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Can the Low-Altitude Economy Drive Synergistic Development of Carbon Reduction, Pollution Mitigation, Green Transition, and Economic Growth? Empirical Evidence from China

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Abstract

As an emerging technology-intensive industry, the low-altitude economy (hereafter LAE) has attracted growing attention for its potential contribution to sustainable development. However, little is known about whether its expansion can simultaneously promote environmental improvement and economic growth. Using panel data from 30 Chinese provinces from 2012 to 2023, this study examines the relationship between the LAE and the synergistic development of carbon reduction, pollution mitigation, green transition, and economic growth (hereafter CPGE). Green technological innovation (hereafter GT) is incorporated as a mediating variable, while artificial intelligence (hereafter AI) is introduced as both a moderating and a threshold variable to explore the underlying mechanisms and nonlinear effects. The results show that the LAE is significantly and positively associated with CPGE. GT exhibits a significant negative mediating effect, suggesting that the benefits of green innovation may not yet have been fully translated into coordinated green development outcomes during the sample period. AI not only strengthens the positive association between the LAE and CPGE but also exhibits a significant threshold effect. The contribution of the LAE becomes substantially stronger once AI development surpasses a critical level, highlighting the important role of digital intelligence in amplifying the environmental benefits of emerging industries. In addition, the impact of the LAE displays pronounced regional heterogeneity, with stronger effects observed in non-resource-based and non-central regions. This study contributes to the literature by revealing that the environmental effects of the LAE depend not only on innovation channels but also on the level of digital intelligence development. AI serves as a critical enabling condition for translating the growth potential of the LAE into coordinated green development. By revealing the mediating role of GT and the moderating and threshold effects of AI, this study provides new evidence on how emerging industries contribute to sustainable development. The findings underscore the importance of aligning LAE development with AI-driven digital transformation to advance sustainable regional development.

Keywords: low-altitude economy; synergistic development of carbon reduction, pollution mitigation, green transition, and economic growth; green technological innovation; AI; threshold effect

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1. Introduction

Increasing carbon emissions and pollutant discharges have intensified global environmental challenges, including climate change, ecosystem degradation, and ecological pollution. Promoting low-carbon transformation and achieving long-term sustainable development have therefore become important tasks for countries worldwide. In response to these challenges, the United Nations released the report Synergy Solutions for a World in Crisis: Tackling Climate and SDG Action Together [1]. The report highlights the need to coordinate climate action with sustainable development objectives in order to simultaneously improve environmental quality and socioeconomic well-being. Under these circumstances, maintaining harmony between ecological conservation and economic development is increasingly regarded as an essential pathway toward sustainable and resilient growth.

Since the implementation of the reform and opening-up policy, China's economy has experienced sustained growth. Nevertheless, the development pattern relying heavily on resource consumption and pollutant emissions has imposed considerable pressure on the environment. As economic expansion and ecological conservation become increasingly difficult to reconcile, the traditional growth model emphasizing output expansion at the expense of environmental protection has become less viable [2]. To address these challenges, the Report to the 20th National Congress of the Communist Party of China introduced the concept of coordinated carbon reduction, pollution mitigation, green transition, and economic growth (CPGE), providing policy guidance for advancing China's green and high-quality development agenda [3].

CPGE can be understood as a comprehensive governance approach that integrates environmental protection with sustainable economic development. Instead of pursuing environmental improvement or economic growth separately, it stresses the coordinated progress of carbon reduction, pollution mitigation, green transition, and economic growth. Although CPGE has received increasing attention in recent years, empirical studies examining how these four dimensions can be advanced simultaneously are still insufficient. Investigating the determinants of CPGE is therefore important for supporting China's carbon neutrality objectives and ecological civilization construction, and may also offer useful references for developing economies facing comparable environmental and development pressures.

Against this context, the LAE has gradually evolved into a new economic activity system based on low-altitude airspace utilization and enabled by digital technologies, high-end manufacturing, and producer services. The continuous development of unmanned aerial vehicles, aerial logistics, intelligent inspection systems, and remote sensing applications has expanded the application scope of the LAE to logistics transportation [4], ecological monitoring [5], agricultural protection [6], cultural tourism, and emergency rescue. These application scenarios exhibit strong industrial spillover effects and considerable green development potential [7].

The LAE is characterized by electrification, intelligent operation, and three-dimensional spatial utilization [7,8]. These technological characteristics may improve resource allocation efficiency, optimize transportation structures, and alleviate environmental pollution. Moreover, intelligent monitoring systems and low-altitude sensing technologies can strengthen ecological governance and enhance environmental supervision capabilities. Consequently, the development orientation of the LAE is broadly consistent with the objectives of CPGE. However, the environmental implications of the LAE are not unequivocally positive. While UAVs and eVTOL technologies have the potential to improve transportation efficiency and reduce operational emissions, their environmental benefits should be evaluated from a broader lifecycle perspective. The production of aircraft, batteries, and supporting infrastructure requires substantial material and energy inputs, which may generate considerable

carbon emissions and ecological footprints. In addition, the expansion of low-altitude transportation networks may stimulate new demand for air mobility services, giving rise to rebound effects whereby efficiency gains are partially offset by increased utilization. Potential environmental costs may also arise from noise pollution, biodiversity disturbance, and land-use changes associated with low-altitude infrastructure development. Therefore, the LAE may simultaneously generate green enabling effects and environmental burdens. Whether its overall impact contributes to long-term coordinated green development ultimately depends on the balance between these opposing forces. This theoretical ambiguity highlights the necessity of rigorous empirical investigation into the relationship between the LAE and CPGE.

Existing studies on the LAE mainly focus on technological development, application scenarios, and industrial expansion. Previous studies have shown that low-altitude flight technologies possess broad application value in smart logistics, environmental monitoring, urban governance, and emergency delivery services [8,9]. In addition, the development of the LAE may also affect social equity and regional coordinated development [10]. Regarding environmental performance, ref. [6] quantified the carbon emission characteristics of drones using a lifecycle assessment approach, while ref. [11] further evaluated the economic and environmental impacts of drone delivery and reported that drones exhibit certain green advantages throughout their lifecycle. Nevertheless, existing studies largely emphasize the technological and industrial value of the LAE [12,13], while insufficient attention has been paid to its environmental synergistic effects from the perspective of coordinated green development.

At the same time, studies on CPGE mainly examine the roles of technological innovation [14], green finance [15], environmental regulation, and industrial policy [16]. Existing evidence generally suggests that industrial upgrading and emerging industries are important drivers of regional green coordinated development. However, systematic research on the environmental effects of the LAE remains relatively limited. More importantly, empirical evidence regarding whether the LAE can simultaneously promote carbon reduction, pollution mitigation, green transition, and economic growth is still insufficient.

It should also be noted that the green effects of the LAE may not follow a simple linear relationship. On the one hand, intelligent operation systems and green technologies may improve resource allocation efficiency and strengthen green transformation capability. On the other hand, large-scale infrastructure investment and industrial expansion related to the LAE may intensify short-term environmental pressure through increased resource consumption and energy demand. In addition, the green dividends generated by technological innovation and intelligent governance may exhibit significant stage-specific and nonlinear characteristics. Therefore, whether the LAE can effectively promote CPGE, through which transmission mechanisms this process operates, and whether heterogeneous or threshold effects exist, still require further investigation.

Based on the existing literature, several research gaps remain. First, previous studies have not incorporated the LAE into a unified analytical framework of CPGE, and systematic empirical evidence regarding its green synergistic effects is still lacking. Second, the transmission mechanism through which the LAE affects CPGE has not been sufficiently explored, especially the mediating role of GT. Third, limited attention has been paid to the empowering role of digital technologies in strengthening the environmental effects of the LAE, while the moderating role of artificial intelligence (AI) remains underexplored. Fourth, most existing studies adopt a linear analytical perspective, whereas insufficient attention has been given to nonlinear characteristics, threshold effects, and regional heterogeneity.

To address the above research gaps, provincial panel data covering 30 Chinese provinces during 2012–2023 are employed to explore the relationship between the LAE

and CPGE. Composite indicators are developed for both systems, and a two-way fixed effects framework is adopted for estimation. GT is incorporated to capture a potential mediating channel, whereas AI is treated as both a moderating factor and a threshold variable. Additional analyses are carried out to examine regional differences and possible nonlinear features of the environmental effects associated with LAE development.

This study contributes to the current literature in three respects. First, it integrates the LAE into the CPGE analytical framework, enriching research on emerging industries and green coordinated development. Second, it identifies the mediating role of GT together with the moderating and threshold effects of AI, providing new evidence on the innovation and digital intelligence mechanisms underlying the environmental impacts of the LAE. Third, it reveals nonlinear characteristics and regional heterogeneity in the relationship between the LAE and CPGE, offering empirical support for differentiated development strategies.

The remainder of this article is structured as follows. Section 2 surveys the existing literature. Section 3 presents the theoretical framework and develops the hypotheses. Section 4 describes the data, variable construction, and empirical specifications. Section 5 reports the estimation results. Section 6 compares the findings with previous studies and discusses their implications. Section 7 summarizes the main conclusions and outlines policy recommendations.

2. Literature Review

2.1. Research on the Coordinated Development of CPGE

The concept of CPGE captures the simultaneous pursuit of declining carbon emissions, reduced pollutant discharges, expanded ecological space, and sustained economic growth. A composite system synergy model has been widely used to measure this multidimensional coordination. Using panel data of 279 Chinese cities from 2009 to 2022, ref. [3] found that urban CPGE generally increased from weak dissynergy to moderate synergy, with notable spatial autocorrelation. The economic subsystem remained positively synergistic throughout the study period, while the environmental subsystem shifted from weak dissynergy to moderate synergy after 2014. Renewable energy policy attention emerged as a significant driver: by displacing fossil fuels, renewables directly lower CO_2 and SO_2 emissions [17]. However, the economic returns of renewable energy are often delayed due to high upfront investment and long payback periods [18]. Spatial spillover effects also matter: CPGE improvements in one region can influence neighboring areas through policy imitation, knowledge diffusion, and shared infrastructure [19]. The effectiveness of renewable energy policies is moderated by local conditions such as resource endowment, industrial structure, city size, and dependence on the energy industry [3]. For example, resource-based cities benefit less from renewable energy policy attention than non-resource-based cities because they are locked into fossil-fuel systems [20]. Cities with a more advanced industrial structure (a higher share of tertiary industry) experience stronger positive effects due to lower energy intensity and greater adaptability [21]. Large cities may see some gains offset by overstretched environmental carrying capacity [22]. Most existing CPGE studies focus on traditional manufacturing and energy sectors, with limited attention to emerging industries such as the LAE. Therefore, whether the LAE can promote CPGE and through what mechanisms it influences green synergistic development remains largely underexplored.

2.2. Research on the LAE

The LAE refers to the exploitation of low-altitude airspace resources using unmanned aerial vehicles (UAVs), communication technologies, and related innovations [7]. It spans multiple sectors, including low-altitude flights, air tourism, regional passenger transport, logistics, and emergency rescue. The electric vertical takeoff and landing (EVTOL) vehicle

is a representative technology; an efficiency index has been developed to evaluate EVTOL designs based on economic viability, convenience, and low-noise emissions [23]. From a technological perspective, integrated sensing and communication (ISAC) is critical for large-scale commercial flight activities, as real-time data exchange between UAVs and ground infrastructure ensures safe and efficient operations [8]. Energy-efficient UAV-aided target-tracking systems based on edge computing have been proposed to reduce energy consumption while maintaining tracking accuracy [24]. Wireless power transfer strategies have also been developed to extend UAV mission endurance without requiring return to base [25].

