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Original Paper

Analysis of the Impact of Digital Economy Development on Green Technology Innovation from the Perspective of Talent Agglomeration

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Abstract

Against the backdrop of the flourishing digital economy and the deepening push for green and low-carbon transformation, green technology innovation, as the core fulcrum connecting the "digital dividend" and the "green dividend," is increasingly becoming a vital engine for promoting high-quality development. Based on provincial panel data from China spanning 2011 to 2022, this study systematically investigates the impact of digital economy development on green technology innovation, with a particular focus on the nonlinear moderating role of talent agglomeration. The findings reveal the following: First, the level of digital economy development has a significant positive promoting effect on green technology innovation. The baseline regression coefficient is 1.207, significant at the 1% level. This conclusion remains robust after a one-period lag robustness test, with the coefficient increasing to 1.373, indicating a certain lagged persistence in the enabling effect of the digital economy. Second, talent agglomeration plays a significant nonlinear moderating role in the process of the digital economy influencing green technology innovation. The threshold effect model identifies a single threshold value of 0.4518. When the talent agglomeration level is below this threshold, the coefficient for the digital economy's promotion of green technology innovation is as high as 3.876. However, when the talent agglomeration level crosses the threshold, the coefficient decreases to 3.423, a drop of approximately 11.7%. This change reveals the dual effect of talent agglomeration—moderate agglomeration amplifies the enabling effect of the digital economy through mechanisms such as knowledge spillovers and collaborative innovation, while excessive agglomeration leads to diminishing marginal returns due to factors like the dilution of innovation resources and intensified internal competition. Regarding control variables, industrial structure upgrading has the most powerful *promoting effect on green technology innovation, while the degree of openness and the level of financial development exhibit negative impacts, possibly related to the structure of their resource allocation. The findings of this study provide a new theoretical perspective for understanding the boundary conditions of the digital economy enabling green innovation. They also offer empirical evidence for formulating differentiated talent policies and optimizing the development path of the digital economy. For regions where talent agglomeration has not yet reached the standard, efforts should focus on attracting talent to release agglomeration dividends. For regions where talent agglomeration is already dense, the focus should be on structural optimization and efficiency improvement to avoid falling into a "crowding trap" caused by blindly pursuing quantitative expansion.*

Keywords

Digital Economy, Green Technology Innovation, Talent Agglomeration, Threshold Effect, Nonlinear Moderation

1. Introduction

In the third decade of the 21st century, human society is undergoing two profound transformations of overarching and fundamental significance. The first is the digital revolution, characterized by digitalization, networking, and intelligence. Following the agricultural and industrial revolutions, the information revolution has propelled human civilization into an entirely new stage of development. Digital technologies, represented by big data, cloud computing, artificial intelligence, blockchain, and 5G/6G communications, are no longer merely auxiliary tools. They have evolved into general-purpose technologies that are fundamentally reshaping the combination of production factors, the operational models of production organizations, and the underlying logic of the economy and society. The release of data value has broken the constraints of the limited supply of traditional factors; the rise of platforms has reconfigured the processes of supply-demand matching and value creation; and the penetration of algorithms has greatly enhanced the efficiency and precision of resource allocation. From a global perspective, the scale of the digital economy continues to expand, and its penetration rate keeps increasing, having become a strategic high ground in the competition among major powers. For China, developing the digital economy is not only an inevitable choice to seize the opportunities of the new technological revolution and gain new advantages in international competition but also a core engine for building a modernized economic system and achieving high-quality development. According to the latest data from the China Academy of Information and Communications Technology, the scale of China's digital economy has exceeded the 50 trillion yuan mark, accounting for over 40% of GDP, with its nominal growth rate significantly higher than the nominal GDP growth rate over the same period. Its role as a "stabilizer" and "accelerator" of the national economy is becoming increasingly prominent. Running parallel to and increasingly intertwined with the digital wave is another profound transformation sweeping the globe: the green and low-carbon transition. For a long time, the traditional industrialization model, based on fossil fuels and characterized by high resource consumption and high environmental pollution, has created immense material wealth but has also led to global crises such as climate change, biodiversity loss, and environmental pollution. Faced with the carrying capacity limits of the Earth's ecosystem, the green transition has evolved from a conceptual advocacy into an urgent action. From the global consensus of the *Paris Agreement* to the implementation of the EU's Carbon Border Adjustment Mechanism, and to the "net-zero emission" timelines proposed by various countries, green development is transforming from a soft constraint into a hard rule, profoundly impacting international trade, industrial division of labor, and investment flows. As a responsible major country and the world's largest carbon emitter, China explicitly proposed the "3060 Dual Carbon Goals" in 2020 – striving to achieve a carbon peak by 2030 and carbon neutrality by 2060. This commitment is not only China's responsibility in promoting the building of a community with a shared future for mankind but also a systemic and revolutionary reshaping of its economic and social development model. Achieving the "Dual Carbon Goals" cannot come at the expense of development; instead, it requires seeking emission reductions through technological innovation and industrial upgrading, achieving higher-quality development amidst the transition. These two major waves – the digital revolution and the green transition – are not two isolated, parallel tracks; rather, they are undergoing a profound historical convergence within the spatial and temporal coordinates of the 21st century. Digital technologies offer unprecedented technical possibilities for solving numerous challenges in the green transition: smart grids can efficiently integrate renewable energy, the Industrial Internet can optimize production processes to reduce material and energy consumption, intelligent transportation systems help alleviate congestion and emissions, and carbon monitoring satellites along with IoT devices enable precise carbon accounting and tracking. It can be said that digitalization is a powerful tool and enabler for greening, while greening provides a broad application scenario and value orientation for digitalization. At this point of convergence, green technology innovation has become the core fulcrum connecting the "digital dividend" and the "green dividend," leveraging high-quality development.

