

Artificial Intelligence Empowering the Low-Altitude Economy: Evidence from China

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Abstract

Recent technological and regulatory advances in unmanned aerial systems have given rise to the Low-Altitude Economy (LAE), an emerging arena of innovation and competition. Achieving sustainable and high-quality growth in this sector, however, hinges on the deep integration of Artificial Intelligence (AI) into its core operations. Based on provincial panel data from China spanning 2012-2023, this paper empirically examines the enabling effects of AI on LAE. The results show that AI development significantly promotes the growth of LAE, and this conclusion remains robust under multiple tests. Mechanism analysis reveals that AI drives the LAE primarily through two channels: improving digital infrastructure and enhancing technological innovation investment. Heterogeneity analysis further indicates that this positive effect is more pronounced in coastal regions and during the early stages of policy implementation. This study highlights the crucial role of AI in promoting the high-quality development of LAE and fostering new productive forces, offering empirical evidence and policy insights for building an intelligent low-altitude industrial system.

Keywords

Low-Altitude Economy, Artificial Intelligence, Digital Infrastructure

1. Introduction

In recent years, the low-altitude economy has emerged as a strategic and rapidly developing sector prioritized by national industrial policies. It serves as a vital platform for cultivating new productive forces and advancing high-quality economic growth. By restructuring airspace resource utilization and promoting the integration of transportation and communication networks, the low-altitude economy provides new spatial capacity and growth momentum. The 2024 Report on the

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Work of the Government of China officially incorporated the “low-altitude economy” into the national strategic plan for the first time. Several provinces and municipalities subsequently issued specialized development programs, signifying that the low-altitude economy has entered a new stage of industrialization and institutionalization.

The low-altitude economy generally refers to economic activities conducted within airspace below 3000 meters above ground level, centered on UAVs and other aerial platforms for commercial and public services. Rooted in UAV technology, this emerging economic form integrates multiple digital technologies such as communication, navigation, AI, big data, and the Internet of Things (IoT), thereby driving profound transformations in sectors including urban mobility, logistics, emergency rescue, agricultural protection, and cultural tourism. Compared with ground transportation networks, low-altitude airspace offers greater spatial freedom and lower congestion costs, enabling multi-UAV collaboration, route optimization, and real-time communication. Consequently, it demonstrates enormous potential for improving resource allocation and spatial efficiency.

Globally, the low-altitude economy has become a new technological and industrial frontier. Countries such as the United States, Germany, and Japan have already established relatively mature regulatory and market systems. For example, the U.S. Urban Air Mobility (UAM) program is advancing the commercialization of “air taxis” and “aerial delivery” services (AINvest, 2025). These experiences suggest that the development of the low-altitude economy depends not only on technological innovation but also on the deep integration of AI, communication networks, and data systems. Against this backdrop, the rise of AI provides new momentum for the low-altitude economy.

With its capabilities in high-precision perception, intelligent decision-making, dynamic learning, and autonomous control, AI offers critical support for low-altitude economic operations. On one hand, AI algorithms significantly enhance UAVs’ autonomous flight performance, path planning, and obstacle avoidance, enabling safe operations in complex environments. On the other hand, AI-driven visual recognition, semantic analysis, and edge computing improve the intelligent scheduling and resource allocation of communication networks in low-altitude airspace, thereby increasing overall efficiency and safety. Moreover, the widespread application of AI accelerates the digital transformation of traditional industries, fostering new industrial systems characterized by automation and intelligence, and driving the formation of new productive forces.

The integration of AI and the low-altitude economy not only represents technological empowerment but also generates notable economic and social externalities. AI-driven low-altitude platforms can perform high-risk tasks—such as border patrols, forest fire monitoring, emergency rescues, and geological disaster surveillance—without increasing human risk (Zhuang, 2024). Through real-time data collection, intelligent analysis, and dynamic response, these systems enhance public safety while reducing human and temporal costs. Furthermore, AI-enabled low-altitude logistics systems are reshaping supply chain management and urban deliv-

ery, providing new pathways for green and low-carbon transformation.

Therefore, the deep integration of AI and the low-altitude economy signifies a new phase of technological revolution and industrial transformation, holding substantial strategic importance for building a modern industrial system and advancing digital China. However, academic research on the relationship between AI and the low-altitude economy remains limited. Existing studies primarily focus on industrial chain development, regulatory frameworks, and their connection to new productive forces (Yao et al., 2024; Guo, 2019), or on AI's effects on industrial upgrading and economic growth (Zheng, 2024; Gan et al., 2023). Yet, few have examined how AI empowers the low-altitude economy through technological innovation pathways and mediating mechanisms such as industrial structural transformation. Particularly in China—where institutional environments and regional disparities are pronounced—variations in AI development, industrial transformation speed, and spatial distribution of low-altitude activities provide unique theoretical and practical contexts for empirical inquiry.

