Research on the Impact of High-Tech Industry Agglomeration on Green Innovation in Fujian Province under the Digital Economy

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Abstract: This paper empirically analyzes the impact of high-tech industry agglomeration on green innovation and the moderating role of the digital economy, utilizing panel data from Fujian Province spanning 2010 to 2023, and employing the location quotient and two-way fixed effects models. The findings reveal: First, high-tech industry agglomeration significantly promotes green innovation; for each unit increase in the agglomeration level, the number of green patent applications rises by 26.6% (coefficient 0.266, $p < 0.01$). Second, although the digital economy individually exerts a positive effect on green innovation, its moderating effect suppresses the positive impact of agglomeration. The interaction term coefficient is -2.405 ($p < 0.01$), indicating that uneven distribution of digital resources or virtual agglomeration may weaken the knowledge spillover effects of traditional agglomeration. Third, openness to the outside world significantly enhances innovation efficiency (coefficient 0.637, $p< 0.05$), whereas the level of human capital inhibits green innovation efficiency (-0.286, $p <0.01$).This study provides empirical evidence for optimizing regional industrial layout and coordinating policies related to the digital economy and green innovation.

Keywords: High-Tech Industry; Industrial Agglomeration; Digital Economy; Green Innovation

1. Introduction

In the context of the new era, the digital economy has become a crucial factor in China's economic development. As a typical knowledge- and technology-intensive industry, the high-tech industry not only attracts a substantial amount of cutting-edge innovation resources but also, by virtue of its resource-conserving and environmentally friendly green characteristics, serves as the core industrial support for regions and countries seeking pathways for green innovation and development. Moreover, the high-tech industry exhibits distinct spatial agglomeration characteristics [1]. The agglomeration scale, benefits, and capabilities of the high-tech industry agglomeration system generate corresponding externalities that influence the development of related industries through the spillover effects of agglomeration [2]. Concurrently, green innovation acts as a powerful driving force, enabling enterprises to create products with green differentiation. Once these unique green products are introduced to the market, they can stimulate new waves of market demand, opening up new growth spaces with significant potential for enterprises.

Studying the relationship between high-tech industry agglomeration and corporate green innovation, and clarifying the mechanisms between them, holds substantial practical significance for promoting the high-quality development of the high-tech industry and fostering green innovation. However, current domestic and international research on the impact of regional high-tech industry agglomeration on corporate green innovation is relatively scarce. Moreover, previous studies have often adopted a macro perspective, focusing on the industrial agglomeration of China as a whole or multiple regions within the country. In contrast, this study concentrates on the high-tech industry agglomeration in Fujian Province, offering stronger regional specificity and practical guidance.

Under the digital economy, how does the agglomeration of high-tech industries in Fujian Province influence regional green innovation development? Is this effect influenced by other types of disparities? What specific role does the digital economy play between agglomeration and green innovation? Addressing these questions, this paper investigates the effect of high-tech industry agglomeration on green innovation in Fujian Province and explores the underlying influencing mechanisms. By comprehensively and deeply examining the characteristics and trends of high-tech industry agglomeration, as well as its impact mechanisms, actual contributions to green innovation, and synergistic development strategies, this study aims to provide support for green innovation and high-quality development in Fujian Province and the nation as a whole..

2. Literature Review

Regarding the measurement of industrial agglomeration levels, existing research has primarily developed two quantitative approaches: one utilizes indicators such as location quotient, industry concentration ratio, Herfindahl-Hirschman Index (HHI), spatial Gini coefficient, and EG index for calculation [3]; the other characterizes the spatial agglomeration degree of industries by constructing geographical concentration indices or employing the spatial Gini coefficient [4,5].

Concerning the measurement of green innovation levels, current research has mainly formulated two paradigms: the indicator system evaluation method and the efficiency measurement method. Mainstream tools for efficiency evaluation include Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). Compared to SFA's strict requirements regarding the specific form of the production function and the distribution of the error term, the DEA method does not require presupposing the production frontier function and can better adapt to efficiency assessment needs in multi-input and multi-output contexts, thus being widely applied in green innovation research [6,7]. Other scholars approach from the perspective of innovation outcomes, using the number of granted green invention patents and green utility model patents as proxy indicators for green innovation activities to systematically investigate the driving effects of environmental policies on green innovation [8].