In environmental monitoring, smart drone systems using recurrent neural networks have been deployed for air-quality monitoring and forecasting, providing high-spatial-resolution pollution data [5]. Urban air mobility (UAM) is a core application; macroscopic fundamental diagrams for low-altitude air-city transport offer a theoretical framework for traffic-flow management, suggesting that UAM can alleviate ground congestion [26]. A lifecycle techno–economic–environmental analysis of UAVs indicates that while UAVs offer operational advantages, their carbon footprint remains a concern unless powered by clean energy [6]. Early industry estimates suggested that the commercial drone market could generate substantial economic impacts. In China, the LAE has developed rapidly, though some researchers have called for more cautious growth, pointing to unresolved technical challenges in management system safety, supporting facilities, and airspace regulation [27]. Empirical evidence from 282 Chinese cities shows that LAE significantly raises total factor productivity but also increases carbon emission intensity, leading to a decline in green total factor productivity—a pattern attributed to the current heavy reliance on fossil fuels [28]. Thus, the net environmental effect of LAE is not uniformly positive and depends on energy sources, infrastructure design, and regulatory frameworks. Recent studies have further emphasized that the environmental implications of the LAE should be evaluated from a lifecycle assessment (LCA) perspective [29]. Beyond operational emissions, the production of aircraft, batteries, and supporting infrastructure may generate substantial environmental burdens [30]. Moreover, efficiency improvements associated with low-altitude transportation may induce rebound effects, whereby increased accessibility and reduced transportation costs stimulate additional demand, partially offsetting environmental gains [31]. Concerns regarding noise pollution, biodiversity disturbance, and land-use changes have also been raised in the literature. These findings suggest that the environmental consequences of the LAE remain complex and context-dependent. Therefore, whether the LAE ultimately promotes the CPGE remains an open empirical question.

Although existing studies have examined the technological and industrial characteristics of the LAE, systematic analyses linking the LAE with CPGE synergistic development remain insufficient. In particular, the environmental consequences of the LAE may exhibit significant conditional and nonlinear characteristics, which deserve further empirical investigation.

2.3. GT and CPGE Research

GT is widely regarded as a key strategy for reducing environmental impact, yet a body of research has documented conditions under which its effects may be limited or even negative. At the firm level, GT often involves high pollution-control costs that crowd out resources for productive activities, thereby depressing overall performance [32]. Because green technologies generate positive externalities—social benefits exceed private returns—firms have weak incentives to invest in genuine R&D, sometimes producing low-quality strategic patents merely to comply with regulations [33]. In China's construction industry, corporate environmental responsibility improves GT, but financing constraints

only mediate strategic, not substantive, innovation, indicating that many green patents are of low quality [34]. China's green credit policy has been found to promote strategic GT among heavy polluters while significantly inhibiting essential green innovation, suggesting an absence of the Porter effect [35]. Resource misallocation induced by such policies can increase financing constraints, reduce R&D investment, and shrink employment. At the regional level, GT can generate vertical collaborative innovation along supply chains, but positive spillovers are often offset by regional competition and technology lock-in, leading to zero-sum outcomes in some areas [36]. Consequently, the environmental benefits of GT are conditional on innovation quality, regional coordination, resource allocation efficiency, and policy design.

These findings imply that GT may not always generate immediate environmental dividends. In the context of the rapid expansion of the LAE, innovation resources may increasingly flow toward aviation-related technologies and digital infrastructure, potentially crowding out substantive GT in the short term. Therefore, GT may serve as a stage-dependent transmission mechanism through which the LAE influences CPGE.

2.4. AI and Green Development Research

AI has been recognized as an important enabler of environmental sustainability, technological progress, and the development of new quality productive forces. In the LAE, AI-driven technologies are central to UAV data acquisition, intelligent control, and autonomous operations. AI algorithms enable real-time perception, path planning, obstacle avoidance, and multi-vehicle coordination, thereby lowering energy consumption and emissions per flight task [7]. Machine learning and computer vision enhance UAVs' ability to monitor carbon emissions, assess renewable energy potential, and trace pollution sources, all of which contribute to low-carbon smart cities [37]. At a broader level, AI is a key driver of new quality productivity; AI-enabled technologies reshape production functions by improving energy efficiency, optimizing resource allocation, and fostering industrial upgrading [38]. In the context of the LAE, technological innovation—in which AI plays a central role—has been identified as a major mechanism for economic growth [28]. Integrating AI with renewable energy systems can accelerate the energy transition and cut carbon emissions; for example, deep learning methods have been used to manage hybrid electric UAV energy efficiently, expanding flight distances while lowering environmental impact [9]. In smart-city contexts, AI-based systems help reduce building energy consumption, optimize traffic flows, and improve waste management, all of which support CPGE [39].

However, the positive environmental effects of AI depend on the availability of clean electricity to power data centers and the adoption of energy-efficient algorithms [40]. Thus, AI's contribution to environmental outcomes is conditional on the energy mix and on the efficiency of the underlying computing infrastructure. As AI technology matures and its diffusion expands, its capacity to reduce carbon intensity and improve resource efficiency tends to increase, often in a nonlinear fashion. Therefore, AI may not only moderate the relationship between the LAE and CPGE but may also act as a threshold condition affecting the environmental performance of the LAE.

2.5. Literature Review Summary

In summary, while renewable energy policies, GT, and AI have been extensively studied in relation to environmental and economic performance, the specific role of the LAE in shaping the synergistic development of CPGE remains largely underexplored. Most existing CPGE research focuses on traditional manufacturing and energy sectors, with limited attention to emerging industries. Furthermore, the environmental effects of

the LAE are not inherently positive or negative; they depend on technological choices, energy sources, and regulatory conditions. GT does not always yield net environmental benefits, as its effectiveness is contingent on innovation quality and policy design. AI offers considerable potential to enhance environmental performance, but that potential is conditional on the energy mix and the stage of technological diffusion.

To further understand the environmental effects of the LAE, this study draws on panel data from 30 Chinese provinces during 2012–2023 and examines its influence on CPGE. The analysis considers the mediating role of GT, the moderating and threshold functions of AI, as well as regional heterogeneity. By doing so, this study provides new evidence on the mechanisms and heterogeneous characteristics through which the LAE facilitates green and high-quality development.

3. Theoretical Analysis

The LAE, characterized by green attributes, technological intensity, and industrial spillover effects, is highly consistent with the development requirements of CPGE. As an emerging strategic industry integrating digital technology, intelligent equipment, and low-carbon transportation systems, the LAE provides new pathways for regional green transformation and sustainable development [41].

A growing body of research has emphasized that innovation activities and industrial upgrading play an important role in promoting regional green development, mainly through improving resource allocation efficiency, reshaping industrial structures, and strengthening technological diffusion [42,43]. The development of the LAE further strengthens this process by facilitating the integration of digital technologies and green production systems. This not only promotes the transformation of traditional production modes but also enhances the coordination between economic development and environmental governance. Regarding pollution mitigation, electric low-altitude transportation systems can partially substitute traditional high-carbon ground transportation [44], thereby reducing pollutant emissions and fossil energy dependence [45]. Meanwhile, the growing adoption of drones, remote sensing technologies, and IoT systems offers new approaches for ecological management. These technologies allow environmental information to be obtained more efficiently and help identify pollution problems at an earlier stage [7]. This process strengthens environmental governance capacity throughout the entire chain from pollution prevention to terminal treatment.

With respect to carbon reduction, the LAE promotes regional low-carbon transition through clean energy application and intelligent carbon monitoring systems [46]. Existing studies have demonstrated that drones and low-altitude sensing technologies are widely used in urban carbon emission estimation, renewable energy assessment, and environmental monitoring [47]. The integration of intelligent sensing technologies and low-altitude application scenarios improves carbon source identification efficiency and enhances regional carbon governance capability.

From the perspective of ecological enhancement, intelligent ecological monitoring and drone-assisted ecological governance can effectively overcome geographical constraints in mountainous and remote areas [48]. This process facilitates ecological restoration, vegetation monitoring, and ecological patrol activities while improving ecosystem governance efficiency and ecological carbon sequestration capacity [49]. In particular, low-altitude intelligent technologies further enhance the precision and dynamic management capability of ecological governance.

Furthermore, the expansion of low-altitude economic activities and the wider use of digital technologies in existing industries may support the formation of new growth opportunities compatible with regional green transformation. The integration of the LAE with

logistics, agriculture [50,51], tourism, and intelligent manufacturing accelerates industrial upgrading and improves resource allocation efficiency through technological spillover and industrial collaboration effects. Meanwhile, the agglomeration of innovation factors and intelligent production systems further enhances regional green total factor productivity and sustainable development capability.

It should be noted that the impact of the LAE on CPGE is not necessarily positive. On the one hand, the LAE may improve transportation efficiency, strengthen environmental monitoring, and facilitate green technological applications, thereby contributing to coordinated green development. On the other hand, aircraft manufacturing, infrastructure construction, battery production, and increased energy demand may generate additional environmental burdens [29,30]. Furthermore, rebound effects may arise if improvements in transportation efficiency stimulate additional demand for low-altitude mobility services [31]. Therefore, the overall impact of the LAE on CPGE depends on the balance between its green enabling effects and potential environmental costs.

Overall, the LAE is expected to promote CPGE through environmental governance enhancement, carbon emission reduction, ecological restoration, industrial upgrading, and factor allocation optimization. Although certain environmental costs may arise during its development, the green enabling effects are likely to outweigh the associated environmental burdens under appropriate technological and institutional conditions. Accordingly. Based on this, we propose the following:

H1. *The development of the LAE significantly promotes regional CPGE.*

GT is widely regarded as an important driving force for green transformation and sustainable development [52,53]. Through cleaner production technologies, green process innovation, and energy efficiency improvement [54], GT facilitates the coordination between economic growth and environmental governance [55,56].

The rapid development of the LAE provides new technological application scenarios and industrial demand support for GT. The integration of intelligent technologies, digital infrastructure, and low-altitude industrial systems accelerates knowledge spillover and technological diffusion processes, thereby improving regional green innovation capability. Meanwhile, industrial collaboration and innovation factor agglomeration generated by the LAE further strengthen the transformation and application of green technologies.

However, the environmental and economic effects of GT may exhibit significant stage-specific characteristics [57,58]. Existing studies have shown that GT is often characterized by long research cycles, uncertain returns, and delayed environmental dividends. During the early stage of LAE expansion, capital, talent, infrastructure, and technological resources are more likely to concentrate within the low-altitude industrial chain. This process may generate a certain crowding-out effect on traditional green technology research and development activities under limited resource constraints.

In addition, the environmental effects of GT may lag behind technological investment and industrial expansion. On the one hand, the development, commercialization, and diffusion of green technologies still require continuous resource and energy inputs [59]. On the other hand, improvements in production efficiency and resource utilization may reduce production costs and stimulate industrial expansion, thereby generating rebound effects that partially offset the environmental benefits of green technologies [60]. As a result, the impact of GT on CPGE may not exhibit a simple linear relationship.

Nevertheless, as the LAE gradually matures, GT can continuously release green dividends through technology diffusion, industrial linkage, and green factor agglomeration effects. New low-altitude application scenarios further facilitate the integration of green technologies and intelligent production systems while strengthening cleaner production

efficiency and ecological governance capability. This process ultimately reinforces the promoting effect of the LAE on CPGE. Based on this, we propose the following:

H2. *GT plays a mediating role in the relationship between the LAE and CPGE.*

AI, as a representative general-purpose technology in the digital economy era, has become an important driving force for industrial transformation and green development [61,62]. Existing studies have shown that AI can significantly improve production efficiency and governance capability through intelligent identification, data analysis, algorithm optimization, and automated decision-making [63]. The integration of AI and industrial systems further strengthens technological collaboration and resource allocation efficiency [64], thereby promoting green transformation and sustainable development [65,66].

The development of AI provides important technical support for the intelligent and green transformation of the LAE [67]. Through intelligent scheduling systems, dynamic route optimization [68], and energy management platforms, AI improves the operational efficiency and energy utilization efficiency of low-altitude transportation systems while reducing pollution emissions and operational costs [69]. This process enhances the green governance capability of the LAE and strengthens its contribution to pollution mitigation and carbon reduction.