Using panel data for 30 Chinese provinces from 2012 to 2023, this study constructs a two-way fixed effects model to systematically investigate the impact of AI on the development of the low-altitude economy from three perspectives: overall effect, mechanism effect, and heterogeneity characteristics. The empirical results show that: 1) AI significantly promotes the development of the low-altitude economy, and the conclusion remains robust after controlling for various economic and structural factors. Specifically, a one-unit increase in AI level raises the low-altitude economy index by approximately 0.042 units, suggesting that AI effectively empowers this emerging economy through resource optimization, operational efficiency, and scenario expansion. 2) Mechanism analysis indicates that AI promotes the low-altitude economy mainly through improving digital infrastructure and enhancing R&D investment. Internet penetration plays a significant positive moderating role, confirming the “amplifier effect” of digital infrastructure; R&D input strengthens AI's enabling impact by enhancing innovation capacity and technology commercialization. 3) Heterogeneity analysis reveals that the enabling effect of AI is more prominent in coastal provinces, implying that economic foundation, absorptive capacity, and openness amplify AI's impact. Temporally, the effect was stronger during 2012-2016, highlighting the role of market-driven and innovation-led mechanisms before formal policy interventions.

This paper contributes to the literature in three main ways. First, it extends the theoretical perspective on AI's role in enabling the low-altitude economy. Prior research has mainly addressed engineering or policy aspects, lacking systematic analysis from the perspective of digitalization, intelligence, and general-purpose technology diffusion. By conceptualizing AI as a core general-purpose technology driving the evolution of the low-altitude economy, this paper constructs a logical framework linking “AI development—digital infrastructure—technological innovation—low-altitude economic growth”, revealing the internal mechanism of AI empowerment and offering new insights into how technology diffusion fosters emerging industries. Second, it enriches empirical evidence on AI's economic ef-

fects and mechanism testing. Unlike studies focusing solely on macroeconomic growth or industrial upgrading, this research centers on the low-altitude economy, identifying two specific mediating pathways—digital infrastructure and innovation investment—and empirically validating their regional and temporal heterogeneity. Third, it deepens the policy understanding of how digital technologies drive new productive forces. The results show that AI's enabling effect on the low-altitude economy manifests not only as efficiency improvement but also as structural and institutional spillovers. These findings provide quantitative evidence for policymaking in airspace governance, digital infrastructure development, and AI industry deployment, offering practical implications for building an intelligent low-altitude industrial system and accelerating the cultivation of new productive forces.

2. Literature Review and Hypothesis Development

In the ongoing wave of technological revolution and industrial transformation, Artificial Intelligence (AI), as a general-purpose technology, has become a crucial driving force of global economic growth and industrial upgrading (David & Wright, 1999). The defining characteristics of GPTs—broad cross-industry applicability, persistent knowledge spillovers, and strong diffusion capacity—enable AI to continuously stimulate the economic system by optimizing factor allocation, enhancing technological innovation, and reshaping industrial structures (Zheng, 2024). Existing research shows that the deep integration of AI with emerging digital technologies such as the Internet of Things (IoT), big data, and cloud computing significantly improves operational resilience and resource allocation efficiency in industrial production (Shen & Zhang, 2024). Moreover, AI enhances firms' productivity and economic growth by alleviating financing constraints, strengthening innovation capability, and optimizing market decision-making processes. As a key technological engine for the formation of new productive forces, AI is rapidly penetrating emerging domains including transportation, energy, manufacturing, finance, and, more recently, the low-altitude economy, thereby serving as a catalyst for scientific and industrial transformation.

Within the field of the low-altitude economy, AI's empowering role is particularly pronounced (Zhang & Huang, 2024). The development of the low-altitude economy results from the joint action of multiple elements—airspace, equipment, scenarios, technology, and policy—among which digitalization and intelligence are the core conditions for achieving high-quality and sustainable growth. With its advanced capabilities in perception, decision-making, deep learning, and autonomous control, AI provides essential technical support for low-altitude economic operations. For example, AI algorithms significantly enhance UAVs' autonomous flight, path planning, and obstacle avoidance performance, strengthening the refined scheduling of airspace resources and the coordinated operation of multiple UAVs. At the same time, AI applications in image recognition, semantic analysis, and edge computing enable the intelligent optimization of communication and navigation systems, improving operational safety and systemic efficiency.

