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EMPOWERING EFFECT OF ARTIFICIAL INTELLIGENCE ON URBAN INNOVATION CAPACITY

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Abstract. The rapid advancement of technology and industrial transformation has made digital transformation imperative for enterprises. This study aimed to assess the micro-level digitalization of firms and empirically investigate its effects on labor division using machine learning, revealing significant enhancements in specialization among Chinese listed companies. Digital transformation fosters specialization mainly by improving supply chain efficiency, increasing business concentration, and strengthening workforce skills. Our findings clarify the pathways through which digital technologies extend value chains and also provide micro-level evidence for integrating digital and real economies, providing evidence for digitalization policies and high-quality economic development.

1. Introduction

Scientific and technological innovation has become a key driver of national or regional economic growth [14]. All microscale innovation activities take place, and scientific and technological innovation materializes in cities. Hence, improving urban innovation capacity may lay a foundation for implementing the national innovation-driven development strategy [29]. The 14th Five-Year Plan for Scientific and Technological Innovation issued in 2022 proposed "making full use of the city's agglomeration effect and space-carrying capacity and making efforts to promote the accumulation of innovations to achieve a qualitative leap in China's urban innovation capacity." China has been prioritizing efforts to promote urban innovation capacity. However, its urban innovation capacity has an imbalanced and inadequate development pattern, which requires urgent attention.In recent years, China's artificial intelligence development has been at the forefront of global competitiveness, with the scale of its AI market continually expanding. Consequently, how to effectively harness the power of artificial intelligence to drive urban innovation has become a widely discussed topic among the government and all sectors of society.

So, are there any regional variations in the impact of artificial intelligence on enhancing urban innovation capabilities? What specific ways does AI contribute to urban innovation? The impacts of artificial intelligence are profound and multifaceted. The available literature on this topic is limited to the following sources. For example, artificial intelligence has influenced economic growth, productivity, technological innovation, employment, income distribution and inequality, market structure, and industrial organization [5]. Despite the significant advancements of

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AI in practical applications, there is a substantial lack of empirical research to precisely evaluate its role in enhancing urban innovation capacities. While many scholars agree that AI can boost innovation capabilities, the specific pathways through which it exerts its influence are not yet fully understood. Most discussions revolve around AI's potential to "improve R&D efficiency." Therefore, the exploration of AI's impact on urban innovation continues to be an ongoing debate. AI has the capacity to optimize the innovation environment and attract talent, thereby fostering urban innovation [10]. Its inherent learning ability enables AI to deliver increasingly accurate data analysis, facilitating the flow of innovation resources and offering new directional insights for creative endeavors [27]. To address these questions comprehensively, it is crucial to conduct empirical studies that integrate relevant theories with the actual context of China, providing an opportunity for this paper to make incremental contributions to the field.

Existing theoretical frameworks posit that AI will become a general-purpose technology, meeting three essential criteria: widespread adoption, continuous updates and upgrades, and the capability to drive corresponding innovative activities, thereby bringing profound changes to the world [2, 13]. The evolution of the human capital structure positively influences the surrounding environment, enhancing labor productivity in economic and social development [31]. High-level human capital exhibits strong externalities [1]. The integration of AI with other digital technologies connects individuals and enterprises into a network, using big data and other technologies for precise matching and rapid adjustment of the human capital structure, leading to its upgrading [25, 33, 42].

However, a critical question remains: What is the primary mechanism through which AI promotes urban innovation and development? Previous studies have not provided a unified framework to answer this question. To bridge this gap, this paper focuses on examining the impact of AI on urban innovation capabilities. A region's innovation capacity encompasses both actual and potential aspects [24]. From this standpoint, the paper aims to explore how AI can enhance urban innovation capabilities within a comprehensive framework. Additionally, by selecting the city level as the regional unit of analysis, this study can investigate AI's impact on urban innovation at a more granular spatial scale.