Regarding environmental governance, AI-enabled drone systems and intelligent sensing platforms improve the precision and real-time capability of environmental monitoring through data collaboration and dynamic identification technologies [24]. Existing studies have demonstrated that digital intelligent technologies can significantly enhance environmental supervision efficiency and ecological governance performance. The integration of AI and low-altitude application scenarios further strengthens the role of the LAE in pollution mitigation, ecological monitoring, and smart environmental governance [70].

From the perspective of ecological enhancement, AI improves the intelligent perception and dynamic management capability of low-altitude systems in forest monitoring, ecological restoration, and disaster prevention [71]. This process facilitates intelligent ecological patrol, vegetation restoration, and ecological rehabilitation while enhancing ecosystem governance efficiency and ecological resilience. In particular, intelligent technologies strengthen the precision and coordination capability of regional ecological governance systems.

In terms of industrial development, the integration of AI and the LAE accelerates the cultivation of new industrial forms, including smart logistics, intelligent aviation [72], digital tourism, and unmanned services. Meanwhile, AI enhances data collaboration, technological integration, and factor allocation efficiency within the low-altitude industrial chain, thereby improving industrial coordination capability and regional green development efficiency. This process further strengthens the contribution of the LAE to regional high-quality development.

Existing studies have suggested that digital technologies and technological innovation exhibit strong synergistic effects in the process of industrial upgrading and green transformation [73]. Once intelligent technologies become deeply integrated into industrial systems, their empowering effects on resource allocation optimization, technological innovation, and environmental governance become significantly stronger. As a core component of intelligent development, AI can therefore amplify the positive impact of the LAE on CPGE through intelligent governance enhancement, technological empowerment, and digital collaboration effects.

Accordingly, the following hypothesis is proposed:

H3. *AI positively moderates the relationship between the LAE and CPGE.*

The effect of LAE on CPGE could display marked nonlinearity, deviating from a straightforward linear association. Existing studies have shown that the green transformation effects of emerging technologies and industrial upgrading processes are often constrained by digital infrastructure, technological accumulation, and intelligent governance capability. As an important foundation for intelligent development, AI may therefore act as a critical threshold condition affecting the green development effect of the LAE.

In regions where AI technology is less mature, both the digital infrastructure and the capacity for intelligent coordination tend to be underdeveloped. Under such conditions, the LAE still relies heavily on traditional operational models and factor input expansion. Although the LAE can partially improve industrial efficiency and transportation structure, its advantages in intelligent governance, energy management, and environmental monitoring cannot be fully realized. Meanwhile, the rapid expansion of low-altitude infrastructure construction and aviation equipment manufacturing may increase energy consumption and environmental pressure in the short term, thereby weakening its green synergistic effect.

As AI continues to develop, intelligent technologies become more deeply integrated into the operational and governance systems of the LAE. AI can significantly improve operational management efficiency, flight scheduling capability, and environmental governance performance through large-scale data collaboration, intelligent algorithms, and automated decision-making systems [74,75]. This process promotes the intelligent, green, and efficient transformation of the LAE. while strengthening its contribution to pollution mitigation, carbon reduction, and ecological governance [76].

Meanwhile, higher levels of AI development further strengthen technological spillover, industrial collaboration [77], and resource allocation optimization effects [78,79]. The integration of intelligent technologies and low-altitude application scenarios accelerates green technology diffusion and enhances the coordination between low-altitude industries and green production systems. Existing studies have suggested that once digital technologies and innovation capabilities cross a certain critical level, their promoting effects on industrial upgrading and green transformation become significantly stronger [80]. Therefore, differences in AI development levels may generate heterogeneous and stage-specific impacts of the LAE on CPGE.

Accordingly, the following hypothesis is proposed:

H4. *The impact of the LAE on CPGE exhibits significant nonlinear threshold characteristics with AI serving as the threshold variable.*

Underdeveloped digital infrastructure and limited intelligent coordination are often observed where AI technology remains immature. Specifically, the LAE can directly promote CPGE through environmental governance enhancement, industrial upgrading, and resource allocation optimization. Meanwhile, GT serves as an important mediating channel in this process, although its environmental effects may exhibit certain stage-dependent characteristics. In addition, AI further strengthens the green empowering effect of the LAE through intelligent governance, technological collaboration, and digital integration effects, while its development level may also generate significant threshold characteristics in the relationship between the LAE and CPGE. Based on this, the theoretical mechanism framework of this study is constructed, as shown in Figure 1.

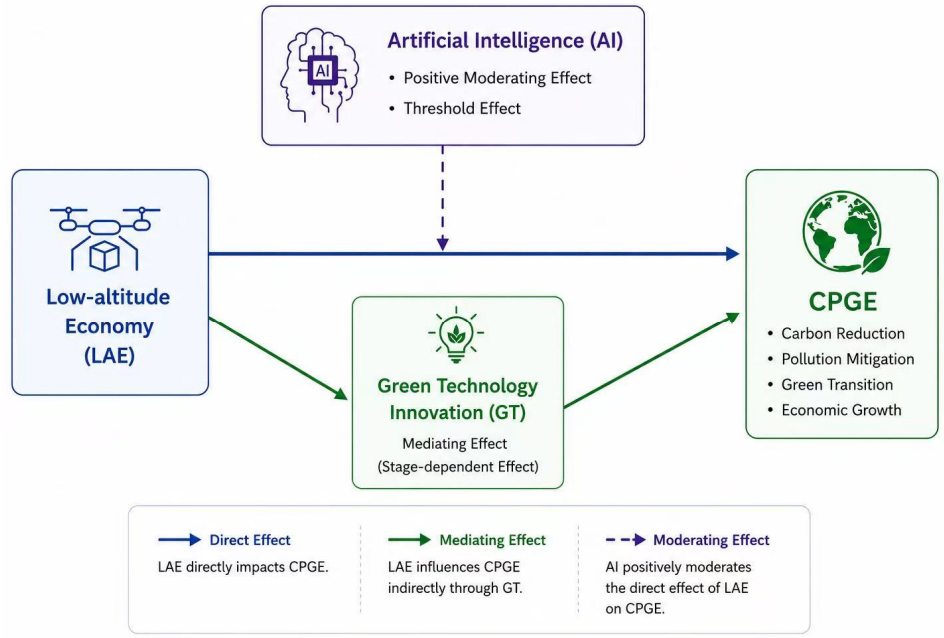

Figure 1. Mechanism Diagram.

4. Research Design

4.1. Variable Selection

4.1.1. Dependent Variable

The dependent variable in this study is CPGE. To characterize its development level, four dimensions are considered, including carbon reduction, pollution mitigation, green transition, and economic growth. Based on these dimensions, the entropy-weighted TOPSIS method, together with the coupling coordination degree model, is applied to calculate the CPGE index. The indicator system is shown in Table 1.

First, to eliminate the dimensional differences among indicators, all original indicators are standardized. For positive indicators, the standardization formula is expressed as:

$$X'_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \tag{1}$$

For negative indicators, the standardization formula is expressed as:

$$X'_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \tag{2}$$

where X'_{ij} denotes the standardized value of indicator j in province i. To avoid the influence of zero values during the entropy calculation process, a minimum constant term θ is added to the standardized indicators, where $\theta = 0.0001$.

After standardization, the entropy method is employed to calculate the weights of indicators, and the weighted decision matrix is constructed as follows:

$$R = (r_{ij})_{m\times n} = \left(w_j X'_{ij}\right)_{m\times n} \tag{3}$$

where w_j denotes the weight of indicator j.

Subsequently, the positive ideal solution and negative ideal solution are determined:

$$R^+ = \{\max(r_{1j}, r_{2j}, \ldots, r_{ij})\} \tag{4}$$

$$R^- = \{\min(r_{1j}, r_{2j}, \ldots, r_{ij})\} \tag{5}$$

Afterward, the Euclidean distance is employed to determine the proximity of each evaluation unit to the positive and negative ideal solutions:

$$D_i^+ = \sqrt{\sum_{j=1}^{n}\left(r_{ij} - R_j^+\right)^2} \tag{6}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}\left(r_{ij} - R_j^-\right)^2} \tag{7}$$

Accordingly, the relative closeness coefficient is calculated as:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{8}$$

where C_i represents the comprehensive evaluation value of each subsystem. A larger value of C_i indicates a higher level of subsystem development.

Table 1. Indicator System for the Synergistic Development in CPGE.

Primary Indicator	Secondary Indicator	Attribute
Carbon Reduction	CO_2 emissions	Negative
	Coal consumption	Negative
Pollution Mitigation	SO_2 emissions	Negative
	Nitrogen oxide emissions	Negative
	Ammonia nitrogen emissions	Negative
	Chemical Oxygen Demand (COD) emissions	Negative
	Emission of smoke (powder) dust	Negative
	PM10 concentration	Negative
	Volume of industrial solid waste generated	Negative
	The rate of harmless treatment of domestic waste	Positive
	Total amount of industrial solid waste utilized comprehensively	Positive
	Daily wastewater treatment capacity for urban areas	Positive
Green Transition	Green coverage rate of the built-up area	Positive
	Land area covered with trees	Positive
	Rural greening rate	Positive
Economic Growth	Agricultural labor productivity	Positive
	Social security share	Positive
	The level of industrial structure sophistication	Positive
	The intensity of R&D expenditure investment	Positive
	Proportion of R&D personnel investment	Positive
	Level of coordination between urban and rural incomes	Positive

After obtaining the comprehensive evaluation values of the four subsystems, the coupling coordination degree model is employed to further measure the coordinated development level among CPGE. The coupling degree is calculated as follows:

$$C = \left[\frac{U_1 \times U_2 \times U_3 \times U_4}{\left(\frac{U_1+U_2+U_3+U_4}{4}\right)^4}\right]^{\frac{1}{4}} \tag{9}$$

where U_1, U_2, U_3 and U_4 represent the comprehensive evaluation indices of CPGE, respectively.

The comprehensive coordination index is calculated as:

$$T = \alpha U_1 + \beta U_2 + \gamma U_3 + \delta U_4 \tag{10}$$

Considering that the four subsystems are equally important, the weights are set as $\alpha = \beta = \gamma = \delta = 0.25$.

Based on the above results, the coupling coordination degree is determined using the following formula:

$$D = \sqrt{C \times T} \tag{11}$$

where D denotes the CPGE synergistic development level. A larger value of D indicates a higher level of coordinated development among CPGE.

Figure 2 illustrates the spatial distribution and temporal evolution of CPGE across Chinese provinces from 2012 to 2023. Overall, the level of CPGE exhibits a continuous upward trend during the sample period, indicating that the coordination among CPGE has gradually improved in China.

