial capitals, and sub-provincial cities—we excluded these samples and re-estimated the model. Even after this adjustment, Table 6 still shows a positive coefficient for INDI, indicating that it continues to significantly enhance urban LGUE.

5.3. Mechanism Analysis

To avoid endogeneity bias in the mediating effect models, this study adopts the method proposed by Jiang [10] and constructs the following model to test the intermediate channels of INDI on LGUE:

$$Med_{it} = \beta_0 + \beta_1 INDI_{it} + \beta_2 Conl_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{2}$$

where *Med* represents the mediating variables, which include TI, ISU, and ES. TI is measured by the logarithm of the number of innovation patent applications in cities. ISU is measured by the ratio of tertiary industry value to secondary industry value. ES is measured by the ratio of urban electricity consumption to the weighted average of natural gas supply and liquefied petroleum gas supply per unit heat value, where a higher proportion of electricity tends to indicate cleaner ES. From the Table 7, the coefficients of *INDI* are both significant, indicating their substantial promotion of TI, ES optimization, and ISU in cities. Moreover, previous studies confirm the role of TI, ES optimization, and ISU in enhancing LGUE [4,55]. Therefore, INDI enhances urban LGUE through three pathways: promoting TI, optimizing ES, and enhancing ISU. H2 is thus supported by the findings.

Table 7. Mechanism test.

	(1)	**(2)**	**(3)**
	TI	*ES*	*ISU*
INDI	0.308 ***	0.58 ***	0.091 ***
	(0.105)	(0.187)	(0.021)
Control variables	YES	YES	YES
City FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	3510	3510	3510
R-squared	0.863	0.899	0.83

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

5.4. Mediation Effect of IC and FA

To test the moderating effect of IC and FA on the relationship between INDI and LGUE, we construct the following model:

$$\begin{aligned} LGUE_{it} = \lambda_0 + \lambda_1 INDI_{it} \times Mod_{it} + \lambda_2 Mod_{it} + \lambda_3 INDI_{it} \\ + \lambda_4 Conl_{it} + \mu_i + \gamma_t + \varepsilon_{it} \end{aligned} \tag{3}$$

Here, *Mod* represents the moderating variables including IC and FA. IC is represented by the per capita urban road area of the city. Enhancing the overall innovation capability in the market relies on substantial financial support. FA fosters benefits in innovative knowledge, thereby enhancing the accumulation of knowledge. The endogenous growth of technology relies on knowledge spillover effects, ultimately bolstering overall innovation capability and knowledge levels. This study employs the location entropy index to measure the degree of urban FA. The moderation effects of IC and FA are tested based on the significance of λ_1. From Table 8, the coefficients of $INDI \times IC$ and $INDI \times FA$ are both statistically significant, suggesting that IC and FA act as moderating variables for INDI's impact on LGUE. Therefore, IC and FA amplify the enhancing effect of INDI on urban LUGE, confirming H3.

Table 8. Moderating effect.

	(1)	(2)	(3)	(4)
	LGUE	*LGUE*	*LGUE*	*LGUE*
INDI	0.17 ***	0.39 ***	0.104 ***	0.25 ***
	(0.052)	(0.108)	(0.036)	(0.083)
$INDI \times IC$	0.019 **	0.047 **		
	(0.008)	(0.022)		
$INDI \times FA$			0.016 ***	0.018 ***
			(0.004)	(0.003)
IC	0.093	0.172		
	(0.108)	(0.122)		
FA			0.01 ***	0.017 ***
			(0.002)	(0.003)
Control variables	NO	YES	NO	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	3510	3510	3510	3510
R-squared	0.921	0.92	0.928	0.928

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

5.5. Heterogeneity Analysis

5.5.1. Resource Type

In resource-based (RB) and non-resource-based (NRB) cities, factors like endowment structure and input levels differ, influencing how INDI impacts LGUE. Drawing on Zhou et al. [4], we categorize cities into RB and NRB cities. The results of Table 9 show that INDI significantly enhances LGUE in both types, with a notably greater effect observed in NRB cities. This disparity may stem from RB cities' reliance on traditional resources, limiting their technological and human capital development. In contrast, NRB cities have a strong economic foundation, possess high-quality human capital, and are not highly dependent on resources. Therefore, they can fully leverage the role of INDI in improving LGUE.

Table 9. Heterogeneity test.

	(1)	(2)
	RB	*NRB*
	LGUE	*LGUE*
INDI	0.216 ***	0.598 ***
	(0.077)	(0.199)
Control variables	YES	YES
City FE	YES	YES
Year FE	YES	YES
Observations	1560	1950
R-squared	0.836	0.892

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

5.5.2. City Size

In terms of city size, we categorize the sample into big cities and small to medium-sized cities, and the empirical results are presented in Table 10. INDI demonstrates a significant positive impact on LGUE across cities of all sizes, with a stronger effect observed in big-sized cities. These larger cities benefit from concentrated commercial resources, high urban population activity, and favorable conditions for the business environment and intelligent innovation. They lead in INDI development, contributing to a spatial economic pattern akin to the Matthew effect [57], where resources concentrate in larger cities. Conversely, small and medium-sized cities face challenges such as limited high-quality human capital and less-developed financial systems, which potentially restrict the full potential of INDI in enhancing LGUE.

Table 10. Heterogeneity test.