2. Current research status

China's research on artificial intelligence and urban innovation capacity is still in its infancy. Previous studies have focused on the sources of variability in national innovation capacity [18], the spillover effect of regional innovation capacity [32], the factors influencing regional innovation capacity [3], and the concept of urban innovation capacity [16]. Chinese scholars have analyzed the factors influencing China's regional innovation capacity at the provincial and municipal levels and for western China alone [12, 28, 40, 43]. Studies have suggested that urban innovation capacity is the ability of a city to transform knowledge, technology, and other elements, and represents the comprehensive strength of all elements and actors combined within the urban technological innovation system [15]. However, only a few studies have reported on the effect of artificial intelligence on China's urban innovation capacity.

In terms of research progress, the present study focused on the following aspects:

(1) Factors influencing urban innovation capacity: Some of the identified influencing factors include the agglomeration of technical talents [7], agglomeration of innovation input elements [6], and industrial co-agglomeration [22], contributing to the improvement in urban innovation capacity. Agglomeration usually results in a larger market, where a complementary effect is produced to increase the benefits that can be reaped by the enterprises. This further promotes innovations undertaken by individual enterprises, thereby improving the overall urban innovation capacity.

(2) Regional innovative effects of artificial intelligence: Studies have shown that artificial intelligence can improve research and development efficiency [30] and agricultural production efficiency [39]; accelerate the development of intelligent agriculture, intelligent manufacturing, and innovation [11]; and raise the intelligence level of production equipment [34]. Although the development of artificial intelligence has injected new momentum into economic development, low- and moderate-skilled workers may suffer from unemployment or are forced to choose low-end jobs [44]. Artificial intelligence may have two starkly opposite impacts on employment [4]. Nevertheless, it has helped map a new direction for urban innovation due to its stunning learning capacity, thus enabling increasingly precise data analysis and promoting the flow of regional innovation resources.

(3) Influence of artificial intelligence on urban innovation capacity: Artificial intelligence offers the following benefits: helps break industrial boundaries and promote integration innovation [26]; optimizes the innovation environment, brings talents together [10]; lowers the costs of innovation, increases the outputs of innovation, and improves urban innovation capacity.

In brief, artificial intelligence does have a promoting effect on urban innovation capacity. Regarding the pathway artificial intelligence follows to influence urban innovation capacity, most studies have proposed tentative influence mechanisms from the perspectives of lowering operational costs, accelerating the intelligent transformation of infrastructure, and improving production efficiency. This article constructs a theoretical analysis framework from the perspective of urban innovation capability, incorporating the unique attributes of artificial intelligence. Based on this framework, it measures the innovation capability levels of 287 cities from 2012 to 2021 and uses the density of robot penetration to illustrate the development level of artificial intelligence. The national industry-level robot data is matched to the city level according to the employment numbers in each region, resulting in city-level robot penetration indicators. Various econometric methods are employed to empirically test the impact of artificial intelligence on urban innovation capability and its underlying mechanisms. The research results indicate that artificial intelligence significantly enhances urban innovation capability, with the upgrading of human capital structure and industrial collaborative agglomeration being important influencing mechanisms. These conclusions remain robust after rigorous checks.

The potential marginal contributions of this article are threefold:

(1) Comprehensive Measurement: It draws on existing literature to provide a comprehensive measurement of artificial intelligence and innovation capability at the urban level, allowing for a more nuanced discussion of their relationship. This

enables a detailed understanding of how AI interacts with various aspects of urban innovation.

(2) Unified Framework: The article explores the fundamental question of how artificial intelligence primarily influences regional innovation capability within a unified framework. It comprehensively assesses the role of artificial intelligence in enhancing urban innovation capability and supports the path influence of robot penetration on urban innovation capability, thereby deepening existing literature. This holistic approach provides new insights into the mechanisms through which AI drives innovation.

(3) Expanded Heterogeneity Test: The study further expands the heterogeneity test, enabling a more accurate measurement of the differential characteristics of artificial intelligence at the regional level compared to previous studies. This refined analysis allows for a better understanding of regional variations in AI's impact on urban innovation, contributing to more targeted policy recommendations.