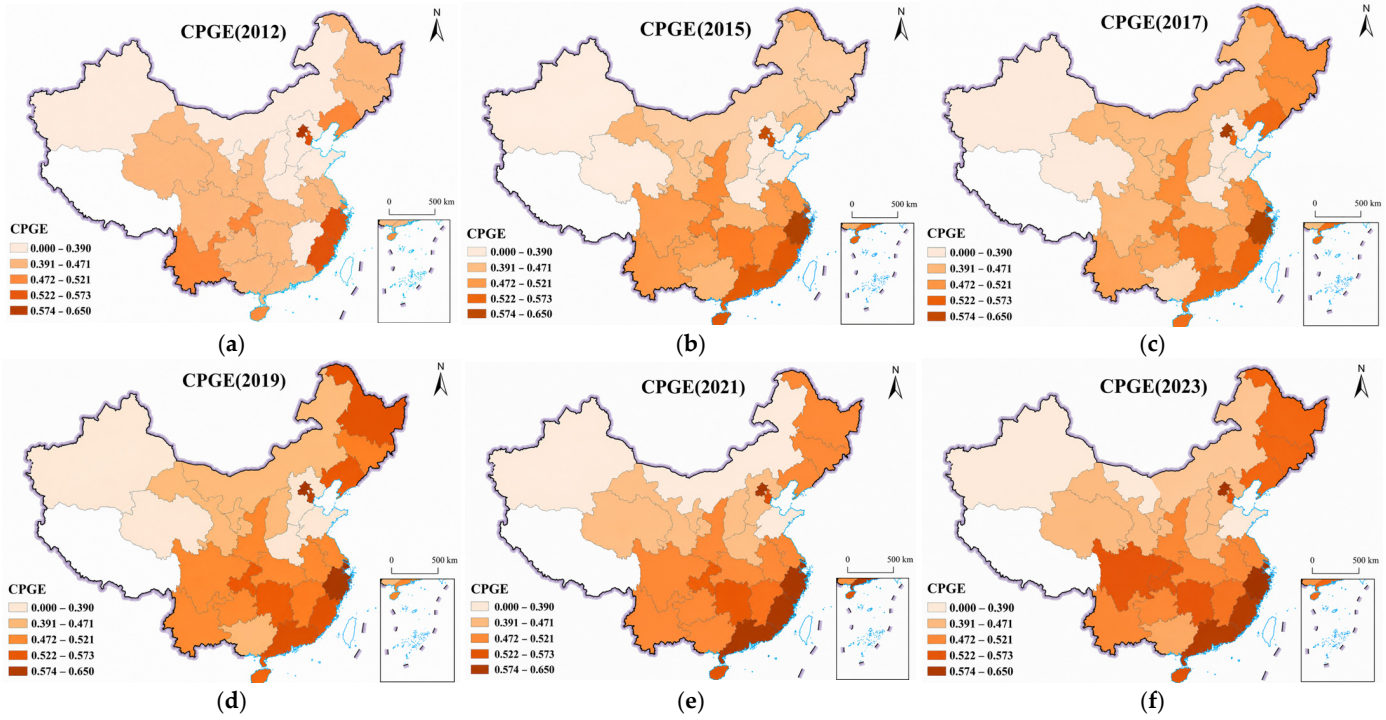

Figure 2. Spatial–temporal evolution of CPGE across Chinese provinces from 2012 to 2023. (**a**) Spatial distribution of CPGE in 2012; (**b**) Spatial distribution of CPGE in 2015; (**c**) Spatial distribution of CPGE in 2017; (**d**) Spatial distribution of CPGE in 2019; (**e**) Spatial distribution of CPGE in 2021; (**f**) Spatial distribution of CPGE in 2023.(Note: This map is compiled based on the standard map with the map approval number GS (2023) No. 2767 downloaded from the Standard Map Service website of the Ministry of Natural Resources, and no modifications have been made to the base map.).

From the spatial perspective, significant regional heterogeneity can be observed. Provinces in the eastern coastal region generally maintain relatively higher CPGE levels, while western inland provinces remain at comparatively lower levels. In the early stage, most provinces were concentrated in the lower and middle intervals of CPGE. Over time, however, an increasing number of provinces entered the higher-level intervals, suggesting that regional green coordinated development capacity has been steadily strengthened.

From the temporal perspective, the spatial agglomeration characteristics of CPGE became increasingly evident after 2015. High-value regions gradually expanded from the eastern coastal areas toward parts of central China, reflecting the gradual improvement in regional environmental governance capacity, industrial upgrading, and green development quality. By 2023, the overall CPGE level of China had improved substantially compared with that in 2012, although interregional disparities still existed.

In general, the evolution pattern of CPGE demonstrates a dynamic trend characterized by overall improvement accompanied by persistent regional imbalance, highlighting the uneven progress of green coordinated development across provinces in China.

4.1.2. Core Explanatory Variable

The core explanatory variable in this study is the development level of the LAE. It represents economic activities related to low-altitude airspace utilization and low-altitude flight services. An evaluation framework containing six dimensions is established, including operational support, industrial development, innovation capacity, policy support, social impact, and market development. The entropy-weighted TOPSIS approach is employed to derive a comprehensive index measuring the development of the LAE across provinces.

It should be noted that there is currently no unified statistical standard for measuring the development level of the LAE. To capture the multidimensional features of the LAE, this paper develops an evaluation framework consisting of six dimensions: operational support, industrial development, innovation capability, policy support, social influence, and market development. Although several indicators, such as passenger throughput, cargo throughput, and aircraft takeoffs and landings, are traditionally associated with the aviation sector, they are included only as proxies for market activity and infrastructure support. These indicators constitute one dimension of the composite index and do not dominate the measurement of the LAE.

Specifically, (1) Operational support of the LAE includes the number of certified airports, the number of enterprises whose business scope or patents cover drones, the number of "specialized and sophisticated" small-and-medium enterprises, and the number of high-tech enterprises. These indicators reflect the infrastructure support and the degree of market entity cultivation for the LAE. (2) Industrial development covers the number of enterprises in the upstream, midstream, and downstream segments of the LAE industrial chain, characterizing the completeness and agglomeration level of the industrial ecosystem. (3) Innovation level is measured by the level of education development and the number of domestic patent applications granted, reflecting the regional R&D potential and knowledge stock of the low-altitude industry. (4) Policy support is measured by the total length of air postal routes, reflecting the extent to which institutional supply supports low-altitude flight activities. (5) Social influence is represented by the number of employees in the air transport sector, indicating the role of the LAE in supporting employment growth and generating wider socioeconomic benefits. (6) Market development is measured by cargo and mail throughput, passenger throughput, and the number of takeoffs and landings at transport airports. Although these indicators are traditionally used in aviation studies, they are employed here to capture market vitality, operational intensity, and infrastructure support conditions associated with the expansion of low-altitude economic activities.

The raw data for the indicators involved in this study are sourced from provincial statistical yearbooks, Viewing Civil Aviation from Statistics, and other similar publications. During the analysis, certain indicator data were calculated and cleaned. Given the large number of missing values for Tibet, the analysis is conducted on panel data of 30 provinces from 2012 to 2023. The specific indicator system is shown in Table 2.

Table 2. Indicators System for the Development Level of the LAE.

Primary Indicator	Secondary Indicator	Attribute
Operational Support	Number of certified airports	Positive
	Number of companies engaged in drone operations	Positive
	Number of companies whose patents involve drones	Positive
	Number of specialized, innovative enterprises operating in the drone industry	Positive
	Number of enterprises specializing in and innovating drones for which patents have been granted	Positive
	Number of high-tech enterprises engaged in drone technology within the business scope	Positive
	Number of high-tech enterprises whose patents involve drones	Positive
Industry Development	Upstream enterprises in the LAE industrial chain	Positive
	Midstream enterprises in the LAE industrial chain	Positive
	Downstream enterprises in the LAE industrial chain	Positive
Level of Innovation	Level of Educational Development	Positive
	Number of domestic patent applications granted	Positive
Policy Support	Low-altitude flight approval	Positive
Social Influence	Low-altitude employment creates jobs	Positive
Market Development	Transport airport cargo and mail throughput	Positive
	Transport airport passenger throughput	Positive
	Number of takeoffs and landings at the transport airport	Positive

4.1.3. Mediating Variable

GT is represented by green patent applications per million people. The indicator sums green invention and green utility model patent applications in a region. This total is then divided by the year-end resident population (per million). The per capita metric removes the influence of population size differences. It more accurately reflects the per capita level of green innovation activity and the capacity for green technology development. Compared with aggregate patent counts, this measure better captures the intensity and sustainability of regional green innovation.

4.1.4. Threshold and Moderating Variable

This study uses the number of AI-related enterprises in each region as a proxy variable for the level of AI development. This indicator reflects the scale of regional AI market entities, industrial agglomeration capacity, and the overall vitality of AI industry development. In general, a larger number of AI-related enterprises indicates stronger regional capabilities in digital technological innovation, intelligent application scenarios, and industrial digital transformation. Therefore, this variable can effectively characterize the regional foundation for AI development and its supporting role in empowering the LAE and promoting the synergistic development of CPGE.

4.1.5. Control Variables

To reduce potential bias caused by omitted variables, five control variables are included in the analysis. These variables represent regional innovation input, industrial development, income disparity, human capital, and technology market activity. Specifically, research and

development intensity (RDI) is measured by the ratio of R&D expenditure to regional GDP. Industrialization level (IND) is proxied by the share of industrial value added in regional GDP. The urban–rural income gap (GAP) is calculated as the ratio of urban disposable income per capita to rural disposable income per capita. Human capital level (HCL) is measured using the share of students enrolled in higher education institutions within the total population, which serves as an indicator of regional human resource reserves. Technology market development level (TML) is expressed as the proportion of technology market transaction value to regional GDP, reflecting the activity of technology transfer and the transformation of innovative outputs.

4.2. Model Construction

4.2.1. Baseline Regression Model

To identify the effect of the LAE on CPGE, the following two-way fixed effects framework is estimated:

$$CPGE_{it} = \alpha_0 + \alpha_1 LAE_{it} + \sum \alpha_k Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (12)$$

where $CPGE_{it}$ denotes the synergistic development level of CPGE in province i during year t; LAE_{it} represents the level of LAE development; $Control_{it}$ denotes a series of control variables; and μ_i and λ_t account for unobserved provincial heterogeneity and common time effects, respectively, whereas ε_{it} denotes the residual term.

The coefficient α_1 captures the direct effect of the LAE on CPGE synergistic development.

4.2.2. Mediating Effect Model

To identify whether GT serves as an intermediate channel between the LAE and CPGE, the following stepwise mediation framework is estimated:

$$GT_{it} = \beta_0 + \beta_1 LAE_{it} + \sum \beta_k Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (13)$$

$$CPGE_{it} = \gamma_0 + \gamma_1 LAE_{it} + \gamma_2 GT_{it} + \sum \gamma_k Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (14)$$

where GT_{it} represents GT.

Equation (2) examines the impact of the LAE on GT, while Equation (3) further tests whether GT transmits the effect of the LAE on CPGE. If both β_1 and γ_2 are significant, the mediating effect exists.

4.2.3. Moderating Effect Model

To investigate whether AI strengthens the effect of the LAE on CPGE, the following moderating effect model is constructed:

$$CPGE_{it} = \delta_0 + \delta_1 LAE_{it} + \delta_2 AI_{it} + \delta_3 (LAE_{it} \times AI_{it}) + \sum \delta_k Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (15)$$

where AI_{it} denotes the development level of AI, and $(LAE_{it} \times AI_{it})$ is the interaction term between the LAE and AI.

The coefficient δ_3 reflects the moderating effect of AI. A significantly positive δ_3 indicates that AI strengthens the promoting effect of the LAE on CPGE.

To validate our empirical strategy, we compare it with alternative approaches in the literature. While some studies on CPGE and low-altitude economy employ spatial econometric models [3] or difference-in-differences [28], we adopt a two-way fixed effects model as our baseline. This choice is justified by the Hausman test results favouring fixed effects and the need to control for both provincial and year-specific unobservables. For mediation, moderation, and threshold analyses, we follow the standard stepwise

procedure, the mean-centred interaction approach, and Hansen's (1999) panel threshold model, respectively. These methods are widely validated in environmental economics and are well suited to our research questions, which do not rely on a quasi-experimental design. Subsample regressions for heterogeneity follow conventional grouping criteria based on geography, resource dependence, and city hierarchy.

4.3. Data Sources

The empirical analysis is based on a balanced panel dataset covering 30 Chinese provinces over the period 2012–2023. Tibet, Hong Kong, Macao, and Taiwan are excluded because of data unavailability, yielding 360 province–year observations. Most variables are compiled from official statistical publications, including the China Statistical Yearbook, China Energy Statistical Yearbook, China Environmental Statistical Yearbook, China City Statistical Yearbook, China Science and Technology Statistical Yearbook, and provincial statistical yearbooks. Carbon emission information is obtained from the China Emission Accounts and Datasets (CEADs). Information on LAE-related enterprises, patent applications, and AI enterprises is gathered from the Qi Chacha database and the public database of the China National Intellectual Property Administration (CNIPA). Missing values account for only a small proportion of the sample and are supplemented using linear interpolation.