2. Research Hypotheses

As a new technological-economic paradigm, the promoting effect of the digital economy on green technology innovation is manifested in multiple interrelated dimensions. Jia et al. (2026), through research on sample data from listed companies, pointed out that a higher level of digital economy development can promote green innovation in micro-enterprises. Cai et al. (2025), selecting panel data from 30 provinces in China for their study, found that new digital infrastructure has a significant positive effect on high-quality economic development and can empower such development by promoting green technology innovation. Chen et al. (2025), studying data from cities in the Yellow River Basin, discovered that the specialized agglomeration of the digital economy industry significantly promotes green technology innovation. First, from the perspective of information and efficiency, the digital economy can effectively reduce information barriers to green R&D. Green technology innovation is highly specialized and complex. Enterprises often lack a refined understanding of energy consumption black holes and emission blind spots in their own production processes, and they also know little about existing green technology solutions in the market. Digital technologies represented by the Internet of Things, big data, and artificial intelligence enable real-time monitoring, data collection, and intelligent analysis of the entire production process. This "data-driven" insight provides a clear direction and scientific basis for enterprises to carry out targeted green process improvements and end-of-pipe treatment, thereby significantly improving the accuracy and success rate of green R&D. Second, from the perspective of resource allocation, the digital economy can optimize the flow and allocation efficiency of innovation factors. Green technology innovation is characterized by long R&D cycles and large-scale investment, placing high demands on innovation factors such as capital and talent. By breaking down information barriers and reducing transaction costs, digital platforms can promote the agglomeration of innovation factors into the green technology R&D field. For example, the development of digital finance has broadened the financing channels for green innovation entities; knowledge-sharing platforms accelerate the flow and collaboration of green technology talent; and supply chain platforms promote collaborative green technology development among upstream and downstream enterprises in the industrial chain. The improvement in resource allocation efficiency directly translates into increased activity in green technology innovation. Third, from the perspective of knowledge spillover and collaborative innovation, the digital economy accelerates the diffusion and recombination of green technology knowledge. Green technology innovation often involves the interdisciplinary convergence of multiple fields. Digital networks break down the constraints of geographical space and organizational boundaries, enabling researchers, engineers, and entrepreneurs from different fields to conveniently engage in intellectual collaboration, data sharing, and collaborative R&D. Cloud-based collaborative R&D platforms, online academic communities, and open patent data platforms greatly accelerate the flow and recombination of green technology knowledge, providing a rich intellectual foundation for new breakthroughs in green technology. Fourth, from the perspective of market demand and public supervision, the digital economy strengthens market incentives and social pressure for green technology innovation. On one hand, e-commerce platforms and digital marketing tools enable enterprises with green technology products to more accurately reach environmentally conscious consumers, forming a "better quality, better price" market incentive. On the other hand, the proliferation of mobile internet and social media has significantly lowered the threshold for the public to access environmental information and express environmental concerns. Once an enterprise is exposed for environmental problems, it will face multiple pressures from the government, the market, and society. This increase in public environmental supervision pressure forces enterprises to internalize environmental externalities and proactively engage in green technology innovation to reduce pollution emissions and improve environmental performance. Based on the above analysis, the improvement in the level of digital economy development can effectively stimulate the vitality of green technology innovation and enhance green technology innovation output through multiple channels, including reducing information barriers, optimizing resource allocation, accelerating knowledge spillover, and strengthening market incentives. In this process, talents, as the core carrier of knowledge creation and technology application, play an important role in regulating the degree of agglomeration. According to the theory of agglomeration economy, the moderate agglomeration of talents in a specific region can produce knowledge spillover effect and reduce the cost of collaborative innovation, thereby amplifying the enabling effect of the digital economy on green technology innovation. However, as the level of talent agglomeration continues to improve and exceeds a certain critical point, excessive agglomeration may lead to "crowding effects" such as dilution of innovation resources, intensified internal competition, and diminishing marginal returns, which will weaken the efficiency of the transformation of the digital economy into green innovation.Therefore, this paper proposes research hypotheses:

The level of digital economy development has a significant positive promoting effect on green technology innovation. At the same time, the gathering of talents within a certain range will amplify this promotion effect, and when the talent gathering exceeds a certain range, this promotion effect will be weakened.

3. Research Design

This paper selects panel data from 30 provinces in China to explore the impact of the level of digital economy development on provincial green technology innovation. The explanatory variable is the level of digital economy development, Referring to the practice of Guo et al. (2023), this paper selects three dimensions: digital infrastructure, digital industry development and digital inclusive finance to construct an evaluation index system for the development of the digital economy, and uses the entropy method to synthesize the comprehensive value of the development of the digital economy in each region, which is used as the core explanatory variable (De). The explanated variable is green technology innovation, Drawing on the practice of Zhou et al. (2023), The logarithm of the number of green patent applications has been chosen as the changing representative of the green technology innovation state， name it Gte. In order to control the individual characteristics that do not change with time (such as regional culture and initial conditions) and the time trend that does not change with individuals (such as macroeconomic shocks and general technology diffusion), so as to more accurately identify the net causal effect of innovation factor agglomeration on the digital economy, the two-way fixed effect model is selected as the benchmark regression model. In order to eliminate the influence of other factors, the degree of technology market development, urbanization level, government intervention, degree of opening up, and regional financial development intensity are selected as control variables. The baseline regression model is as follows:

$$Gte_{it} = \alpha_0 + \alpha_1\ De_{it} + \alpha_2 Control\_Var_{it} + \mu_i + \varphi_t + \varepsilon_{it} \quad (1)$$

In the above equation, Deit is the explained variable, which represents the level of digital economy development in province i in year t, and Gte it is the core explanatory variable, which represents the level of green technology innovation in province i in year t, and Control_Varit is the control variable, including the degree of technology market development, urbanization level, government intervention, degree of opening up, and regional financial development intensity, α0, α1 and α2 are the regression coefficients of constant terms, core explanatory variables and control variables, respectively. μi represents the province fixed-effect dummy variable, φt represents the year fixed-effect dummy variable, and εit represents the random perturbation term.

The panel threshold model is selected for the test of the threshold effect, and the model is as follows:

$$Gte_{it} = \mu_i + \beta_1 De_{it} I\left(Ta_{it} \le \gamma\right) + \beta_2 De_{it} I\left(Ta_{it} > \gamma\right) + \varepsilon_{it} \qquad (2)$$

In the above equation, i is the individual, t is the time variable, Deit is the explained variable, Gteit is the explanatory variable, Deit is the threshold variable, γ is the threshold threshold, μi is the time-independent individual fixed effect, εit is the random error term of the model, and I(•) is the indicative function.