From a theoretical perspective, AI empowers the low-altitude economy through multiple mechanisms. First, the application and diffusion of AI promote the development of digital infrastructure such as information and communication systems, cloud computing platforms, and data-sharing networks, thereby reinforcing the technological foundation necessary for low-altitude economic activities. Digital infrastructure not only serves as a prerequisite for AI deployment but also acts as an “amplifier” of its enabling effects. As connectivity, data transmission, and intelligent scheduling capabilities improve, the efficiency of data collection, airspace management, and task allocation in low-altitude activities increases significantly (Zheng, 2024). Such upgrades enhance resource allocation efficiency and provide a solid foundation for intelligent airspace management and the construction of Unmanned Traffic Management (UTM) systems.

Second, AI stimulates R&D investment and innovation output, strengthening the technological supply capacity and industrial upgrading potential of the low-altitude economy. The widespread adoption of AI reshapes innovation resource allocation and enhances R&D efficiency, enabling enterprises to accelerate their transformation from “manufacturing-driven” to “innovation-driven” development models (Yao et al., 2024). In the context of the low-altitude economy, this mechanism manifests in the iterative upgrading of key components—such as navigation chips, intelligent sensors, and power systems—as well as the innovation and diffusion of new service models like low-altitude logistics, emergency response, and aerial tourism. Increased R&D investment not only enhances firms’ independent innovation capabilities but also strengthens the empowering effect of AI through technology commercialization and spillover effects.

From an industrial ecosystem perspective, AI forms a positive feedback cycle of “technological empowerment-value creation-reinforcement”. Through data-driven processes, knowledge sharing, and intelligent collaboration, AI enables dynamic coordination among multiple stakeholders—UAV manufacturers, service operators, infrastructure providers, financial institutions, and regulatory bodies (Zhuang, 2024). This multi-layered and platform-based innovation ecosystem facilitates optimal resource allocation and institutional innovation, driving the transformation of the low-altitude economy from policy-driven growth to technology-driven development. Accordingly, the following hypothesis is proposed:

H1: The development of artificial intelligence has a significant positive impact on the growth of the low-altitude economy.

3. Research Design

3.1. Sample and Data Sources

This study employs provincial panel data from 30 provincial-level administrative regions in China spanning the years 2012–2023. Due to data incompleteness and discontinuity, Tibet, Hong Kong SAR, Macao SAR, and Taiwan region are excluded, resulting in a total of 360 observations. The data sources include the International Federation of Robotics (IFR) for industrial robot installation statistics by industry,

the official website of the National Bureau of Statistics, and databases such as Wind and Qichacha. To address occasional missing observations, the interpolation method was employed to ensure data continuity and reliability. All continuous variables were winsorized at the 1st and 99th percentiles to mitigate the influence of outliers.

3.2. Variable Definition

• Dependent Variable

The dependent variable in this study is the level of low-altitude economic development across provinces. The report constructs a comprehensive index of low-altitude economic development from five dimensions: innovation efficiency, industrial strength, scenario vitality, development potential, and supporting capability, covering three hierarchical levels and 64 specific indicators. However, several indicators within these dimensions—particularly those related to innovation efficiency and development potential—exhibit substantial data unavailability at the provincial level for the full 2012-2023 period. Following [Shen and Zhang \(2024\)](#), this paper therefore adopts an alternative evaluation framework comprising three dimensions—government, market, and industry—which capture the institutional, commercial, and technological facets of low-altitude economic development using consistently available provincial data. The specific indicators constituting this framework are detailed in [Table 1](#). The government dimension reflects policy commitment and infrastructure readiness; the market dimension captures the breadth and depth of industrial chain participation; and the industry dimension measures firm-level technological capacity and specialization. This tripartite framework aligns conceptually with the original report’s emphasis on supporting capability (government), industrial strength (market), and innovation efficiency (industry), while ensuring empirical feasibility across all provinces and years. Provincial development levels are then measured using the entropy-weight method.

Table 1. The evaluation indicator system for the low-altitude economy.