Table 3 presents the descriptive results for the variables included in the analysis. The wide range of values observed across provinces implies substantial regional disparities, which is conducive to identifying the relationships examined in the following empirical analysis.

Table 3. Descriptive Statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
CPGE	360	0.482	0.076	0.237	0.650
LAE	360	0.100	0.097	0.005	0.728
GT	360	2.985	4.485	0.170	32.181
AI	360	1.163	2.183	0.014	19.576
RDI	360	0.018	0.011	0.002	0.063
IND	360	0.312	0.086	0.069	0.536
GAP	360	2.508	0.384	1.718	3.646
HCL	360	0.021	0.006	0.009	0.044
TML	360	0.020	0.031	0.000	0.180

Specifically, the mean value of CPGE is 0.482 with a standard deviation of 0.076, indicating substantial regional differences in the synergistic development level of CPGE across China. The LAE shows a relatively wide value range, suggesting considerable regional imbalance in LAE development. Significant disparities exist among provinces in terms of industrial foundation, technological application, and industrial system construction related to the LAE.

As the mediating variable, GT also demonstrates considerable variability, reflecting pronounced regional differences in green innovation capability and green technology transformation efficiency, which provides a practical basis for testing the mediating effect of GT. In addition, the AI variable, measured by the number of AI-related enterprises, exhibits substantial regional heterogeneity, indicating uneven development levels of intelligent industries and digital infrastructure across regions in China. This implies that the impact of the LAE on CPGE may vary with different levels of AI development, thereby providing empirical support for the subsequent moderating effect and threshold effect analyses. Overall, the core variables exhibit strong regional heterogeneity, laying a solid foundation for the subsequent regression analysis.

5. Empirical Results and Analysis

Before estimating the regression models, diagnostic tests are carried out to verify the reliability of the empirical framework. The multicollinearity test results are presented in Table 4. The mean VIF is 2.730, and all individual VIF values fall within the range of 1.380–5.970. As these values are substantially lower than the conventional cutoff value of 10, multicollinearity is unlikely to pose a serious problem for the subsequent analysis.

Table 4. Tests for Multicollinearity.

Variable	Variance Inflation Factor (VIF)	1/VIF
LAE	1.540	0.650
GT	2.600	0.385
AI	1.220	0.818
RDI	5.970	0.167
IND	1.380	0.726
GAP	1.980	0.505
HCL	2.410	0.415
TML	4.740	0.210
Mean	**VIF**	**2.730**

Furthermore, Figure 3 reports the correlation matrix for the variables used in this study. CPGE tends to move in the same direction as LAE, GT, AI, RDI, HCL, and TML, whereas opposite patterns are observed for IND and GAP. Notably, RG exhibits a relatively strong positive correlation with both CPGE and GT, suggesting a close association between government support and regional green development as well as innovation activities. All correlation coefficients remain within a reasonable range, and no excessively high pairwise correlation is observed.

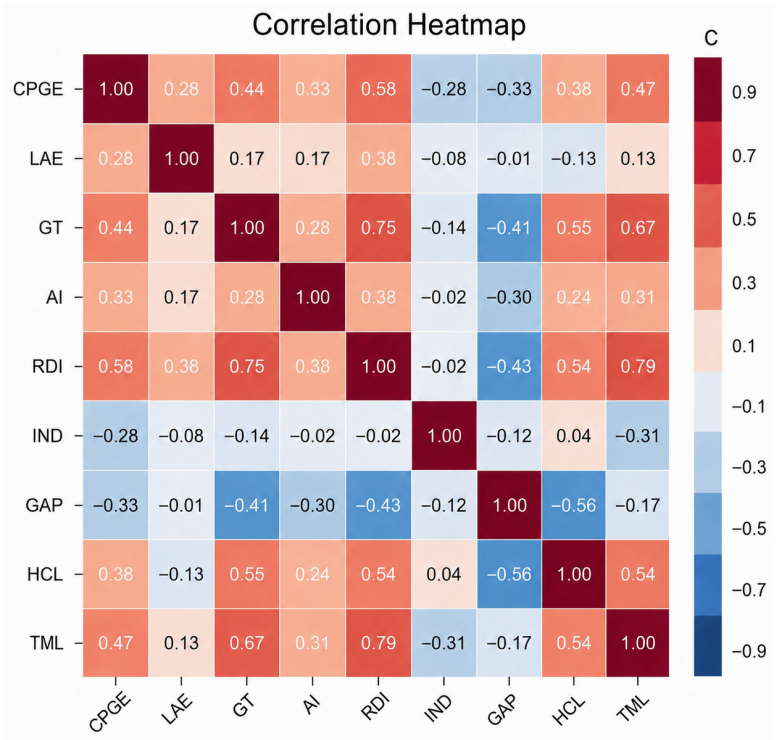

Figure 3. Correlation Heatmap.

Taken together, the VIF and correlation analyses confirm that multicollinearity is not a major concern in this study, thereby supporting the validity of the econometric specification and providing a solid foundation for the subsequent empirical investigations.

5.1. Baseline Regression Tests

Table 5 presents the benchmark regression results examining the impact of LAE on the synergistic development in CPGE. A two-way fixed effects model with region and year fixed effects is employed, and control variables are added sequentially from column (1) to column (6) to assess the stability of the core coefficient.

Table 5. Benchmark Regression Results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	CPGE	CPGE	CPGE	CPGE	CPGE	CPGE
LAE	0.023 (0.023)	0.055 *** (0.021)	0.073 *** (0.020)	0.080 *** (0.021)	0.062 *** (0.021)	0.056 *** (0.021)
RDI		3.618 *** (0.518)	3.088 *** (0.501)	3.027 *** (0.496)	3.265 *** (0.503)	3.182 *** (0.487)
IND			−0.205 *** (0.048)	−0.183 *** (0.050)	−0.091 * (0.051)	−0.120 ** (0.049)
GAP				0.035 * (0.020)	0.055 *** (0.019)	0.074 *** (0.020)
HCL					3.947 *** (0.742)	3.662 *** (0.765)
TML						−0.276 *** (0.095)
Constant	0.480 *** (0.003)	0.412 *** (0.010)	0.484 *** (0.020)	0.389 *** (0.058)	0.224 *** (0.062)	0.199 *** (0.061)
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	360	360	360	360	360	360
R-squared	0.938	0.946	0.950	0.950	0.954	0.955

Note: Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

After accounting for province-specific and year-specific effects, the estimated coefficient of LAE remains positive in all model specifications. In column (1), where only LAE and two-way fixed effects are considered, the coefficient is 0.023 and statistically insignificant. The inclusion of control variables leads to a gradual increase in the coefficient estimate and strengthens its statistical significance. In column (6), the coefficient reaches 0.056 and is significant at the 1% level, implying that a higher level of LAE development contributes to improvements in CPGE. These results indicate that controlling for relevant factors helps reveal the underlying positive effect of LAE on CPGE, thereby supporting Hypothesis 1.

Regarding control variables, research and development intensity exhibits a consistently positive and significant effect on CPGE across all columns, implying that fiscal interventions play a crucial role in facilitating synergistic green development. Human capital level also shows a positive and statistically significant coefficient, suggesting that regions with a more skilled workforce are better positioned to achieve balanced progress in CPGE. In

contrast, industrial structure displays a negative coefficient, indicating that a higher share of secondary industry may temporarily hinder the synergistic effect.

The model fit improves steadily from column (1) to column (6), with the R^2 reaching 0.955 in the full specification, indicating that the included variables explain a substantial portion of the variation in CPGE across provinces. Overall, the benchmark results suggest that the development of the LAE is positively associated with CPGE, and this relationship remains robust after controlling for a range of potential confounding factors.

5.2. Robustness Tests

To verify the reliability of the baseline regression results, this study conducts robustness checks from four dimensions: alternative measurement of the dependent variable, outlier treatment, sample adjustment, and standard error correction. Table 6 presents the corresponding results.

Table 6. Robustness Test Results.

Variable	(1) Alternative Dependent Variable	(2) 1% Winsorization	(3) Excluding Municipalities	(4) Driscoll-Kraay	(5) Lagged LAE
LAE	0.066 ** (0.033)	0.061 *** (2.840)	0.070 *** (3.060)	0.061 *** (5.160)	
L1_LAE					0.040 ** (2.000)
RDI	2.876 *** (0.654)	3.079 *** (3.160)	3.920 ** (2.490)	3.079 *** (11.710)	2.689 *** (5.180)
IND	−0.070 (0.065)	−0.111 (−1.280)	−0.112 (−1.240)	−0.111 *** (−4.420)	−0.100 * (−1.760)
GAP	0.106 *** (0.023)	0.072 ** (2.340)	0.074 (1.620)	0.072 ** (3.050)	0.061 *** (3.130)
HCL	3.935 *** (0.954)	3.729 *** (2.840)	3.591 ** (2.440)	3.729 *** (3.970)	3.485 *** (4.410)
TML	−0.269 ** (0.124)	−0.230 ** (−2.060)	−0.284 * (−1.950)	−0.230 ** (−2.670)	−0.235 *** (−2.730)
Constant	0.132 * (0.076)	0.163 (1.490)	0.143 (1.070)	0.163 * (2.090)	0.298 *** (3.730)
Region fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
Observations	360	360	312	360	330
R-squared	0.929	0.790	0.819		0.965
Number of Groups				30	

Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Column (1) recalculates the CPGE index using the CRITIC method instead of the entropy-weighted TOPSIS approach. Although the two weighting techniques differ in the way indicator weights are assigned, both belong to objective evaluation methods. The estimated coefficient of LAE is 0.066 and remains significant at the 5% level, which is close to the benchmark estimate. This finding suggests that the main conclusion is robust to alternative weighting schemes.

Column (2) performs a 1% two-tailed winsorization for all continuous variables to reduce the potential influence of extreme observations. After this treatment, the coefficient of LAE is 0.061 and remains significant at the 1% level, indicating that the positive effect of LAE on CPGE is not driven by outliers.

Column (3) removes the four municipalities directly under the central government, namely Beijing, Shanghai, Tianjin, and Chongqing, from the sample. This procedure is intended to assess whether provinces with special administrative status affect the benchmark results. After excluding these municipalities, the coefficient of LAE increases slightly to 0.070 and remains significant at the 1% level. The result suggests that the promoting effect of LAE on CPGE is not confined to these municipalities but is also observed in other provinces, which is in line with the regional heterogeneity analysis presented below.

Column (4) adopts Driscoll–Kraay robust standard errors, a standard panel estimation approach that simultaneously corrects for cross-sectional dependence, serial autocorrelation, and heteroskedasticity. After this adjustment, the estimated coefficient of LAE remains at 0.061, with its statistical significance markedly strengthened (t = 5.16), suggesting that the promotive effect of LAE becomes more salient when spatial interdependencies across provincial units are controlled for.

Overall, the four robustness checks—covering alternative weighting specifications, outlier mitigation, sub-sample exclusion, and standard error correction—consistently return a significantly positive LAE coefficient with stable magnitude, which aligns closely with baseline regression estimates. Accordingly, the core conclusion that LAE exerts a significant facilitating effect on CPGE holds with sufficient robustness.

5.3. Mediating Effect Test

To further explore the underlying mechanism through which the LAE affects CPGE, this study introduces GT as a mediating variable. The estimation results are reported in Table 7.