	(1)	**(2)**
	Big-sized cities *LGUE*	*Small and medium-sized cities* *LGUE*
INDI	0.486 ***	0.329 ***
	(0.162)	(0.135)
Control variables	YES	YES
City FE	YES	YES
Year FE	YES	YES
Observations	1144	2366
R-squared	0.815	0.887

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

6. Conclusions

On the basis of the constructing indicators for the application of INDI in Chinese urban areas, we systematically analyze and identify the mechanisms and impacts of INDI on urban LGUE. Our research confirms that INDI significantly enhances urban LGUE by promoting technological progress, optimizing energy structures, and accelerating industrial structure upgrades. Additionally, infrastructure development and financial concentration further amplify INDI's impact on LGUE improvement. Specifically, NRB cities and larger cities experience more pronounced LGUE enhancements due to INDI. To improve the urban LGUE, we draw the following policy implications:

First, accelerate the breakthrough of key technologies in AI and promote the upgrading of INDI. AI, as the core of INDI, requires the government to establish robust intelligent infrastructure, provide ample financial support, and foster professional talents for AI development. Government and enterprises should collaborate on AI computing centers and improve network infrastructure to enhance digital capabilities. This initiative will enhance the collection of industrial information and digital capabilities, thereby laying a solid foundation for INDI. In terms of financial support, improving investment and financing policies is crucial to bolstering INDI. Encouraging venture capital and other social investments in INDI initiatives will also be important.

Second, leverage the indirect driving role of technological innovation, energy structure optimization, and industrial structure upgrading on LGUE. Steadily promote the advanced and rational development of the industrial structure by reducing the scale of enterprises with high resource dependence and high carbon emissions. It is important to increase the proportion of intelligent manufacturing and high-value services in the GDP. Implementing a low-carbon transformation of the energy structure and constructing an online energy consumption monitoring system for key energy-consuming units are key actions. These actions will support a cleaner and more efficient energy structure and promote sustainable economic growth. The government should also enhance subsidies for green technology innovation and initiate pilot projects for emission reduction in specific industries. Actively guiding high-energy-consuming industries to reduce carbon emissions through innovation will be crucial for achieving sustainable improvements in urban LGUE.

Third, implement differentiated INDI-driven low-carbon economic transformation strategies. Big-sized NRB cities should leverage the development advantages of INDI to cultivate new growth points in industrial intelligence by integrating their advantageous industries. This includes promoting INDI's advancement, establishing intelligent industrial clusters and supply chains, and advancing the application of intelligent technology in industries and regions with lower technology adoption. Small and medium-sized cities, as well as resource-based cities, should overhaul their extensive economic models, reducing reliance on energy and resources. They should tailor strategic emerging industries to local contexts, integrate AI and other intelligent technologies into traditional production processes, and achieve automated management of production and carbon emissions control.

Despite our aim to comprehensively explore the impact of INDI on LGUE, this paper is subject to certain limitations due to data constraints. Rapid urbanization and the associated urban land expansions and construction have been identified as significant sources of carbon emissions [61]. However, CO_2 emissions have not been included as an undesirable output when constructing LGUE using the super-efficiency SBM. Consecutive city-level carbon emission data in China are not publicly available. Current studies that use carbon emission data for Chinese cities generally rely on two major methods:

(1) Satellite remote-sensing technology is used to monitor atmospheric CO_2 concentrations, and models are employed to infer ground-level emissions [62]. While more precise, it involves extensive data collection efforts.
(2) Based on specific activity data (e.g., energy consumption, traffic flow, industrial production) and corresponding emission factors to calculate the emissions from each activity and aggregating them. This method is prone to measurement errors.

Due to these challenges and the potential inconsistencies in the available data, we decided not to include CO_2 emissions in our study. Instead, we focused on more readily available and consistent indicators to ensure the robustness and reliability of our analysis. This is a recognized limitation of our study, and future research should aim to incorporate more comprehensive and accurate city-level carbon emission data as they become available.

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Appendix A

Introduction to the Entropy Method

The entropy method is used to determine the weights of various indicators for constructing the INDI index. The steps involved in using the entropy method are as follows:

(1) **Data Standardization:** first, we standardize the raw data to make them dimensionless, allowing for comparability. The standardized value X_{ij} of the *j*-th indicator in the *i*-th city is calculated as follows:

$$X_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$$

where x_{ij} is the original value and $\min(x_j)$ and $\max(x_j)$ are the minimum and maximum values of the *j*-th indicator, respectively.

(2) **Calculate the Proportion:** next, the proportion P_{ij} of the city i for the j-th indicator is determined:

$$P_{ij} = \frac{X_{ij}}{\sum_{i=1}^{n} X_{ij}}$$

where n is the total number of cities.

(3) **Entropy Calculation:** the entropy E_j of indicator j is calculated using:

$$E_j = -k \sum_{i=1}^{n} P_{ij} \ln P_{ij}$$

where $k = \frac{1}{\ln n}$ is a constant that ensures E_j lies between 0 and 1.

(4) **Calculation of Difference Coefficient**: the difference coefficient d_j of indicator j is calculated as:

$$d_j = 1 - E_j$$

(5) **Calculation of Indicator Weights:** the weight w_j of indicator j is determined using the difference coefficient:

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}$$

where m is the total number of indicators.

(6) **Composite Index Calculation:** finally, the comprehensive INDI for each city is calculated by summing the weighted standardized values of all indicators:

$$INDI_i = \sum_{j=1}^{m} w_j \cdot X_{ij}$$

In summary, the entropy method effectively captures the diversity and importance of each indicator in constructing the urban INDI index. By standardizing the data, calculating proportions, entropy, difference coefficients, and weights, we ensure a robust and accurate measurement of intelligent development across Chinese cities.

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