Overall, this in-depth exploration of the impact of artificial intelligence on urban innovation capability in China aims to add marginal contributions to research in this field. It provides certain references for the sustainable development of artificial intelligence and offers a decision-making basis for enhancing urban innovation capability.

3. Theoretical basis and assumptions

(1) Direct effects of artificial intelligence on urban innovation capacity

Deep learning and autonomous learning are subfields of artificial intelligence that continuously empower the processing and integration of all types of information involved in regional innovation. This further facilitates improvements in the innovation mode and efficiency at the urban level. From the perspective of resource allocation, artificial intelligence incorporates new knowledge from outside the city or enterprise and then shares it among the actors, making up for the lack of innovation resources within the city or enterprise [17]. From the perspective of technology spillover, knowledge and technologies spill over from high-tech sectors to low-tech sectors. Low-tech sectors learn the knowledge and technologies through intelligent pipelines and imitate the practice among the high-tech sectors, thus reinforcing knowledge externalities [41] and stimulating the innovation vitality of the city [35]. In terms of costs of innovation, artificial intelligence empowers statistical analyses and trend fitting, reducing the costs of innovation [44]. Based on these analyses, we proposed the first hypothesis.

H1: Artificial intelligence promotes urban innovation capacity.

(2) Mechanism underlying the effect of artificial intelligence on urban innovation capacity

Artificial intelligence has an indirect promoting effect on urban innovation capacity by facilitating the human capital structural upgrading within the industry and collaborative agglomeration across the industries. Artificial intelligence promotes human capital structural upgrading in cities at the microscopic level by creating and supplying high-skilled talents and matching them to the most suitable tasks. This is an important driving force behind the development of urban innovation capacity.

Artificial intelligence and other digital technologies together create a network comprising individuals and enterprises. Within this network, precise matching of talents is enabled by Big Data, which helps adjust human capital structure and promotes human capital structural upgrading. First, the increasing adoption of artificial intelligent technologies has raised the demand for and consequently given rise to a larger number of high-skilled talents, thus creating new jobs, such as those related to programming and design. This increase in the employment of high-skilled talents has led to higher labor and capital productivity, initiating product and technology innovations [37]; Second, artificial intelligence has pushed up the supply of high-tech workforce. It has penetrated deeper into production and life, replacing some nonskilled labor in enterprises while raising the demand for a labor force skilled in intelligent operation and data analysis [23] High-competence labor is needed to meet new demands in artificial intelligence development. Third, a matching effect exists between artificial intelligence and high-skilled labor. Labor-intensive and low-tech enterprises learn technologies from high-tech enterprises and those skilled in artificial intelligence. As the number of high-end talents increases for a region, regional enterprises tend to recruit a larger number of high-end talents [38]. Based on the aforementioned analysis, we proposed the second hypothesis.

H2: Artificial intelligence promotes urban innovation capacity by facilitating human capital structural upgrading.