Column (1) presents the effect of the LAE on GT. The coefficient of LAE is −0.021 and statistically significant at the 10% level, indicating that the expansion of the LAE is associated with a reduction in GT during the sample period. This finding indicates that the expansion of the LAE is associated with a decline in GT during the sample period. One possible explanation is that the current development stage of the LAE remains largely focused on infrastructure construction, equipment deployment, and industrial expansion, which may temporarily divert resources away from green innovation activities. However, this mechanism cannot be directly verified within the scope of the present study and therefore should be interpreted with caution. Column (2) incorporates both LAE and GT into the CPGE regression model. LAE maintains a positive and statistically significant coefficient with a value of 0.045, whereas the coefficient of GT registers a significantly negative result at the 1% level (−0.298). Moreover, the significance of the indirect effect is validated by both the Sobel and Bootstrap tests, which demonstrate that GT acts as a mediating mechanism connecting LAE and CPGE, thereby supporting Hypothesis 2.

Notably, the mediating effect is negative rather than positive. This finding suggests that GT has not yet been effectively translated into improvements in CPGE during the sample period. Nevertheless, this finding warrants cautious interpretation, as the current study does not directly investigate the specific mechanisms underlying the negative mediating effect.

Table 7. Results of the Mechanism Test.

Variable	(1)	(2)
	GT	CPGE
LAE	−0.021 * (−0.011)	0.045 * (−0.023)
RDI	−1.013 (−1.000)	2.963 *** (−0.966)
IND	0.096 (−0.066)	−0.096 (−0.064)
GAP	0.090 *** (−0.024)	0.102 *** (−0.036)
HCL	−2.101 (−1.275)	2.871 ** (−1.362)
TML	0.288 * (−0.152)	−0.192 (−0.121)
GT		−0.298 *** (−0.085)
Constant	−0.218 ** (−0.084)	0.094 (−0.105)
Region Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Observations	360	360
R-squared	0.576	0.789

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Several potential explanations may account for this finding. First, green innovation activities often require substantial R&D investment and relatively long commercialization cycles, implying that their environmental and economic benefits may not be immediately realized. Second, during the early stage of LAE development, firms may prioritize infrastructure construction, equipment deployment, and market expansion, which could temporarily weaken the contribution of GT to coordinated green development outcomes. Third, the effectiveness of GT may depend on factors such as patent quality, technology diffusion, and commercialization efficiency, which are not directly captured in the current empirical framework. As a result, the observed negative mediating effect may reflect transitional characteristics of the development process rather than a persistent inhibitory role of GT.

Therefore, caution should be exercised when interpreting this result. Rather than concluding that GT hinders CPGE, the findings indicate that the environmental and economic benefits of green innovation may not yet have been fully realized during the sample period. Subsequent studies may further differentiate between invention patents and utility-model patents, assess patent quality and commercialization outcomes, and investigate potential lagged effects of green innovation to more precisely characterize the underlying mechanisms. As the diffusion and commercialization of green technologies continue to improve, the positive contribution of GT to coordinated green development may become more evident.

5.4. Moderating Effect of AI

AI may influence the extent to which the LAE contributes to CPGE. To assess this possibility, the interaction between LAE and AI is incorporated into the baseline regression. Since the explanatory variable, the moderating variable, and their interaction may be highly

correlated, a centralized moderation analysis is further performed. The estimation results are reported in Table 8.

Table 8. The Moderating Effect Results.

Variable	(1)	(2)
	CPGE (Moderating Effect)	**CPGE (After Centralization)**
LAE	0.032 (−0.025)	
AI	−0.006 ** (−0.002)	
LAE × AI	0.025 *** (−0.006)	
LAE_C		0.061 ** (−0.021)
AI_C		−0.004 * (−0.001)
LAE_C × AI_C		0.025 *** (−0.006)
RDI	3.212 ** (−0.952)	3.212 ** (−0.952)
IND	−0.153 * (−0.069)	−0.153 * (−0.069)
GAP	0.084 * (−0.039)	0.084 * (−0.039)
HCL	3.453 * (−1.558)	3.453 * (−1.558)
TML	−0.230 (−0.132)	−0.230 (−0.132)
Constant	0.191 (−0.104)	0.190 (−0.105)
Region Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Observations	360	360
Adj. R-squared	0.951	0.951

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Column (1) displays the estimation outcomes prior to variable centralization. The coefficient of the interaction term is significantly positive at the 1% level, indicating that AI reinforces the promotive effect of LAE on CPGE.

Column (2) shows the estimation results following the centralization procedure. The magnitude and statistical significance of the interaction coefficient remain consistent, verifying that the positive moderating effect of AI is robust and not susceptible to interference from multicollinearity.

Overall, these empirical findings confirm that AI significantly amplifies the synergistic effect of LAE on CPGE. Although the direct effect of AI alone appears negative, its interaction with LAE is positive and highly significant, suggesting that AI serves as an important enabling condition that strengthens the environmental and economic benefits generated by LAE development, thereby supporting Hypothesis 3.

A possible explanation is that AI improves resource allocation efficiency, enhances real-time information processing capabilities, and reduces operational uncertainty in low-altitude activities. Through intelligent scheduling, data-driven decision-making, and smart environmental monitoring, AI can facilitate the more efficient deployment of low-altitude technologies and infrastructure. AI may also improve governance efficiency and environmental supervision, enabling the potential benefits of LAE development to be utilized more effectively. Consequently, regions endowed with more robust AI capabilities are better positioned to achieve parallel advances in both environmental quality and economic performance.

These findings suggest that the environmental benefits of LAE are not solely determined by industrial expansion itself but also depend on the supporting level of digital intelligence development. Therefore, AI plays a critical role in amplifying the green coordination dividends associated with LAE development.

5.5. Threshold Effect Test

Our baseline estimations and moderating effect analyses have verified that AI exerts a positive moderating influence on the linkage between LAE and the synergistic advancement of CPGE. Nevertheless, a key question remains unresolved: Does this moderating effect exhibit nonlinear properties? More specifically, is there a critical threshold at which the role of AI transitions from marginal to prominent? To address this inquiry, this study employs the classic panel threshold regression model, sets AI as the threshold variable, and conducts 300 bootstrap replications to examine the statistical significance of the threshold effect.

Table 9 reports the threshold effect test results. The F-statistic of the single-threshold model reaches 35.930, which surpasses the 1% critical value (41.757), confirming the existence of a statistically significant single-threshold effect. In comparison, the double-threshold and triple-threshold specifications generate F-statistics of 7.420 and 6.540, respectively, both falling below the 10% critical values. Collectively, these findings indicate that the moderating role of AI in the LAE-CPGE nexus is characterized by a single threshold rather than multi-threshold attributes.

Table 9. The Threshold Effect Results.

Threshold Variable	Threshold Type	F-Stat	10% Critical Value	5% Critical Value	1% Critical Value
Artificial Intelligence	Single Threshold	35.930	24.410	28.130	41.757
	Double Threshold	7.420	19.359	23.537	35.296
	Triple Threshold	6.540	15.303	18.013	23.313

Table 10 presents the estimated threshold value and its corresponding confidence interval. The single-threshold estimate stands at 0.0524, with an associated *p*-value of 0.030 and a 95% confidence interval of (0.051, 0.053). The narrow range of this confidence interval suggests that the threshold estimate features high statistical precision.

Table 10. Threshold Estimates and Confidence Intervals.

Threshold Variable	Threshold Type	Threshold Value	*p*-Value	95% Confidence Interval	Bootstrap Replications
AI	Single Threshold	0.0524	0.030	(0.051, 0.053)	300

Figure 4 illustrates the distribution of the likelihood ratio (LR) statistic across varying values of the threshold variable. The LR curve reaches its lowest point at the estimated threshold value of 0.0524, and the statistic falls below the 5% critical value line throughout the confidence interval, further verifying the reliability of the single-threshold estimation result.

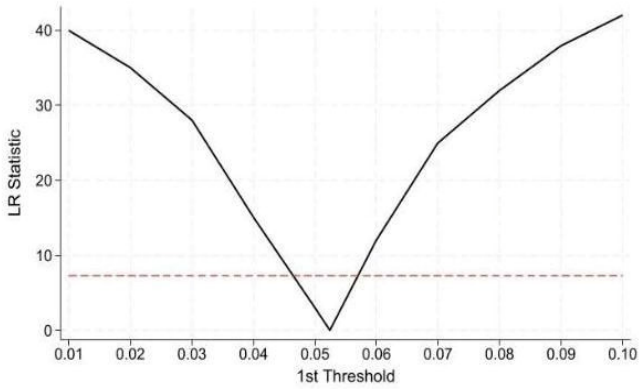

Figure 4. First threshold. (Note: The curve shows the LR statistic of the first threshold test, and the horizontal red dashed line is the 95% critical value of the likelihood ratio test.)

Table 11 presents the parameter estimation results of the threshold regression model. Once AI development crosses the threshold value (AI > 0.0524), the coefficient of LAE turns positive at 0.127 and remains statistically significant at the 1% level. This finding suggests that the positive association between LAE and CPGE is considerably strengthened when the level of AI development is relatively high. One plausible rationale is that more sophisticated AI capabilities improve information processing efficiency, intelligent decision-making, resource allocation, and environmental monitoring capacity, which in turn creates more favorable conditions for aligning LAE development with green transformation objectives, thus providing empirical support for Hypothesis 4.

Overall, these findings reveal a nonlinear relationship between LAE and CPGE, with the effect of LAE varying across different stages of AI development. The single-threshold effect suggests that the contribution of LAE to CPGE is closely associated with the level of digital intelligence development. When AI remains below the threshold, limitations in digital infrastructure, intelligent governance, and data utilization capacity may constrain the potential benefits of LAE. As AI development advances beyond the threshold, the positive association between LAE and CPGE becomes more pronounced.

These findings imply that the green development benefits associated with LAE may depend not only on industrial expansion itself but also on the supporting capacity of digital intelligence technologies. Accordingly, bolstering AI development may help foster more enabling conditions for achieving the integrated goals of carbon reduction, pollution mitigation, green transition, and economic growth.

Table 11. The Threshold Regression Results.

Variables	(1)
	CPGE
LAE (AI $\leq$ 0.0524)	−0.334 ***
	(0.082)
LAE ($AI \geq$ 0.0524)	0.127 ***
	(0.023)
RDI	3.448 ***
	(0.508)
IND	−0.338 ***
	(0.039)
GAP	0.009
	(0.013)
HCL	3.672 ***
	(0.678)
TML	0.003
	(0.104)
Constant	0.413 ***
	(0.051)
Region fixed effects	YES
Year fixed effects	YES
Observations	360
R-squared	0.715

Robust standard errors are reported in parentheses. *** $p < 0.01$.

5.6. Heterogeneity Analysis

The baseline estimation results show that LAE exhibits a positive correlation with CPGE. However, substantial disparities in economic conditions, industrial compositions, and technological endowments across Chinese regions may result in heterogeneous impacts. To investigate such regional heterogeneity, we partition the full sample into eastern, central, and western subsamples and re-perform the baseline regression for each subgroup. The corresponding estimation outcomes are summarized in Table 12.

Regional disparities are clearly observed. In the eastern region, the coefficient of LAE reported in Column (1) is 0.035 but remains statistically insignificant. This result implies that the contribution of LAE to CPGE has not yet become apparent in this region. One possible reason is that eastern provinces generally face relatively stringent environmental requirements and already maintain a high level of green development, leaving limited scope for additional improvements.

For the central region, the coefficient of LAE in Column (2) is 0.005, which is also insignificant. This suggests that the environmental benefits associated with LAE development have not yet been fully realized. A potential explanation is that traditional manufacturing still occupies a relatively large share of the regional economy, while the positive effects of emerging industries may take longer to emerge.

A distinct pattern emerges in the western region. Column (3) yields an estimated coefficient of 0.127, which is statistically significant at the 10% level. This finding indicates that LAE makes a positive contribution to CPGE in western China. Compared with the eastern and central regions, western provinces may obtain larger marginal gains from LAE expansion because low-altitude applications can compensate for deficiencies in conven-

tional transportation systems. Preferential policies supporting western development may also have accelerated the construction of low-altitude infrastructure and related facilities.

Table 12. Regional Heterogeneity: Baseline Regression Results.