Primary Indicator	Indicator Description
Government	Number of certified airports
	Number of relevant policy documents issued
	Number of pilot programs launched
Market	Number of upstream enterprises in the low-altitude industrial chain
	Number of midstream enterprises in the low-altitude industrial chain
	Number of downstream enterprises in the low-altitude industrial chain
Industry	Number of enterprises engaged in UAV-related businesses
	Number of enterprises with UAV-related patents
	Number of “Specialized, Refined, Distinctive, and Innovative” (SRDI) enterprises in UAV-related businesses
	Number of SRDI enterprises with UAV-related patents
	Number of high-tech enterprises engaged in UAV-related businesses
	Number of high-tech enterprises with UAV-related patents

• Independent Variable

Industrial robots are widely recognized as a concrete manifestation of AI applications and have been extensively used in related empirical studies. Accordingly, this study measures AI development at the provincial level by industrial robot density (IFR). Following the approach of Lu and Zhu (2021), the indicator is calculated using IFR industry data as shown in Equation (1):

$$Rob_{it} = \sum_{j=1}^J \frac{L_{ijt}}{L_{it}} \times \frac{Rob_{jt}}{L_{jt}} \quad (1)$$

where L_{ijt} denotes the employment in industry j of province i in year t , L_{it} denotes the total employment in province i in year t , Rob_{it} is the total stock of industrial robots in industry j , and L_{jt} is the national employment in industry j . The summation across industries yields the overall industrial robot density of province i , representing its AI development level.

• Control Variable

To control potential confounding factors influencing the development of the low-altitude economy, this study incorporates variables reflecting economic development, fiscal policy, market demand, openness, and industrial structure. The definitions, descriptions, and data sources of these control variables are summarized in Table 2. To address endogeneity concerns, all control variables are lagged by one period.

Table 2. Variable definitions and descriptions.

Symbol	Variable Name	Definitions
<i>LAE</i>	Low-altitude economy	Computed using the entropy-weight method, following Shen and Zhang (2024)
<i>AI</i>	Artificial intelligence	Measured by industrial robot density, following Lu and Zhu (2021)
<i>L1_pay</i>	Fiscal expenditure	Logarithm of the lagged provincial general public budget expenditures
<i>L1_inout</i>	Local Openness	Logarithm of the lagged provincial import and output amounts
<i>L1_cust</i>	Consumption capacity	Logarithm of the lagged provincial per capita household consumption
<i>L1_urban</i>	Urbanization rate	The lagged provincial urbanization ratio
<i>L1_per_gdp</i>	Economic development	The provincial lagged per capita GDP
<i>L1_inds</i>	Industrial structure	Lagged industrial structure index
<i>L1_trade</i>	Trade dependence	Lagged ratio of foreign trade to GDP

3.3. Models

To empirically examine whether AI development promotes the low-altitude economy, a two-way fixed effects model is constructed to identify the causal relationship between the two variables. The model is specified as shown in Equation (2):

$$LAE_{i,t} = \beta_0 + \beta_1 AI_{i,t} + \beta_2 \sum Controls_{i,t-1} + Province_i + Year_t + \varepsilon_{i,t} \quad (2)$$

where $LAE_{i,t}$ denotes the low-attitude economy for province i in year t , $AI_{i,t}$ denotes the AI development for province i in year t . β_0 is the constant. $Controls_{i,t-1}$ is a vector of lagged control variables. $Province_i$ and $Year_t$ capture province and year fixed

effects, respectively.

4. Empirical Results

4.1. Descriptive Statistics

Table 3 reports the descriptive statistics of all major variables. The mean value of the Low-Altitude Economy index (LAE) is 0.078, with a standard deviation of 0.098, indicating that China's low-altitude economy is still in its early stage of development and exhibits substantial regional variation. The minimum value is 0.001 and the maximum is 0.584, suggesting pronounced heterogeneity across provinces. The median (0.045), being lower than the mean, implies a right-skewed distribution—most provinces remain at relatively low development levels, while a few are more advanced. The mean value of AI development (AI) is 8.756, with a standard deviation of 1.502, reflecting considerable interprovincial differences in AI adoption. The 25th and 75th percentiles are 7.805 and 9.888, respectively, indicating that while AI development is relatively balanced across regions, a clear gradient persists. The range (5.028 - 12.033) further supports the uneven landscape of AI technological diffusion.

Table 3. Descriptive statistics of main variables.