Next, another important driving force for urban innovation capacity on the macroscopic scale is the expansion of artificial intelligence technologies across the industrial chains. This expansion has helped match the level of intelligence with the manufacturing industry and deepened industrial co-agglomeration continuously. Artificial intelligence is considered an emerging technology to revolutionize the industrial technology paradigm. It can influence industrial co-aggregation by reshaping the evolutionary path of the manufacturing and productive service industry through technical empowerment, technological imitation, and technological diffusion [25]. First, enterprises already using artificial intelligence play an exemplary role and establish a knowledge framework and an intelligent mode to be shared with backward enterprises. Access to artificial intelligence, to a lesser or greater extent, helps break down obstacles to co-agglomeration between enterprises, sectors, and industries [36]. Besides, as upstream enterprises using artificial intelligence technology attract downstream enterprises to cooperate with them in technology, the level of regional industrial co-agglomeration further improves [42]. Second, artificial intelligence facilitates the formation of new modes, business formats, and industries, which is conducive to improving the quality of industrial co-agglomeration. Co-agglomeration has a spillover effect and continuously deepens and widens technological exchanges between industries [9], in turn, promoting industrial co-agglomeration [21]. Introducing artificial intelligence into the industrial chain speeds up the intelligent upgrading of the industrial chain and brings momentum to the improvement in the urban innovation capacity [8]. From the perspective of agglomeration economies in regional economics, agglomeration represents the concentrated clustering of economic entities, including enterprises and the population, within a specific area. By sharing infrastructure, labor markets, and benefiting from knowledge spillovers, costs are reduced, efficiency is enhanced, and innovation is actively promoted.Co - agglomeration, on the other hand, refers to the collaborative convergence of economic entities from diverse industries in the same region. Leveraging industrial linkages and complementary effects, they effectively integrate resources, significantly improving overall efficiency. Therefore, industrial co-agglomeration is a prerequisite for regional innovation activities to happen. The higher the level of industrial co-agglomeration, the higher the potential and actual innovation outputs for a region and the greater the promoting effect on urban innovation capacity for that region. Based on this analysis, we proposed the third hypothesis.

H3: Artificial intelligence promotes urban innovation capacity by accelerating industrial co-agglomeration.

4. Model setting, indicator construction, and data sources

This study delves into the panel data of Chinese prefecture - level and above cities. Unquantifiable inherent characteristics, such as regional resource endowments, can sway the dependent variable. The fixed - effects model adeptly controls individual heterogeneity, curbs endogeneity - induced biases, and centers on intra - individual temporal variations. This aligns seamlessly with our dynamic - focused research, ensuring reliable results.

(1) Model setting

Based on the proposed theoretical hypotheses, we built a fixed-effects model to capture the relationship between artificial intelligence and urban innovation capacity:

$$Innov_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 X_{it} + \mu_i + r_t + \varepsilon_{it} \tag{4.1}$$

where $Innov_{it}$ is the innovation capacity of the ith city in the tth year, AI_{it} is the level of artificial intelligence for the ith city in the tth year, X_{it} is the control variable for the ith city in the tth year, μ_i is the fixed effects of the city, r_t is the fixed effects of the year, and ε_{it} is the random error term.

(2) Variable explanations and data sources

a. Explained variable

The urban innovation capacity (Innov) was chosen as the explained variable, represented by China's urban innovation index[1].

b. Explanatory variable

Artificial intelligence (AI), measured by the industrial robot density in each city, was considered as the explanatory variable [20].

c. Control variables

The control variables were chosen as follows: degree of informationization (Inter), represented by the ratio of mobile Internet users to the regional population at the end of the year; degree of marketization (Mar), represented by the ratio of the number of people employed in the private sector plus the self-employed to the number of people employed in the state-owned sector; urban economic development level (Pgdp), represented by regional GDP

[1] China's urban and industrial innovation index (2001–2021), the research team from the Fudan Institute of Industrial Development, https://mp.weixin.qq.com/s/6kbwFtsoWJaemGWrOmPif

per capita; industrial structure (Is), represented by the ratio of the output value of the tertiary industry to that of the secondary industry; foreign trade (Tra), represented by the ratio of actual inflow of foreign investment to gross domestic product; and market size (Mak), represented by the number of industrial enterprises above the designated size.

d. Mediating variables

In the present study, the human capital structure (Hr) and the industrial co-agglomeration (Cogg) were chosen as mediating variables. The human capital structure was measured by the ratio of university students to the total population at the end of the year. Industrial co-agglomeration was measured by the degree of agglomeration of the manufacturing and productive service industries [37].

(3) Data sources

The data from more than 287 cities in China between 2012 and 2021 were selected for the study. The data sources included the 2023 World Robot Report, China Labor Statistical Yearbook, and China City Statistical Yearbook.