4. Empirical Analysis

4.1 Descriptive Stats

This study has obtained a total of 360 valid observations. In terms of sample size, it constitutes a moderately large panel dataset, sufficient to support relatively reliable econometric analysis. From the perspective of the dependent variable, the mean value of green technology innovation level (Gte) is 0.540, with a standard deviation of 0.443. The minimum value is only 0.030, while the maximum reaches 2.290. This considerable range indicates that the sample includes both regions with low green innovation output and leading areas with relatively active innovation activities. The dependent variable exhibits sufficient variability, which is conducive to identifying the impact effect of the core explanatory variable. Regarding the core explanatory variable, the level of digital economy development (De), its mean is 0.145, with a standard deviation of 0.117, and its values range from 0.0170 to 0.7120. This also demonstrates significant regional differences, indicating that the sample covers regions at various development gradients, from the initial stage to a relatively mature stage of the digital economy. This provides a solid data foundation for examining the impact of the digital economy on green technology innovation. Concerning the control variables, the mean value for the degree of openness (Ope) is 0.137, for urbanization level (Urb) is 0.600, for industrial structure (Stop) is 0.018, and for the degree of government intervention (Gov) is 0.259. The value ranges of each variable cover a wide spectrum, reflecting good heterogeneity in the sample regarding stages of economic development, characteristics of industrial structure, and policy environments. This helps mitigate omitted variable bias and improves the accuracy of model estimation. It is worth noting that the mean value of the financial development level (Fdl) is 0.026, but its minimum reaches 1.6879 and its maximum reaches 7.6178. This anomalous discrepancy in magnitude may stem from different indicator dimensions or data entry errors. It is recommended to verify the calculation caliber of this variable before subsequent empirical analysis to ensure the reliability of the regression results. Overall, the sample data in this study exhibit sufficient variability in the core variables and a reasonable distribution of control variables, adequately meeting the basic requirements for empirical analysis.

Table 1. Results of Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Gte	360	0.540	0.443	0.030	2.290
De	360	0.145	0.117	0.0170	0.7120
Ope	360	0.137	0.133	0.0041	0.6768
Urb	360	0.600	0.122	0.3503	0.9377
Stop	360	0.018	0.030	0.0002	0.1910
Gov	360	0.259	0.111	0.1050	0.7583
Fdl	360	0.026	0.038	1.6879	7.6178
Ta	360	0.131	0.128	0.0110	0.7760