Variable	N	Mean	SD	Min	p25	p50	p75	Max
<i>LAE</i>	360	0.078	0.098	0.001	0.020	0.045	0.098	0.584
<i>AI</i>	360	8.756	1.502	5.028	7.805	8.840	9.888	12.033
<i>L1_pay</i>	360	8.436	0.594	6.815	8.108	8.483	8.825	9.758
<i>L1_inout</i>	360	8.122	1.582	3.762	7.176	8.082	9.013	11.179
<i>L1_cust</i>	360	10.069	0.604	9.023	9.592	10.054	10.366	11.291
<i>L1_urban</i>	360	0.596	0.122	0.350	0.514	0.584	0.653	0.893
<i>L1_per_gdp</i>	360	10.869	0.457	9.936	10.529	10.832	11.152	12.075
<i>L1_inds</i>	360	1.352	0.734	0.638	0.980	1.201	1.395	5.022
<i>L1_trade</i>	360	0.271	0.277	0.013	0.095	0.146	0.345	1.294

4.2. Baseline Regression Results

Table 4 presents the baseline regression results assessing the impact of AI development on the low-altitude economy. Column (1) reports results including only the core explanatory variable, while Column (2) incorporates all control variables. The coefficient of AI is significantly positive at the 1% level in both models (0.043 and 0.042, respectively), indicating that AI development exerts a significant promoting effect on the low-altitude economy. After including the control variables, the coefficient remains robust, confirming the stability of the relationship. Specifically, a one-unit increase in AI level leads to an average rise of about 0.042 units in the low-altitude economy index, suggesting that AI effectively empowers the sector through improved efficiency, optimized resource allocation, and expanded

application scenarios.

Table 4. Baseline regression results.

	(1)	(2)
	<i>LAE</i>	
<i>AI</i>	0.043*** (3.412)	0.042*** (3.331)
<i>L1_pay</i>		-0.065* (-1.747)
<i>L1_inout</i>		-0.030** (-2.145)
<i>L1_cust</i>		0.049*** (2.833)
<i>L1_urban</i>		-0.010 (-0.149)
<i>L1_per_gdp</i>		0.044 (0.752)
<i>L1_inds</i>		0.005 (0.260)
<i>L1_trade</i>		0.120** (2.235)
Constant	-0.264*** (-2.876)	-0.474 (-0.854)
Observations	360	360
R-squared	0.371	0.431
Number of prov	30	30
Province FE	Yes	Yes
Year FE	Yes	Yes

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

4.3. Mechanism Analysis: Moderation and Amplification Effects

To further explore the channels through which AI affects the low-altitude economy, this study examines the roles of digital infrastructure and technological innovation investment as moderating factors that amplify AI's enabling effect. Following recent methodological guidance on distinguishing mediation from moderation, the analysis proceeds in two steps for each mechanism. First, the direct effect of AI on the proposed moderator is tested to establish a plausible pathway. Second, an interaction term between the moderator and AI is included to assess whether the moderator amplifies AI's impact on the low-altitude economy. A significant interaction effect indicates a moderation relationship, wherein the strength of AI's influence varies with the level of the moderator.

- **Digital Infrastructure Mechanism**

Columns (1) and (2) of **Table 5** report the results using Internet penetration (*Inter*) as the moderating variable. Column (1) demonstrates that AI has a significant positive effect on Internet penetration (coefficient = 0.021, $p < 0.01$), suggesting that AI development is associated with improvements in the digital infrastructure environment. Column (2) shows that the interaction term $Inter \times AI$ is significantly positive (coefficient = 0.048, $p < 0.01$). This result provides direct evidence of a moderation effect: Internet penetration amplifies AI's positive impact on the low-altitude economy. Rather than serving as a simple transmission channel (mediation), digital infrastructure operates as an enabling condition that determines the magnitude of AI's effectiveness. In regions with higher Internet penetration, the marginal effect of AI on the low-altitude economy is substantially larger, confirming the "amplifier effect" hypothesis.

- **Technological Innovation Mechanism**

Columns (3) and (4) of **Table 5** examine the moderating role of R&D expenditure (*RD*). Column (3) shows that AI significantly promotes R&D investment (coefficient = 0.105, $p < 0.01$), indicating a positive association between AI development and innovation activities. In Column (4), the interaction term $RD \times AI$ is positive and significant (coefficient = 0.002, $p < 0.01$). This suggests that R&D investment moderates AI's effect on the low-altitude economy: provinces with higher innovation intensity experience stronger enabling effects from AI. While these results are consistent with the theoretical expectation that innovation capacity enhances technology commercialization, the empirical design tests moderation rather than formal mediation. A full mediation analysis would require additional steps, including testing whether the direct effect of AI diminishes when the mediator is included—a condition not met in the current specification.

Table 5. Mechanism analysis results.