5. Regression results and analysis

(1) Baseline regression

AI consistently had a significant promoting effect on urban innovation capacity with or without the introduction of control variables (Table 1). The regression results from model (1) were compared against those from model (2). The influence of artificial intelligence on urban innovation capacity changed from 0.21 to 0.35, and the significance level changed from 5% to 1%. These results indicated that the higher the development level of artificial intelligence, the higher the urban innovation capacity. The influence of control variables on urban innovation capacity was enhanced after introducing the control variables. Hence, hypothesis H1 holds true.

Table 1. Results of baseline regression

	Urban innovation capacity (Innov) (1)	(2)
Level of artificial intelligence	0.21^{**}	0.35^{***}
	(0.01)	(0.02)
Control variable	No	Yes
Year	Yes	Yes
City	Yes	Yes
R2	0.65	0.89
F	58.86	142.14

Note: The values within brackets are robust standard errors. ***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.

(2) Robustness test

A robustness test was performed to prove the reliability of the aforementioned analysis results to prevent errors arising from indicator selection. As the capitals of different provinces enjoy more favorable local policies, a greater number of factors of production usually gather there. The capitals of provinces in China usually enjoy a higher political and economic status than other cities due to the country's political structure. Therefore, another regression analysis was performed after eliminating the data from the capitals of provinces and municipalities directly under the central government.

Table 2. Results of the robustness test

	Urban innovation capacity (Innov) (1)	(2)
Level of artificial intelligence	0.30^{*} (0.00)	0.33^{*} (0.01)
Control variable	No	Yes
Year	Yes	Yes
City	Yes	Yes
R2	0.53	0.78
F	38.67	108.79

Note: The values within brackets are robust standard errors. ***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.

(3) Endogeneity processing

Endogeneity may occur if the industrial robot density in each city is directly used for the empirical analysis. This is because artificial intelligence affects the urban innovation capacity, which further influences the development of artificial intelligence. Bilateral causality between the industrial robot density in each city and the urban innovation index gives rise to errors in the regression. We addressed the endogeneity problem using the instrumental variable (IV) method to estimate the causal relationship.

Considering the correlation and exogeneity requirements for IVs, the IVs should be independent of random disturbance terms and must be correlated with the endogenous variables. The industrial robot density in the city with one phase lag was treated as the IV, and the causal relationship was estimated using the two-stage least squares (2SLS). The regression results are shown in Table 3.

To test the validity of the IVs, we first determined whether the IVs were overidentified. The results showed that the industrial robot density in the city with one phase lag was exogeneous and independent of the disturbance term. Next, we determined whether the IVs were unidentified. The LM statistic was 157.70, and the pH value was less than 0.1. The hypothesis that the IVs were unidentified was rejected at the 1% significance level. Finally, the testing for weak instruments was performed. The F-statistic was 27.93, which indicating that the instruments were not weak. These results indicated that the IVs selected in the present study were valid. The regression results showed that the regression coefficient for the IV was 0.91, indicating a significant correlation, which was consistent with the results of the fixed-effects model for baseline regression. In conclusion, the variables included for regression were reasonable and the regression results were robust.

TABLE 3. Results of the robustness test

	Urban innovation capacity (Innov) (1)	(2)
Level of artificial intelligence	0.62***	0.57*
	(0.00)	(0.00)
IV-Level of artificial intelligence	0.91***	0.82*
	(0.02)	(0.00)
Control variable	No	Yes
Year	Yes	Yes
City	Yes	Yes
R2	0.57	0.81
F	62.10	150.07
Kleibergen–Paap rk LM statistic: 157.70 (0.00)		
Cragg–Donald Wald F-statistic: 27.93		

Note: The values within brackets are t statistic. ***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.

(4) Mechanism analysis

a. Mechanism test

a.1 AI promotes urban innovation capacity by facilitating human capital structural upgrading.