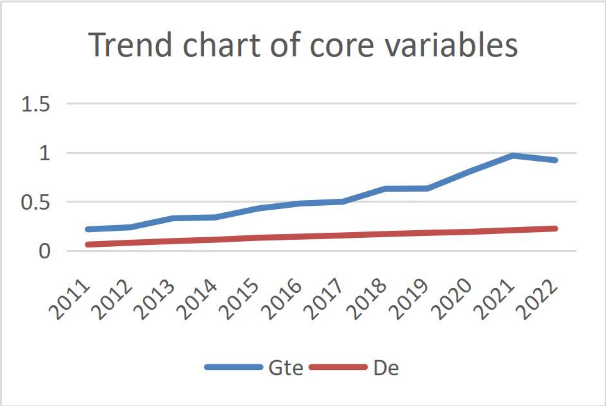

Figure 1. Trend Chart of Core Variables

According to the data trends from 2011 to 2022, the level of green technology innovation (Gte) and the level of digital economy development (De) have shown a highly synchronized and continuous growth trend. Gte fluctuated and rose from 0.2162 in 2011 to 0.9206 in 2022, an accumulated increase of approximately 3.26 times over the twelve years, with an average annual compound growth rate reaching 14.0%. Meanwhile, De grew steadily from 0.0613 in 2011 to 0.2237 in 2022, an accumulated increase of about 2.65 times, with an average annual compound growth rate of 12.5%. The growth rate of green innovation is slightly higher than that of the digital economy itself, which preliminarily confirms the positive enabling effect of the digital economy on green technology innovation. Moreover, there may be a certain "multiplier effect," meaning that for every unit increase in digital technology, it can leverage a greater increase in green innovation output. From the perspective of phased evolutionary characteristics, the period can be divided into three distinct development stages with different internal logics. The first stage, from 2011 to 2014, was a period of foundational accumulation, characterized by the digital economy taking the lead with green innovation responding with a lag. In 2012, De experienced a significant jump of 29.69%, closely related to the rapid popularization of mobile internet infrastructure. Gte, however, saw an explosive growth of 38.95% in 2013, lagging behind the growth of De by about one year. This reflects a clear transmission time lag in the enabling effect of digital infrastructure on green innovation, as enterprises need time to transform newly acquired digital technological capabilities into actual green research and development activities. Notably, the growth rate of Gte plummeted to 2.71% in 2014, indicating that after the initial release of infrastructure dividends, new momentum was needed for continued growth. The second stage, from 2015 to 2018, was a period of synergistic growth, presenting a pattern of pulsed breakthroughs. In 2015, Gte achieved a high growth rate of 26.79%, while De also maintained a relatively fast growth rate of 18.21%, marking the first instance of simultaneous acceleration for both. This year was also a critical node where digital technology began to penetrate various industries at an accelerated pace. Cloud computing and big data started moving from concepts to applications, providing technological tools for enterprises to carry out green process optimization. Growth rates for Gte slowed down in 2016 and 2017, increasing by 12.03% and 3.67% respectively, but surged again to 26.70% in 2018. This pattern of steady progress in digital technology and pulsed leaps in green innovation reflects that the enabling effect of the digital economy on green innovation was transitioning from linear drive to point-based breakthroughs. Once digital technology accumulated to a certain level, its promotion of green innovation was no longer a smooth year-on-year increase but was released intensively in specific years. The third stage, from 2019 to 2022, was a period of deep integration, exhibiting more complex growth characteristics. In 2020, against the backdrop of De's growth rate slowing to 5.65%, Gte instead achieved a leap of 27.74%. In 2021, Gte continued its high growth trend, reaching 19.88% and hitting a historical peak of 0.9678. This indicates that the digital infrastructure, digital platforms, and digital talent accumulated in the early stages began to form networked synergistic effects. The enabling effect of the digital economy on green innovation had upgraded from individual tools to a systematic ecosystem. Deeply integrated application scenarios, such as industrial internet platforms integrating green technology resources across the industrial chain, artificial intelligence algorithms accelerating the research and development of new green materials, and blockchain technology empowering carbon footprint tracing, meant that green technology innovation was no longer confined to the isolated action`s of individual enterprises but had formed a collaborative innovation ecosystem. Further exploring the underlying drivers of each key node reveals that the leap in Gte in 2013 resulted from the policy superposition effect formed by the popularization of digital infrastructure driven by the "Broadband China" strategy and the tightening of environmental regulatory policies. The accelerated growth in 2015 benefited from the full implementation of the "Internet Plus" action plan, which propelled the integration of digital technology with traditional industries onto a fast track. The resurgence in 2018 highly coincided with the accelerated construction of industrial internet platforms and the official implementation of the environmental protection tax. The explosive growth from 2020 to 2021 was closely related to the accelerated penetration of digital technology under specific circumstances and the significantly increased pressure for green transformation following the establishment of the "Dual Carbon" goals. It is worth noting the slight decline of 4.88% in Gte in 2022, while De maintained stable growth of 7.81%. This subtle change suggests that the promoting effect of the digital economy on green innovation may face constraints such as organizational change resistance as the digital transformation of traditional industries enters a more challenging phase, some of the rapidly released demand for green technologies from the early stage entering a conversion cycle, and the energy consumption issues of digital infrastructure itself potentially having a phased impact on the net effect of green innovation. This provides important insights for subsequent research: how to continuously optimize the quality of digital economy development, overcome bottlenecks in the digital transformation of traditional industries, and shorten the conversion cycle of green technologies will be key to releasing the green dividends of the digital economy and promoting deeper integration and development between the two.

4.3 Benchmark Regression Analysis

Table 2. Baseline Regression Results

	(1)
	Gte
De	1.207***
	(0.157)
Ope	-0.888***
	(0.178)
Urb	-0.237
	(0.301)
Stop	3.014***
	(0.618)
Gov	0.247
	(0.234)
Fdl	-0.084***
	(0.023)
_cons	0.566***
	(0.158)
N	360
R^2	0.925