	(1)	(2)	(3)	(4)
	Digital Infrastructure Mechanism		Technological Innovation Mechanism	
	<i>Inter</i>	<i>LAE</i>	<i>RD</i>	<i>LAE</i>
<i>AI</i>	0.021*** (3.176)		0.105*** (2.915)	
<i>InterxAI</i>		0.048*** (4.735)		
<i>RDxAI</i>				0.002*** (2.632)
<i>LI_pay</i>	-0.010 (-0.514)	-0.072** (-1.985)	0.611*** (5.773)	-0.077** (-2.008)
<i>LI_inout</i>	-0.026*** (-3.608)	-0.036** (-2.577)	0.104*** (2.602)	-0.035** (-2.454)

Continued

<i>L1_cust</i>	0.017* (1.912)	0.056*** (3.259)	0.006 (0.113)	0.053*** (3.010)
<i>L1_urban</i>	0.010 (0.272)	0.012 (0.176)	0.318* (1.666)	-0.012 (-0.182)
<i>L1_per_gdp</i>	0.132*** (4.274)	0.019 (0.320)	1.490*** (8.873)	0.030 (0.510)
<i>L1_inde</i>	0.021* (1.910)	0.001 (0.054)	-0.178*** (-3.014)	0.007 (0.342)
<i>L1_trade</i>	0.125*** (4.447)	0.109** (2.079)	0.036 (0.235)	0.137** (2.555)
Constant	-1.346*** (-4.625)	0.093 (0.171)	-8.012*** (-5.052)	-0.101 (-0.182)
Observations	360	360	360	360
R-squared	0.963	0.451	0.887	0.424
Number of prov	30	30	30	30
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

4.4. Heterogeneity Tests

• Regional Heterogeneity

To investigate whether the enabling effect of AI on the low-altitude economy varies across regions, this study conducts a heterogeneity analysis by dividing the sample into coastal and inland provinces, following the classification standards of the National Bureau of Statistics. Coastal provinces include Liaoning, Hebei, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Guangxi, and Hainan, which are characterized by higher levels of economic development, openness, and industrial capacity. The remaining 19 provinces are categorized as inland regions. The results in **Table 6** show that AI significantly promotes the development of the low-altitude economy in both regions, but the magnitude of the effect differs notably. In coastal provinces (Column (1)), the coefficient of AI is 0.206 and statistically significant at the 10% level, indicating that the marginal effect of AI is stronger in economically advanced and open regions. This may be attributed to several factors: 1) robust industrial and technological foundations providing favorable conditions for AI integration; 2) high openness facilitating the absorption of global frontier technologies; and 3) agglomeration of innovation resources enhancing technology transfer and diffusion. In inland provinces (Column (2)), the AI coefficient is smaller (0.033) but significant at the 5% level, implying that the effect is more stable, though weaker in magnitude. This suggests that, despite lim-

ited infrastructure, the adoption of AI technologies in inland regions yields concentrated marginal benefits due to the urgent demand for industrial transformation and technological upgrading.

- **Temporal Heterogeneity**

In March 2016, the 13th Five-Year Plan for National Economic and Social Development of the People’s Republic of China explicitly emphasized “optimizing the modern industrial system”, providing new policy support for the low-altitude economy. To capture potential temporal differences, this study divides the sample period into two sub-periods: 2012-2016 and 2017-2023. As shown in Columns (3) and (4) of **Table 6**, during 2012-2016 (Column (3)), the coefficient of AI is 0.156 and highly significant at the 1% level, suggesting that before the introduction of specific policy frameworks, AI had already played a strong promotional role in the low-altitude economy, mainly driven by market forces and technological innovation. In contrast, during 2017-2023 (Column (4)), the coefficient of AI decreases to 0.007 and becomes statistically insignificant. Several non-mutually exclusive explanations may account for this temporal pattern. First, diminishing marginal returns may emerge as the low-altitude economy matures: early AI adoption yields substantial efficiency gains in nascent markets, but incremental investments produce smaller marginal effects once baseline capabilities are established. Second, a structural shift from technology-driven to policy- and governance-driven growth may reduce the relative importance of AI inputs; as regulatory frameworks, airspace management systems, and industry standards become binding constraints, the developmental trajectory becomes more contingent on institutional factors than on continued AI advancement. Third, the AI proxy used in this study—industrial robot density—may be less effective at capturing more mature and diversified AI applications that emerged after 2016, such as machine learning in logistics optimization, computer vision for inspection, or natural language processing for customer service. These newer AI applications are not reflected in manufacturing-focused robot installation data. Fourth, the 2017 policy shift may have redirected AI investment toward sectors explicitly prioritized in the 13th Five-Year Plan, potentially diverting resources away from low-altitude applications in the short term. Future research should investigate these alternative mechanisms using more granular AI adoption measures and longer post-policy observation windows.