According to the aforementioned theoretical analysis, artificial intelligence indirectly promotes urban innovation capacity by facilitating human capital structural upgrading. We constructed the following model to further verify the indirect effects of artificial intelligence on urban innovation capacity:

$$Hr_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 X_{it} + \mu_i + r_t + \epsilon_{it}, \tag{5.1}$$

$$Innov_{it} = \gamma_0 + \gamma_1 AI_{it} + \gamma_2 Hr_{it} + \gamma_3 X_{it} + \epsilon_{it} \tag{5.2}$$

where Hr_{it} is the human capital, AI_{it} is the core explanatory variable, and X_{it} is the control variable. The definitions of all these variables are consistent with those provided in equation (4.1).

The regression results in Table 4 show that the regression coefficient measuring the effect of artificial intelligence on human capital was 0.19. The regression coefficient was 0.43 after introducing the control variable. The artificial intelligence promoted human capital structural upgrading at the 10% significance level. This indicated that the development and application of artificial intelligence had a positive influence on human capital structural upgrading. Besides, the regression coefficient for the combined effect of artificial intelligence development and human capital structural upgrading as explanatory variables was 0.33. The regression coefficient changed to 0.27 after introducing the control variable. Therefore, hypothesis H2 that artificial intelligence promotes urban innovation capacity by facilitating human capital structural upgrading is true.

a.2 Artificial intelligence promotes urban innovation capacity by elevating the level of industrial co-agglomeration.
According to the aforementioned theoretical analysis, artificial intelligence indirectly promotes urban innovation capacity by facilitating industrial co-agglomeration. We constructed the following model to further verify the indirect effects of artificial intelligence on urban innovation capacity, we constructed the following model:

$$Cogg_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 X_{it} + \mu_i + r_t + \epsilon_{it}, \tag{5.3}$$

$$Innov_{it} = \gamma_0 + \gamma_1 AI_{it} + \gamma_2 Cogg_{it} + \gamma_3 X_{it} + \epsilon_{it} \tag{5.4}$$

where $Cogg_{it}$ is industrial co-agglomeration, AI_{it} is the core explanatory variable, and X_{it} is the control variable. The definitions of all these variables are consistent with those provided in equation (4.1).

TABLE 4. Regression results

Variable	Human labor capital (Hr) Urban innovation capacity (Innov)	Level of industrial co-agglomeration (Cogg)		
	Model (1)	Model (2)	Model (3)	Model (4)
Level of artificial intelligence (AI)	0.19^{*} (0.01)	0.43^{**} (0.03)	0.15^{*} (0.28)	0.48^{**} (0.34)
(AI/Hr)(AI/Cogg)	0.33^{**} (0.00)	0.27^{*} (0.00)	0.13 (0.01)	0.19^{*} (0.01)
Control variable	No	Yes	No	Yes
Year	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
R2	0.68	0.88	0.34	0.78
F	67.08	124.72	37.93	308.29

Note: The values within brackets are robust standard errors. ***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.

Table 4 shows that the regression coefficient indicating the effect of artificial intelligence on industrial co-agglomeration was 0.15. The regression coefficient was 0.48 after introducing the control variables. With or without introducing the control variables, artificial intelligence promoted industrial co-agglomeration at a significance level of 10%. Moreover, the regression coefficient for measuring the combined effect of artificial intelligence development and industrial co-agglomeration as explanatory variables was 0.13. The coefficient was 0.19 after introducing the control variable. Thus, hypothesis H3 that artificial intelligence promoted urban innovation capacity by accelerating industrial co-agglomeration holds true.

b. Indirect effect test
The significance analysis based on the aforementioned three-step method alone hardly ensured the reliability of the results. Therefore, mediating variables were included in the model, and the verification method [20] was used.

The indirect effects of mediating variables were tested by bootstrap. The mediating effect was tested based on the amount of decrease in the effect of the independent variable on the dependent variable. The confidence intervals were estimated by bootstrap. The number of repeated samplings was set to 1000. If no zero values were found within the confidence intervals, it implied the existence of indirect effects. If the indirect effects were significant, then the reliability of the results of mediating effect analysis was assessed correspondingly. The mediating variables considered in the present study were human capital structure and level of industrial co-agglomeration. The results of the mediating effect test are shown in Table 5.