Variables	(1)	(2)	(3)
	CPGE (Eastern)	CPGE (Central)	CPGE (Western)
LAE	0.035 (0.019)	0.005 (0.019)	0.127 * (0.059)
RDI	3.612 * (1.851)	1.921 (1.587)	2.896 (1.923)
IND	−0.177 (0.176)	−0.072 (0.084)	−0.013 (0.057)
GAP	0.049 (0.122)	0.033 (0.047)	0.130 * (0.062)
HCL	2.566 (3.660)	7.034 ** (2.027)	3.518 (2.509)
TML	−0.039 (0.280)	−0.204 (0.124)	−0.024 (0.260)
Constant	0.271 (0.367)	0.191 (0.105)	−0.069 (0.171)
Region fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES
Observations	132	96	132
R-squared	0.694	0.944	0.744

Robust standard errors are reported in parentheses. ** $p < 0.05$, * $p < 0.1$.

Regarding control variables, human capital level exhibits a positive and significant coefficient in the central region $(7.034,\ p < 0.05)$, suggesting that a skilled workforce plays a crucial role in enabling CPGE in this area. A marginally significant positive impact of R&D intensity is detected exclusively in the eastern region, whereas the corresponding estimated coefficients for the central and western regions lack statistical significance.

Overall, the impact of LAE on CPGE demonstrates substantial regional heterogeneity. The facilitative effect is most salient in the western region, whereas it does not reach statistical significance in the eastern and central regions. One plausible rationale is that western provinces are generally characterized by a relatively lower level of industrialization and a weaker transportation infrastructure base. Consequently, the development of LAE may generate larger marginal benefits through improving transportation accessibility, optimizing resource allocation, and fostering industrial upgrading. In addition, the vast geographical coverage and complex terrain of many western regions create greater demand for low-altitude applications in logistics, emergency services, environmental monitoring, and public services, thereby enhancing the contribution of LAE to coordinated green development.

By contrast, eastern and central regions already benefit from relatively mature transportation networks, stronger industrial foundations, and higher levels of economic development. As a result, the marginal contribution of LAE development to CPGE may be comparatively limited during the sample period. Therefore, the environmental and economic benefits associated with LAE appear to be more evident in regions where low-altitude technologies can effectively compensate for existing infrastructure and accessibility constraints.

These empirical results underscore the necessity of implementing region-tailored development strategies when advancing LAE initiatives. Instead of rolling out a one-size-

fits-all policy framework, local authorities are advised to devise customized development trajectories in line with regional resource endowments, infrastructure status, and localized development demands.

The foregoing estimation outcomes confirm that the impact of LAE on CPGE exhibits marked regional heterogeneity, whereby a statistically significant facilitative effect is detected exclusively in western China. It is thus warranted to further explore whether the moderating effect of AI also presents regional disparities. For this purpose, we partition the full sample into eastern, central, and western geographic units and run the moderating effect model independently for each subgroup. All variables undergo mean-centering processing, and the corresponding estimation outputs are presented in Table 13.

Table 13. Regional Heterogeneity: Moderating Effect Results.

Variables	(1)	(2)	(3)
	CPGE (Eastern)	CPGE (Central)	CPGE (Western)
LAE_C	0.022 (0.034)	−0.028 (0.033)	0.304 *** (0.064)
AI_C	−0.006 ** (0.002)	−0.000 (0.004)	0.011 ** (0.003)
LAE_C × AI_C	0.032 ** (0.010)	−0.053 (0.034)	0.190 * (0.067)
RDI	2.966 (1.499)	1.863 (1.660)	3.117 (1.645)
IND	−0.197 (0.215)	−0.074 (0.091)	0.028 (0.065)
GAP	0.099 (0.104)	0.040 (0.046)	0.153 * (0.054)
HCL	1.650 (2.952)	7.296 * (2.093)	3.030 (1.992)
TML	−0.645 * (0.227)	−0.258 * (0.086)	−0.060 (0.365)
Constant	0.258 (0.277)	0.211 (0.103)	−0.064 (0.138)
Region fixed effects	YES	YES	YES
Year fixed effects	YES	YES	YES
Observations	132	96	132
Adj. R-squared	0.951	0.955	0.940

Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Regional differences in the moderating effect of AI are evident. In the eastern region, the interaction coefficient reported in Column (1) is 0.032 and significant at the 5% level. This result suggests that AI strengthens the contribution of LAE to CPGE in eastern China. Although the coefficient of LAE_C (0.022) is statistically insignificant, improvements in AI development appear to enhance the environmental and economic benefits associated with LAE. One possible explanation is that eastern provinces possess relatively advanced digital infrastructure and a high level of AI adoption, providing favorable conditions for intelligent technologies to support LAE development.

For the central region, the interaction coefficient in Column (2) is −0.053 but remains statistically insignificant. This finding implies that AI has yet to generate a detectable moderating effect in this region. A potential reason is that traditional manufacturing still accounts for a considerable share of economic activities, while the current level of AI

development may be insufficient to effectively support the green transformation associated with LAE.

A different pattern emerges in western China. Column (3) reports an interaction coefficient of 0.190, which is significant at the 10% level, while the coefficient of LAE_C reaches 0.304 and is significant at the 1% level. Compared with eastern China, the interaction effect is considerably larger, suggesting that AI plays a stronger supporting role in the western region. This outcome may be related to the relatively low development baseline and wider geographical coverage of western provinces, where intelligent technologies can help overcome limitations in transportation accessibility and infrastructure provision. In addition, the relatively low baseline level of development in western provinces may allow intelligent technologies to generate larger marginal benefits, thereby strengthening the green coordination effects associated with LAE.

These findings are consistent with the regional heterogeneity results of the benchmark regression, which show that both the direct impact of LAE on CPGE and its interaction effect with AI are strongest in the western region. A possible explanation is that western regions generally face greater constraints in transportation accessibility, industrial upgrading, and environmental governance. Under such conditions, the integration of AI with LAE may generate larger marginal benefits through intelligent resource allocation, real-time environmental monitoring, and more efficient public service delivery. In addition, the vast geographical coverage and relatively dispersed economic activities in western China may increase the demand for low-altitude applications, allowing AI-enabled LAE technologies to play a more prominent role in supporting coordinated green development.

By contrast, eastern and central regions already possess relatively mature digital infrastructure, transportation systems, and industrial networks. Consequently, the additional contribution of AI-enabled LAE development may be less pronounced during the sample period. These findings further highlight the necessity of adopting region-specific and differentiated policies when leveraging AI to empower the green synergistic development of LAE.

Marked disparities exist between resource-based and non-resource-based cities in terms of industrial structure, technological endowments, and environmental governance capacity. Such structural variations may give rise to heterogeneous impacts of LAE and AI on CPGE. Accordingly, we categorize the full sample into resource-based and non-resource-based city subgroups in accordance with the official classification criteria released by the State Council of China. Columns (1) and (2) in Table 14 display the baseline regression outcomes, whereas Columns (3) and (4) summarize the estimation results of the moderating effect model.

Differences between the two groups can be clearly observed. In non-resource-based cities, the coefficient of LAE reported in Column (1) is 0.044 and significant at the 5% level, suggesting that LAE contributes positively to CPGE in these regions. By contrast, the coefficient of LAE in resource-based cities shown in Column (2) is 0.129 but remains statistically insignificant. This result implies that the environmental and economic benefits associated with LAE have yet to become evident in resource-dependent areas. One possible explanation is that resource-based cities are still highly dependent on traditional industries, which may limit the short-term contribution of emerging industries to coordinated green development.

The moderating role of AI is further examined in Columns (3) and (4). In non-resource-based cities, the interaction coefficient between LAE_C and AI_C is 0.022 and significant at the 5% level, while the coefficient of LAE_C remains positive and significant (0.072, $p < 0.01$). These results suggest that AI strengthens the contribution of LAE to CPGE in non-resource-based cities. A potential reason is that these regions generally possess relatively better

digital infrastructure and stronger innovation capabilities, allowing intelligent technologies to support the green transformation process more effectively.

Table 14. Heterogeneity Analysis by Resource Dependence.

Variables	(1)	(2)	(3)	(4)
	CPGE (Non-Resource-Based)	**CPGE (Resource-Based)**	**CPGE (Non-Resource-Based)**	**CPGE (Resource-Based)**
LAE	0.044 ** (0.021)	0.129 (0.093)		
LAE_C			0.072 *** (0.017)	0.006 (0.103)
AI_C			−0.001 (0.002)	−0.012 ** (0.003)
LAE_C × AI_C			0.022 ** (0.007)	−0.140 * (0.055)
RDI	2.577 * (1.026)	10.531 ** (2.426)	2.405 * (1.067)	9.121 ** (2.082)
IND	−0.082 (0.072)	−0.281 (0.150)	−0.094 (0.080)	−0.228 (0.132)
GAP	0.073 (0.044)	0.095 (0.082)	0.072 (0.046)	0.170* (0.057)
HCL	3.768 * (1.366)	−3.947 (4.134)	3.979 * (1.494)	−4.318 (3.984)
TML	−0.123 (0.110)	−0.976 * (0.402)	−0.091 (0.122)	−0.372 (0.283)
Constant	0.215 (0.115)	0.211 (0.264)	0.222 (0.115)	0.026 (0.194)
Region fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	252	108	252	108
R-squared	0.960	0.894	0.963	0.903

Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In contrast, a distinctly different empirical pattern is identified for resource-based cities. The interaction term yields a coefficient of −0.140 that is statistically significant at the 10% threshold, whereas the estimated coefficient of LAE fails to reach statistical significance. This finding suggests that the positive association between LAE and CPGE is not strengthened by AI in resource-based regions and may even be weakened under certain conditions. A possible explanation is that resource-based cities are often characterized by path dependence, industrial lock-in, and relatively limited digital transformation capacity. As a result, the integration of AI into LAE-related activities may face greater institutional and technological constraints, limiting its effectiveness in promoting coordinated green development.

In addition, resource-based regions tend to rely heavily on traditional resource-intensive industries, where the adoption of AI may initially require substantial investment in digital infrastructure, technological upgrading, and workforce retraining. During this transition period, the costs associated with digital transformation may temporarily outweigh the environmental and economic benefits generated by AI-enabled LAE development, thereby contributing to a weaker moderating effect.

Collectively, these empirical findings uncover a pronounced disparity between resource-based and non-resource-based cities. While non-resource-based cities reap gains from both the direct impact of LAE and the amplifying moderating effect of AI, resource-based cities present a weaker LAE-CPGE nexus and fail to derive equivalent supporting benefits from AI advancement. This divergence highlights the importance of accounting for local industrial structures and development conditions when formulating policies to promote the integration of LAE and AI. For resource-based regions, strengthening digital infrastructure, improving technological absorptive capacity, and accelerating industrial transformation may help create more favorable conditions for realizing the potential synergies between LAE, AI, and coordinated green development.

Central cities—including provincial capitals and municipalities directly under the central government—typically enjoy greater policy support, more advanced infrastructure, and higher human capital accumulation than non-central cities. These disparities may shape how LAE and AI influence CPGE. To verify this pattern, we partition the full sample into central and non-central city subgroups. Table 15 reports the results, with columns (1)–(2) presenting the baseline effect and columns (3)–(4) incorporating the moderating role of AI.

Table 15. Heterogeneity Analysis by City Hierarchy.