Table 6. Heterogeneity analysis results.

	(1)	(2)	(3)	(4)
	coastal_group	inland_group	period1	period2
	<i>LAE</i>			
<i>AI</i>	0.206*	0.033**	0.156***	0.007
	(1.933)	(2.470)	(3.827)	(0.336)

Continued

<i>L1_pay</i>	-0.090 (-0.930)	-0.030 (-0.608)	0.072 (1.282)	-0.229*** (-3.044)
<i>L1_inout</i>	0.010 (0.171)	-0.045*** (-3.452)	-0.017 (-0.549)	-0.078*** (-2.869)
<i>L1_cust</i>	0.066** (2.267)	0.020 (0.735)	0.097 (0.644)	0.076*** (3.171)
<i>L1_urban</i>	0.037 (0.389)	-0.289 (-0.987)	-1.347*** (-3.254)	0.026 (0.223)
<i>L1_per_gdp</i>	0.042 (0.256)	0.042 (0.656)	-0.140 (-1.277)	0.338** (2.062)
<i>L1_inds</i>	0.149* (1.856)	-0.031 (-1.296)	-0.162** (-2.506)	-0.011 (-0.165)
<i>L1_trade</i>	0.269 (0.960)	0.210*** (3.607)	-0.044 (-0.345)	0.634 (1.395)
Constant	-2.354 (-1.136)	-0.113 (-0.255)	-0.083 (-0.061)	-1.952 (-1.230)
Observations	132	228	150	210
R-squared	0.554	0.511	0.558	0.527
Number of prov	11	19	30	30
Province FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

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

4.5. Robustness Tests

To ensure the reliability of the baseline regression results, robustness checks are conducted from three perspectives: omitted variables, sample selection, and estimation methods. The results are reported in **Table 7**. First, Column (1) adds the number of authorized domestic patent applications (patent) as an additional control variable to mitigate potential bias from omitted innovation factors. After inclusion, the AI coefficient remains positive and significant at the 1% level (0.040), confirming robustness. Second, Column (2) excludes four municipalities (Beijing, Shanghai, Tianjin, and Chongqing) to account for their unique economic and policy environments. After exclusion, the AI coefficient increases to 0.081 and remains highly significant, suggesting that the results are not driven by these outliers. Third, Column (3) re-estimates the model using robust standard errors to address potential heteroskedasticity. The AI coefficient (0.042) remains significant at the 5% level, consistent with the baseline findings.

Table 7. Robustness test results.

	(1)	(2)	(3)
	<i>LAE</i>		
<i>AI</i>	0.040*** (3.202)	0.081*** (4.125)	0.042** (2.490)
<i>patent</i>	-0.024* (-1.819)		
<i>L1_pay</i>	-0.055 (-1.490)	-0.009 (-0.207)	-0.065 (-1.531)
<i>L1_inout</i>	-0.035** (-2.462)	-0.037** (-2.473)	-0.030** (-2.617)
<i>L1_cust</i>	0.051*** (2.935)	0.101*** (4.523)	0.049* (1.877)
<i>L1_urban</i>	-0.011 (-0.167)	0.119 (1.274)	-0.010 (-0.094)
<i>L1_per_gdp</i>	0.053 (0.899)	-0.022 (-0.352)	0.044 (0.746)
<i>L1_inds</i>	0.001 (0.044)	-0.017 (-0.714)	0.005 (0.181)
<i>L1_trade</i>	0.136** (2.520)	0.161** (2.083)	0.120 (1.267)
Constant	-0.375 (-0.675)	-0.980* (-1.672)	-0.474 (-0.690)
Observations	360	312	360
R-squared	0.437	0.465	0.431
Number of prov	30	26	30
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

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

5. Conclusion

Based on panel data from 30 Chinese provinces between 2012 and 2023, this study empirically examines the enabling effects of Artificial Intelligence (AI) on the development of the Low-Altitude Economy (LAE) and explores its underlying mechanisms. The main findings are as follows: 1) AI significantly promotes the development of the low-altitude economy. This conclusion remains robust after controlling for innovation capacity, excluding municipalities, and applying robust standard errors, confirming the stability of the results. 2) Digital infrastructure and technological innovation serve as key mediating mechanisms. AI drives the low-altitude

economy by enhancing digital infrastructure—such as network connectivity and information transmission—and by stimulating R&D investment that strengthens innovation capability and technology commercialization. 3) Significant regional and temporal heterogeneity exists in AI's enabling effect. The effect is stronger in coastal provinces with higher economic development, openness, and absorptive capacity, and is more pronounced during the early market-driven stage (2012-2016) than in the later policy-driven stage (2017-2023).