TABLE 5. Regression results

	t	Bootstrap std. err.	Z	P
Indirect effects Hr	0.2955**	0.17	2.83	0.01
Indirect effects $Cogge$	0.5613*	0.13	1.65	0.00
Direct effects	0.6079**	0.11	3.58	0.00
Total effects	0.8167	0.19	5.69	0.10

Note: ***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.

The 95% confidence intervals were estimated by bootstrapping 1000 times. As shown in Table 5, none of the confidence intervals for either the human capital structure or industrial co-agglomeration was zero. It was believed that the mediating effects were significant in the statistical sense. Moreover, the coefficient for the mediating effect of human capital structure and industrial co-agglomeration was 0.29 and 0.56, respectively. Both were significantly positive, indicating the existence of mediating effects.

Based on the mechanism test, we further demonstrated that the indirect effect of artificial intelligence on urban innovation capacity was not zero. Therefore, the mediating effects of human capital structural upgrading and industrial co-agglomeration on urban innovation capacity were verified. Thus, hypotheses H2 and H3 hold true.

(5) Heterogeneity analysis

China has a vast territory, but it differs considerably in the levels of infrastructure and economic development across the cities. This results in a large variability in the development of artificial intelligence. The development status of urban innovation capacity also points to significant regional variability. Following the standard by the National Bureau of Statistics, 287 sample cities were divided into four major economic regions: eastern, northeastern, central, and western China. Subsequently, the regression analysis was performed again between artificial intelligence and urban innovation capacity to test the regional variability of the effect of artificial intelligence on urban innovation capacity. The results of the empirical analysis are shown in Table 6.

Table 6. Heterogeneity test for urban innovation capacity

centering

	Eastern		Northeastern		Central		Western	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)	Model (8)
Level of artificial intelligence (AI)	0.45*	0.53**	0.10	0.29*	0.27*	0.59**	0.23	0.10*
	(0.37)	(0.58)	(0.77)	(0.58)	(0.82)	(0.02)	(0.01)	(0.02)
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.61	0.38	0.40	0.55	0.90	0.67	0.57	0.67
F	8.34	87.00	7.11	74.88	7.34	80.11	7.04	79.31

Note: The values between brackets are robust standard errors. ***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.

6. Results and discussion

The panel data on more than 287 cities of China from 2012 to 2021 were used for an empirical analysis on the influence of artificial intelligence on urban innovation capacity. The following conclusions were drawn from this analysis:

First, artificial intelligence has a significant promoting effect on urban innovation capacity. Artificial intelligence promotes urban innovation capacity through the following pathway: It optimizes the efficiency of urban innovation resource allocation and stimulates continuous technological innovation, thereby reducing innovation costs and enhancing the vitality of urban innovation. Furthermore, artificial intelligence has an indirect promoting effect on urban innovation capacity by facilitating human capital structural upgrading and industrial co-agglomeration.

Second, the control variables affect urban innovation capacity. Informatization development promotes the diversity and efficiency of urban innovation. Foreign trade has a direct market size effect, which encourages enterprises to step up investments on innovation. As opening up intensifies the competition, enterprises are much more motivated to innovate. The higher the urban economic development level and the more abundant the factors of production, the greater the externalities of technology. This attracts a massive influx of talents and technologies into cities. Finally, an increasing market size has a significantly positive influence on technological innovation ability, promoting the agglomeration of technological innovation resources. Moreover, enterprises, driven by growing market competition and demands, increase their investments in technological innovations, which finally improves urban innovation capacity.

Third, The samples were classified into different groups based on geographic location, and the regression was performed for each major region of China separately. A heterogeneity test was performed based on the geographical division. Our empirical analysis showed a significant positive influence of artificial intelligence on all four major regions under study. The influence was more pronounced in eastern and central China, highlighting the regional variability of the effect of artificial intelligence.