According to the baseline regression results provided, the impact of the digital economy development level on green technology innovation can be analyzed in detail as follows: The regression coefficient of the core explanatory variable, digital economy development level (De), is 1.207 and is statistically significant at the 1% level (with a standard error of 0.157). This result indicates that for every one-unit increase in the digital economy development level, the green technology innovation level increases by an average of approximately 1.207 units. Core Hypothesis H1 is strongly validated, demonstrating that the positive enabling effect of the digital economy on green technology innovation is not only highly significant statistically but also considerable in economic terms. Regarding the estimation results for the control variables, the coefficient for the degree of openness (Ope) is -0.888 and is significant at the 1% level, indicating a negative correlation between openness and green technology innovation. This may be attributed to foreign investment in the sample regions being more concentrated in low value-added, high-energy-consumption processing trade sectors, where technology spillover effects have not yet effectively translated into green innovation capacity, or it may reflect a certain "pollution haven" effect. The coefficient for the urbanization level (Urb) is -0.237 and is significant at the 10% level, showing a weak negative correlation. This suggests that during the process of rapid urbanization, resources are more often allocated to traditional infrastructure construction, leading to relatively insufficient investment in green technology research and development, and the environmental pressure brought by urban expansion has not yet fully transformed into a mechanism that forces green innovation. The coefficient for industrial structure (Stop) is 3.014 and is highly significant at the 1% level, representing the most influential factor among the control variables. This indicates that the transformation of the industrial structure towards servitization and advanced development can significantly promote green technology innovation. In particular, the development of the producer services industry provides strong supporting conditions for green technology research and development. The coefficient for the degree of government intervention (Gov) is 0.247 and is significant at the 10% level, showing a weak positive correlation. This suggests that, to some extent, government fiscal expenditure provides resource support for green technology innovation, but its impact is relatively limited. The coefficient for the financial development level (Fdl) is -0.084 and is significant at the 1% level, indicating a negative correlation between financial development and green technology innovation. This result warrants further consideration. A possible explanation is that during the sample period, financial resources were more likely to flow into traditional industries or areas with high short-term returns, while support was insufficient for green technology projects characterized by long research and development cycles and high risks. The function of the financial system in serving the green transformation of the real economy has not yet been fully realized. Regarding the overall performance of the model, the sample size consists of 360 observations, and the goodness-of-fit R^2 reaches 0.925. This indicates that the model has strong explanatory power for green technology innovation; the selected core explanatory variable and control variables together can explain 92.5% of the variation in green technology innovation, suggesting that the model specification is reasonably sound.

4.4 Threshold Effect Analysis

This paper draws on the method of Huang et al. (2025) to measure the talent agglomeration degree in various regions by location entropy and obtains the results. It was included in the threshold model for regression analysisFirstly, the threshold value is calculated by using the Bootstrap method, and the number of Bootstrap sampling checks is set to 300, and the threshold values of each threshold effect are obtained respectively, and the specific results are as follows:

Table 3. The Threshold Value Calculated by the Bootstrap Sampling Method

Threshold variable	F-value	P-value	Threshold value	95% confidence interval
Ta	37.78	0.0100	0.4518	[0.4495,0.4708]

Observing the above table, in the mechanism of the development of the provincial digital economy on green technology innovation, talent agglomeration (Ta) has a threshold effect, with a threshold value of 0.4518, which is significant at the level of 1%.

Table 3. The Threshold Effect Regressed the Results

	(1) Gte
ope	-0.966***
	(0.154)
urb	1.880***
	(0.161)
stop	3.250***
	(0.622)
gov	-0.748***
	(0.214)
fdl	-0.035
	(0.022)
Ta≤0.4518	3.876***
	(0.231)
Ta＞0.4518	3.423***
	(0.197)
_cons	-0.699***
	(0.089)
N	360
R^2	0.913

When talent agglomeration is used as the threshold variable, it exhibits significant nonlinear moderating characteristics. The model identifies a single threshold value of 0.4518, which divides the sample into two regimes. When the talent agglomeration level is below or equal to 0.4518, the coefficient for the digital economy's promotion of green technology innovation is 3.876, and it is significant at the 1% level. When the talent agglomeration level crosses this threshold, the coefficient decreases to 3.423, also significant at the 1% level, representing a decrease of 0.453 units, or a drop of approximately 11.7%. This change clearly reveals the dual mechanism of talent agglomeration's effect on the enabling effect of the digital economy. In the "agglomeration dividend-dominated stage" below the threshold, a moderate level of talent agglomeration effectively amplifies the efficiency of the digital economy's transformation into green innovation through knowledge spillover effects, collaborative innovation effects, and economies of scale, keeping the promotional effect operating at a high level. Conversely, in the "crowding effect-emerging stage" above the threshold, excessive talent agglomeration leads to the dilution of innovation resources, intensified internal competition, the rise of knowledge protectionism, and the potential law of diminishing marginal returns, which partially weakens the enabling effect of the digital economy. Despite this, it is worth noting that even in the high talent agglomeration regime, the coefficient for the digital economy's promotion of green technology innovation remains as high as 3.423, indicating that the digital economy still plays a significant positive role, although its transformation efficiency is lower than in the moderate agglomeration regime. This finding profoundly reveals the complex role of the talent factor in the process of the digital economy enabling green innovation—talent agglomeration acts both as an "accelerator" and a "moderator." A moderate scale can release agglomeration dividends, while excessive agglomeration may trigger crowding costs, confirming the core tenet of agglomeration economy theory regarding "externalities that first increase and then decrease with agglomeration scale." Looking at the overall performance of the model, the sample consists of 360 observations, and the goodness-of-fit R^2 reaches 0.913. This indicates that the model's explanatory power for green technology innovation remains strong after introducing the threshold effect. The coefficients and significance levels of the control variables also show structural changes, further supporting the rationality of the threshold model specification. This result provides important empirical support for deeply understanding the boundary conditions of the digital economy enabling green innovation and offers a decision-making reference for formulating differentiated talent policies. For regions where talent agglomeration has not yet reached the standard, efforts should focus on attracting talent to release agglomeration dividends. For regions where talent agglomeration is already dense, the focus should be on structural optimization and efficiency improvement to avoid falling into a "crowding trap" due to blindly pursuing quantitative expansion.