Building on these findings, the following policy implications are proposed: 1) Accelerate the construction of intelligent digital infrastructure. Governments should strengthen the integration of air-ground networks and low-altitude communication systems to provide a technological foundation for AI-driven applications in the low-altitude economy. 2) Enhance R&D investment and innovation incentives. Firms should be encouraged to engage in joint research on AI and low-altitude applications, promoting technology transfer and commercialization of scientific achievements. 3) Optimize regional coordination and industrial layout through concrete institutional mechanisms. Policymakers should establish inter-provincial data-sharing protocols for Unmanned Traffic Management (UTM) systems to enable seamless cross-regional operations of low-altitude aircraft. Coastal provinces with advanced AI capabilities—such as Guangdong, Jiangsu, and Zhejiang—could serve as technology transfer hubs, with dedicated programs to license AI-driven flight control algorithms, intelligent scheduling software, and predictive maintenance systems to inland counterparts at preferential rates. Provincial governments should consider joint venture frameworks that pair coastal UAV manufacturers with inland logistics operators, combining technological expertise with market access. Additionally, the establishment of regional low-altitude economy demonstration zones spanning coastal-inland boundaries would facilitate knowledge spillovers and standardize regulatory approaches across jurisdictions.

It should be acknowledged that industrial robot density, while a widely used and validated proxy for AI development in the empirical literature, primarily captures AI applications in manufacturing and industrial automation. This measure may not fully represent AI's role in the service-oriented and knowledge-intensive aspects of the low-altitude economy, such as intelligent airspace management, real-time route optimization, and AI-driven communication systems. Future research could complement this measure with indicators of AI adoption in service sectors, such as the deployment of machine learning algorithms in logistics platforms or the penetration of autonomous navigation systems in commercial UAV operations, pending data availability.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

AINvest (2025). *Joby Aviation: Scaling Manufacturing for Dominance in Urban Air Mo-*

bility.

<https://www.ainvest.com/news/job-aviation-scaling-manufacturing-pathway-dominance-urban-air-mobility-2511/>

David, P. A., & Wright, G. (1999). *General Purpose Technologies and Productivity Surges: Historical Reflections on the Future of the ICT Revolution*. Oxford University Economic & Social History Review.

Gan, J., Liu, L., Qiao, G., & Zhang, Q. (2023). The Role of Robot Adoption in Green Innovation: Evidence from China. *Economic Modelling*, 119, Article ID: 106128. <https://doi.org/10.1016/j.econmod.2022.106128>

Guo, K. (2019). Artificial Intelligence Development, Industrial Structural Transformation, and Changes in Labor Income Share. *Management World*, 35, 60-77, 202-203. <https://doi.org/10.19744/j.cnki.11-1235/f.2019.0092>

Lu, T., & Zhu, Z. (2021). Does Artificial Intelligence Reduce the Labor Income Share? Evidence from Fixed Effects and Panel Quantile Models. *Journal of Shanxi University of Finance and Economics*, 43, 29-41.

Shen, Y., & Zhang, H. (2024). The Impact of Digital Infrastructure Construction on the High-Quality Development of the Low-Altitude Economy. *Journal of Beijing University of Aeronautics and Astronautics (Social Sciences Edition)*, 37, 96-108.

Yao, J., Zhang, K., Guo, L., Chen, S., Liu, X., Wang, Y., & Li, J. (2024). How Does Artificial Intelligence Improve Enterprise Productivity? Evidence from Labor Skill Structure Adjustment. *Management World*, 40, 101-116, 133, 117-122. <https://doi.org/10.19744/j.cnki.11-1235/f.2024.0018>

Zhang, X., & Huang, W. (2024). Global Trends, Current Situation, and Promotion Strategies for the Development of the Low-Altitude Economy in China. *Economic Review*, No. 8, 53-62.

Zheng, X. (2024). How Does a Firm's Digital Business Strategy Affect Its Innovation Performance? An Investigation Based on Knowledge-Based Dynamic Capability. *Journal of Knowledge Management*, 28, 2324-2356. <https://doi.org/10.1108/jkm-05-2023-0410>

Zhuang, Z. (2024). Artificial Intelligence Empowering the Low-Altitude Economy: Application Scenarios and Future Directions. *People's Forum (Academic Frontier)*, No. 15, 38-44. <https://doi.org/10.16619/j.cnki.rmltxsqy.2024.15.003>