It is imperative to contextualize our findings within the broader scholarly discourse on AI-driven urban transformation. Previous literature has extensively documented the transformative potential of AI across various sectors (Brynjolfsson and McAfee, 2014; Manyika et al., 2013), highlighting its capacity to enhance operational efficiencies, stimulate economic growth, and foster innovative business models. Our study aligns with this narrative by demonstrating how AI penetration in cities, proxied by robot density in the manufacturing sector, serves as a catalyst for urban innovation. Echoing the theoretical underpinnings of regional innovation systems theory (Cooke, 2001), our research underscores the significance of knowledge spillovers and collaborative networks in amplifying AI's impact on urban innovation. By upskilling the workforce and facilitating the clustering of AI-related industries, cities can harness the synergistic effects of technological advancements, leading to the development of new products, services, and processes. This resonates with the findings of Acemoglu and Restrepo (2020), who emphasize the role of human capital and industry clustering in promoting innovation in the digital age. Moreover, our results corroborate the insights from recent studies on the role of AI in enhancing urban sustainability and resilience (Glaeser and Kahn, 2020). By optimizing resource allocation, improving public service delivery, and enabling smart infrastructure management, AI can contribute to the development of sustainable and livable cities. This aligns with the United Nations Sustainable Development Goals, which advocate for the integration of technology and innovation in addressing urban challenges. Consistent with the policy recommendations of many studies (World Economic Forum, 2019; Manyika et al., 2017), our findings underscore the need for governments and stakeholders to invest in AI education, research and development, and supportive regulatory frameworks. In summary, our additional discussion not only enriches the understanding of AI's role in urban innovation but also reinforces the relevance of established theories and empirical evidence in the field. We contribute to the ongoing discourse on harnessing AI for sustainable urban development.

7. Conclusions

President Xi Jinping has pointed out that "artificial intelligence is an important driving force for the next round of technological revolution and industrial transformation."[2] China is among the top in the Global Artificial Intelligence Rankings 2023, with exponential growth in its artificial intelligence market. In addition to providing a series of empirical evidence for AI to promote urban innovation and development, the conclusions of this paper also have the following policy implications:

(1) Leveraging Existing Advantages: Cities need to make full use of their existing advantages, including technology, capital, and market strengths. Utilizing high-tech parks, scientific research institutions, and innovation platforms can attract and gather top talents and teams in the field of AI. This strategy will promote the research and development and application of AI technology, enhancing the city's innovation ecosystem.

[2]H. Liu, Artificial intelligence is a key driving force for the development of new quality productive forces. Guangming Net, https://baijiahao.baidu.com/s?id=1805246621221257575&wfr=spider &for=pc

(2) Transforming Traditional Industries: The use of artificial intelligence technology should be applied to transform traditional industries such as manufacturing and agriculture. This will improve production efficiency and service quality while accelerating the development of new industries like intelligent manufacturing and intelligent healthcare. By integrating AI into these sectors, cities can foster economic growth and competitiveness.

(3) Encouraging Collaboration Among AI Enterprises: Cooperation and collaboration between AI enterprises should be encouraged to form a development pattern of upstream and downstream linkage and resource sharing within the industrial chain. The construction of artificial intelligence industrial parks will provide enterprises with a conducive environment for R&D, production, and services, promoting industrial agglomeration and scale effects. This collaborative approach can lead to synergies and innovations that benefit the entire industry.

The conclusions of the study basically verify the research hypothesis, but there are still some areas that can be improved. The selection of robot penetration to measure the development level of artificial intelligence in cities is more representative; however, due to limitations in measurement methods and data acquisition, the assessment of artificial intelligence is not rich or in-depth enough. Additionally, the variables used to measure a city's ability to innovate may not be comprehensive. Therefore, in future research, we can try to select more detailed and abundant variables to interpret and measure AI and urban innovation capabilities more comprehensively. By broadening the scope of research, we can make the results more theoretically robust and practically applicable.

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