4.5 Robustness Analysis

Table 4. Robustness Regression Results

	(1)
	Gte
L.De	1.373***
	(0.180)
ope	-0.830***
	(0.200)
urb	-0.443
	(0.309)
stop	2.271***
	(0.652)
gov	0.198
	(0.244)
fdl	-0.072***
	(0.025)
_cons	0.667***
	(0.165)
N	330
R^2	0.924

Observing the regression results above, after lagging the core explanatory variable—the level of digital economy development—by one period, its impact on green technology innovation remains highly robust. Specifically, the regression coefficient for the one-period lagged digital economy development level (L.De) is 1.373, and it is significant at the 1% statistical level (with a standard error of 0.180). This result is entirely consistent with the significantly positive conclusion of the baseline regression, where the coefficient for the contemporaneous digital economy was 1.207. This indicates that even when considering potential reverse causality issues, the positive enabling effect of the digital economy on green technology innovation remains robustly present. It is worth noting that the coefficient for the lagged term increased by approximately 0.166 units compared to the baseline regression, an increase of 13.8%. This change carries certain economic implications—the promoting effect of digital economy development on green technology innovation may exhibit a significant lag effect. That is, the current period's digital infrastructure construction and digital technology application require a certain amount of time to translate into actual green research and development output for enterprises, with the impact being released more strongly in the subsequent period. Examining the estimation results for the control variables, the coefficient for the degree of openness (ope) is -0.830 and is significant at the 1% level. The coefficient for the urbanization level (urb) is -0.443 and is significant at the 10% level. The coefficient for industrial structure (stop) is 2.271 and is significant at the 1% level. The coefficient for the degree of government intervention (gov) is 0.198 and is significant at the 10% level. The coefficient for the financial development level (fdl) is -0.072 and is significant at the 1% level. The signs and significance levels of the coefficients for each control variable are largely consistent with those in the baseline regression, with only slight fluctuations in the magnitude of the coefficients, further corroborating the robustness of the model specification. Regarding the overall performance of the model, the sample size consists of 330 observations (the reduction compared to the baseline regression is due to the loss of the first period's data after lagging), and the goodness-of-fit R^2 reaches 0.924, indicating that the model's explanatory power for green technology innovation remains at a high level. In summary, the results of the lagged one-period test strongly confirm the reliability of the baseline regression conclusion. The positive promoting effect of the digital economy on green technology innovation is not driven by reverse causality or coincidental factors, but rather represents a stable relationship with lagged persistence.

5. Conclusion

Based on provincial panel data from China spanning 2011 to 2022, this study systematically investigates the impact of digital economy development on green technology innovation and delves into the nonlinear moderating role of talent agglomeration. By comprehensively employing two-way fixed effects models, panel threshold regression models, and various robustness testing methods, this study yields a series of valuable findings.