	(1)	(2)	(3)	(4)
	CPGE (Non-Central City)	**CPGE (Central City)**	**CPGE (Non-Central City)**	**CPGE (Central City)**
LAE	0.088 **	0.021		
	(0.028)	(0.046)		
LAE_C			0.084	0.009
			(0.046)	(0.032)
AI_C			−0.005	−0.008 **
			(0.003)	(0.001)
LAE_C × AI_C			0.018	0.058 **
			(0.049)	(0.009)
RDI	3.019	3.879	3.157 *	2.500
	(1.868)	(1.892)	(1.508)	(0.948)
IND	−0.111	−0.287 *	−0.150 *	−0.144
	(0.074)	(0.073)	(0.064)	(0.078)
GAP	0.087	0.143	0.112 *	0.051
	(0.047)	(0.140)	(0.051)	(0.107)
HCL	3.259 *	5.109 *	2.383	4.455 *
	(1.529)	(1.692)	(1.854)	(1.259)
TML	−0.205	−0.196	−0.098	−0.307
	(0.164)	(0.472)	(0.163)	(0.382)
Constant	0.165	0.055	0.136	0.300
	(0.116)	(0.392)	(0.115)	(0.233)
Region fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	300	60	300	60
R-squared	0.938	0.879	0.942	0.927

Robust standard errors are reported in parentheses. ** $p < 0.05$, * $p < 0.1$.

Columns (1) and (2) present the comparative estimation outcomes of LAE's direct effect. For non-central cities, the estimated coefficient of LAE reaches 0.088 and is statistically significant at the 5% level, verifying that LAE exerts a positive facilitative impact on CPGE. For central cities, the coefficient is 0.021 but statistically insignificant. This divergence may reflect that central cities, despite their stronger overall economic performance, face higher baseline environmental standards and more stringent regulatory constraints, leaving less room for marginal improvements from emerging industries such as LAE. Non-central cities, by contrast, may possess greater untapped potential for leapfrogging green development.

Columns (3) and (4) further introduce the interaction term between LAE and AI. In noncentral cities, the interaction term LAE_C × AI_C is 0.018 but not statistically significant, and the coefficient of LAE_C is also insignificant (0.084). This suggests that in non-central cities, AI has yet to exert a detectable moderating effect on the LAE-CPGE relationship. A plausible explanation is that non-central cities often lag in digital infrastructure and AI penetration, limiting their capacity to harness AI for enhancing green synergy.

For central cities, the estimated interaction coefficient stands at 0.058 yet fails to pass the statistical significance test, which suggests that AI has not produced a statistically identifiable moderating effect on the LAE-CPGE nexus. Despite being numerically higher than the corresponding value for non-central cities (0.018), the statistical insignificance of this coefficient indicates that AI's supportive role in amplifying the green synergistic benefits of LAE remains constrained in central cities. A plausible rationale behind this finding is that the advantages stemming from digital infrastructure construction and AI advancement have not yet been effectively converted into integrated environmental and economic dividends.

By contrast, the moderating effect of AI is statistically significant in non-central cities. This finding implies that AI may play a more important role in supporting LAE development in regions with relatively weaker traditional infrastructure conditions. Strengthening digital infrastructure and improving AI application capabilities may therefore help further enhance the contribution of LAE to CPGE in non-central cities.

6. Discussion

The findings of this study provide new evidence regarding the role of the LAE in promoting coordinated green development. The benchmark regression results indicate that LAE significantly promotes CPGE. This finding is generally consistent with previous studies suggesting that the development of low-altitude industries can improve resource allocation efficiency, facilitate industrial upgrading, and support sustainable development through intelligent technologies and digital transformation [22,30]. Existing research has also shown that UAVs and low-altitude applications can enhance environmental monitoring and improve transportation efficiency [6,27]. Drawing on the extant literature, this study further corroborates that the positive impacts of LAE are not confined to industrial advancement and technological innovation, but also manifest in more comprehensive outcomes of synergistic green development.

However, the results also suggest that the environmental effects of LAE should not be viewed as universally positive. Previous studies have pointed out that the environmental performance of UAVs and low-altitude transportation systems depends heavily on energy sources, infrastructure conditions, and operational efficiency [28,30]. Moreover, recent studies have emphasized that environmental assessments should consider lifecycle impacts rather than focusing solely on operational emissions [28]. Therefore, although LAE is found to promote CPGE overall, its environmental benefits remain conditional and may be influenced by technological, institutional, and regulatory factors.

The mediation analysis reveals a significant negative mediating effect of green technological innovation (GT). This finding differs from the conventional expectation that GT directly promotes green development and environmental improvement [31,35]. One possible explanation is that the realization of green innovation benefits often requires a relatively long commercialization process and effective technology diffusion mechanisms [32,34]. During the early stage of LAE development, resources may be concentrated in infrastructure construction, equipment deployment, and market expansion, limiting the short-term contribution of green innovation to coordinated green development. Therefore, the observed negative mediating effect may reflect transitional characteristics and lagged innovation effects rather than a persistent inhibitory role of GT.

The moderating and threshold analyses further highlight the importance of artificial intelligence (AI). The results indicate that AI significantly strengthens the positive relationship between LAE and CPGE, while the threshold regression confirms that the contribution of LAE becomes substantially stronger after AI development exceeds a critical level. These empirical findings align with conclusions from prior literature, which documents that AI can enhance the efficiency of resource allocation and facilitate industrial upgrading [36,38]. AI has also been shown to enhance environmental governance through intelligent monitoring systems and data-driven decision-making processes [39,41]. The threshold effect identified in this study further suggests that the green development benefits associated with LAE depend not only on industrial expansion itself but also on the supporting capacity of digital intelligence technologies.

The heterogeneity test uncovers pronounced regional variations in the impacts of LAE and AI. In line with prior empirical evidence, regional gaps in resource endowments, industrial structures, and development foundations may account for divergent green development performance [19,20]. Our estimation results indicate that the direct promotional effect of LAE is more salient in non-central and non-resource-based regions, whereas the enabling effect of AI is more prominent in regions with solid digital and innovation foundations. Consistent findings have been reported in CPGE-related studies, highlighting the critical role of regional conditions in driving sustainable development outcomes [15,21]. Collectively, these results suggest that the effectiveness of LAE development is strongly context-specific, shaped by local technological endowments and institutional settings.

Overall, this study makes three key contributions to the current body of literature. First, it broadens the scope of CPGE research by integrating LAE into the analytical paradigm of coordinated green development. Second, it identifies the differentiated functions of GT and AI in influencing the environmental and economic impacts of LAE, which expands the research strand on the transmission channels between emerging industries and sustainable development. Third, it offers fresh empirical evidence for the nonlinearity and heterogeneity features of the LAE–CPGE relationship. Such conclusions help foster a more holistic understanding of the interactive dynamics among emerging industries, digital intelligence, and green transformation against the backdrop of regional sustainable development.

7. Conclusions, Policy Implications, and Limitations

7.1. Conclusions

Against the backdrop of China's green transformation and the robust growth of the LAE, this study explores the nexus between LAE and CPGE using panel data from 30 Chinese provinces over the 2012–2023 period. GT and AI are incorporated into the analytical framework to examine potential transmission mechanisms and nonlinear attributes of this association. The primary empirical findings are outlined as follows.

First, the LAE is closely linked to CPGE. Provinces with a higher level of LAE development generally achieve better performance in coordinated green development. This relationship remains stable after a series of robustness checks.

Second, GT acts as an important transmission channel between the LAE and CPGE. However, the indirect impact of GT is negative during the study period. This finding implies that the environmental and economic gains generated by green innovation may require a longer period to emerge. The relationship between innovation activities and coordinated green development therefore deserves further attention.

Third, AI serves to reinforce the contribution of LAE to CPGE. Regions with more advanced AI development are better positioned to convert the growth potential embedded in LAE into integrated environmental and economic gains. This empirical finding underscores the supportive function of digital intelligence in promoting sustainable development.

Fourth, the relationship between the LAE and CPGE changes with the level of AI development. Once AI development reaches a certain stage, the contribution of the LAE to coordinated green development becomes much stronger. This suggests that digital capabilities are an important prerequisite for releasing the green potential of the LAE.

Finally, the impact of the LAE is not uniform across regions. Differences in economic conditions, innovation capacity, and digital infrastructure lead to diverse outcomes. These findings indicate that development strategies should be designed according to local conditions.

In general, this study expands current research on the environmental performance of emerging industries by considering both GT and AI. It provides additional evidence on the channels, nonlinear characteristics, and regional differences associated with the development of the LAE. These empirical findings can serve as valuable references for advancing the synergistic development of LAE, digital intelligence, and regional green transformation.

Nevertheless, the environmental implications of the LAE should not be viewed as universally positive. From a lifecycle assessment perspective, aircraft manufacturing, battery production, and infrastructure construction may create additional environmental pressures. Improved transport efficiency may also generate rebound effects that offset part of the environmental gains. Noise pollution, biodiversity disturbance, and rising energy demand should also be taken into account. Therefore, achieving sustainable development in the LAE requires not only industrial expansion and technological progress, but also effective environmental regulation, clean energy use, and lifecycle-oriented management.

7.2. Policy Implications

According to the above empirical results, this study puts forward corresponding policy recommendations as follows.

First, efforts should be made to accelerate the development of the LAE while balancing economic expansion and environmental sustainability. Governments should improve low-altitude infrastructure, airspace management systems, and industrial support policies to promote the coordinated development of low-altitude transportation, logistics, emergency services, and intelligent equipment manufacturing. Meanwhile, greater emphasis should be placed on integrating LAE development with carbon reduction, pollution mitigation, green transition, and economic growth objectives. Policymakers should also strengthen environmental impact assessment and lifecycle management of low-altitude industries, paying attention to potential environmental costs associated with aircraft manufacturing, battery production, infrastructure construction, energy consumption, noise pollution, and biodiversity disturbance.

Second, attention should be paid not only to increasing green innovation inputs but also to improving the quality, commercialization efficiency, and practical application of

GT. The empirical results indicate that GT has not yet generated the expected positive contribution to CPGE during the sample period. Therefore, policymakers should strengthen support for high-quality green innovation, improve technology transfer mechanisms, and promote the commercialization and diffusion of green technologies. Particular attention should be given to enhancing the practical application of green innovation within low-altitude industries so that innovation achievements can be more effectively transformed into environmental and economic benefits.

Third, governments should actively promote the deep integration of AI and the LAE. As AI significantly strengthens the positive impact of the LAE on CPGE, greater efforts should be directed toward developing intelligent infrastructure, digital governance platforms, and data-sharing systems. Encouraging the application of AI technologies in low-altitude operation management, intelligent scheduling, environmental monitoring, and public services can further improve resource allocation efficiency and environmental governance performance.

Fourth, differentiated digital development strategies should be implemented to overcome the AI threshold constraint. Since the environmental and economic benefits of the LAE become significantly stronger after AI development reaches a certain level, regions with relatively weak AI foundations should increase investment in digital infrastructure, intelligent industries, and talent cultivation. By enhancing regional AI development capacity, these regions can cross the threshold more rapidly and fully benefit from the green empowerment effect of the LAE.

Finally, region-specific development policies should be adopted according to local conditions. Given the significant regional heterogeneity identified in this study, policymakers should avoid a one-size-fits-all approach. Regions with stronger economic foundations and innovation capacities should focus on promoting technological breakthroughs, industrial integration, and green innovation quality improvement, while less-developed regions should prioritize infrastructure improvement, factor accumulation, and capacity building. Such differentiated strategies will help maximize the environmental and economic benefits of the LAE across different regions while mitigating potential environmental risks.

7.3. Research Limitations and Future Prospects

Despite providing new evidence on the relationship between the LAE and coordinated green development, this study has several limitations.

First, the analysis is based on provincial-level panel data and therefore cannot fully capture heterogeneity across cities, industries, and firms. Future research could employ city-level or firm-level data to further explore the micro-level mechanisms underlying the relationship between LAE and CPGE.

Second, although a significant negative mediating effect of GT is identified, the underlying mechanisms cannot be directly verified in the current framework. Future studies could further examine factors such as patent quality, technology diffusion, and lagged innovation effects to better understand the role of GT.

Finally, while the results indicate that LAE is positively associated with CPGE, the long-term environmental impacts of LAE remain worthy of further investigation. Future research could incorporate lifecycle assessment (LCA) methods to evaluate the environmental costs and sustainability implications of LAE development more comprehensively.

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