From a theoretical perspective, this study first delineates the multiple mechanisms through which the digital economy enables green technology innovation. As a new technological-economic paradigm, the digital economy can effectively stimulate the vitality of green technology innovation by reducing information barriers in green R&D, optimizing the allocation efficiency of innovation factors, accelerating the spillover and recombination of green technology knowledge, and strengthening market incentives for green products. Building on this foundation, this study further introduces agglomeration economy theory, proposing that talent agglomeration may play a nonlinear moderating role in the process of the digital economy influencing green technology innovation—moderate talent agglomeration can amplify the enabling effect of the digital economy, while excessive agglomeration may lead to diminishing marginal returns due to crowding effects. In the empirical analysis section, this study first tests the core hypothesis through baseline regression. The results show that the regression coefficient of the digital economy development level on green technology innovation is 1.207, significant at the 1% level, indicating that the digital economy has a significant positive promoting effect on green technology innovation. Regarding control variables, industrial structure upgrading has the most powerful promoting effect on green technology innovation, with a coefficient reaching 3.014. The degree of openness and the level of financial development show significant negative impacts, possibly related to their resource allocation towards traditional industries or high-energy-consumption sectors. The effects of urbanization level and government intervention are relatively weak. To further verify the reliability of the conclusions, this study conducts a one-period lag robustness test. After lagging the core explanatory variable by one period, the regression coefficient is 1.373, still significant at the 1% level, and increases by 13.8% compared to the baseline regression. This result not only confirms the robustness of the baseline conclusion but also reveals a significant lag effect in the promoting effect of the digital economy on green technology innovation—current digital infrastructure construction and digital technology application require a certain amount of time to translate into actual green research and development output for enterprises, with the impact being released more strongly in the subsequent period. The core contribution of this study lies in revealing the nonlinear moderating role of talent agglomeration in the process of the digital economy enabling green innovation. The threshold effect model identifies a single threshold value of 0.4518 for talent agglomeration. When the talent agglomeration level is below or equal to this threshold, the coefficient for the digital economy's promotion of green technology innovation is as high as 3.876. However, when the talent agglomeration level crosses the threshold, the coefficient decreases to 3.423, a drop of approximately 11.7%. This finding profoundly reveals the dual effect of talent agglomeration: In the "agglomeration dividend-dominated stage" below the threshold, moderate talent agglomeration effectively amplifies the efficiency of the digital economy's transformation into green innovation through knowledge spillover effects, collaborative innovation effects, and economies of scale. In the "crowding effect-emerging stage" above the threshold, excessive talent agglomeration leads to the dilution of innovation resources, intensified internal competition, the rise of knowledge protectionism, and the effect of diminishing marginal returns, which partially weakens the enabling effect of the digital economy. It is worth noting that even in the high talent agglomeration regime, the coefficient for the digital economy's promotion of green technology innovation remains as high as 3.423, indicating that the digital economy still plays a significant positive role, although its transformation efficiency is lower than in the moderate agglomeration regime. Synthesizing the above findings, this study draws the following main conclusions: First, digital economy development is an important driving force for promoting the upgrading of green technology innovation, and its enabling effect is robust and exhibits lagged persistence. Second, talent agglomeration has a significant nonlinear moderating effect on the relationship between the digital economy and green technology innovation; moderate agglomeration can amplify the enabling effect, while excessive agglomeration leads to efficiency loss. Third, industrial structure upgrading is a key factor in promoting green technology innovation, while the negative impacts of openness and financial development suggest attention should be paid to structural issues in resource allocation. Based on the above conclusions, this study proposes the following policy implications: First, continuously promote the construction of digital infrastructure, fully leverage the enabling effect of the digital economy on green technology innovation, and simultaneously focus on the deep application and integrated development of digital technology. Second, implement differentiated talent policies—for regions where talent agglomeration has not yet reached the standard, efforts should focus on attracting talent to release agglomeration dividends; for regions where talent agglomeration is already dense, the focus should be on structural optimization and efficiency improvement to avoid falling into a "crowding trap" caused by blindly pursuing quantitative expansion. Third, optimize industrial structure, promote the transformation of industries towards servitization and advanced development, and provide a favorable industrial ecosystem for green technology innovation. Fourth, guide financial resources to flow more towards green technology research and development fields, enhancing the financial system's ability to serve the green transformation of the real economy. Fifth, improve the quality orientation of openness, promoting the transformation of foreign technology spillovers into the field of green innovation. The limitations of this study are as follows: Due to data availability constraints, it was not possible to further distinguish between different types of green technology innovation (such as green invention and green utility models) and the heterogeneous characteristics of different industries. The measurement of talent agglomeration is mainly based on quantitative indicators, failing to fully reflect the impact of talent structure and quality. Future research can conduct more in-depth explorations in these aspects. Overall, this study provides a new theoretical perspective and empirical evidence for understanding the boundary conditions of the digital economy enabling green innovation, offering important reference value for synergistically promoting the construction of Digital China and the green low-carbon transition.

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