Regarding the impact of industrial agglomeration on green innovation, academic consensus has not yet been reached. Some studies suggest that industrial agglomeration can enhance knowledge spillovers and factor sharing, thereby positively enabling green innovation [9,10]. However, other scholars point out that excessively high levels of industrial agglomeration may lead to resource crowding and increased environmental pollution, generating a "congestion effect" that instead inhibits technological innovation [11,12].

3. Research Hypotheses

3.1 The Relationship between Industrial Agglomeration and Green Technology Innovation

According to relevant theories of New Economic Geography, industrial agglomeration generates agglomeration economies through channels such as labor mobility, knowledge spillovers, and infrastructure sharing, thereby injecting sustained momentum into economic growth under conditions of imperfect competition. For high-tech industries specifically, their geographical spatial agglomeration facilitates the efficient flow and deep integration of innovation factors like knowledge, technology, and talent, thus promoting the construction and improvement of regional innovation ecosystems. In this process, industrial agglomeration continuously stimulates the developmental vitality of green innovation by leveraging scale economy effects, market competition mechanisms, and the synergistic role of policies and demand. As the degree of agglomeration increases, industrial clusters gradually become important carriers for breakthroughs in green technology, not only effectively enhancing regional innovation efficiency but also accelerating the transformation of the regional economy towards high-quality, low-emission development. Based on the above analysis, the following research hypothesis is proposed:

H1: The agglomeration of high-tech industries in Fujian Province has a significant positive promoting effect on green innovation.

3.2 The Moderating Role of the Digital Economy

The theoretical origins of the digital economy can be traced back to the pioneering work of Tapscott, and it later received an authoritative definition at the G20 Hangzhou Summit. Its core connotation is embodied as a new economic form characterized by digitalized knowledge and information as key production factors and modern information networks as vital carriers. In essence, the digital economy, relying on the deep penetration of information and communication technology, drives a systemic transformation of economic operation modes, thereby enhancing the efficiency of resource allocation and promoting the orderly evolution of industrial structures. From the perspective of industrial agglomeration theory, the spatial agglomeration of the digital economy is primarily influenced by six factors: the geographical advantages related to transportation costs, the economic logic of increasing returns to scale, the heterogeneous characteristics of regional market demand, the synergistic linkages within the industrial chain, the dynamic adjustments of trade barriers, and the spatial spillover effects of knowledge and technology. Based on this theoretical framework, this study systematically examines how the digital economy influences the spatial agglomeration of high-tech industries from three dimensions—knowledge spillover effects, the level of informatization development, and industrial structure upgrading—and further explores the mechanism through which this agglomeration effect acts upon the green technology innovation capability of industries.

(1) Knowledge Spillover Effects. Relying on digital innovation network systems, the digital economy effectively dissolves the spatiotemporal constraints on knowledge dissemination. The application of digital tools such as cloud platforms and online collaboration tools breaks down information barriers among universities, research institutions, and enterprises, promoting the efficient transformation of green innovation achievements from academic research to industrial application. Within industrial agglomeration spaces, digital technology further amplifies the “proximity effect” of knowledge spillovers. On one hand, digitized talent mobility mechanisms facilitate the optimal allocation and collaborative sharing of talent among enterprises, accelerating the diffusion of tacit knowledge and practical skills. On the other hand, online patent sharing platforms provide enterprises with convenient tools for patent search and analysis, enhancing the transformation efficiency and application value of patented technologies. Furthermore, virtual R&D communities create open and collaborative spaces for enterprises, enabling them to conduct joint research on common technical challenges, thereby forming sustained and stable mechanisms for knowledge interaction and innovation synergy.

(2) Level of Informatization Development. The widespread application of digital technologies is profoundly reshaping the R&D model of green innovation. In the manufacturing sector, IOT devices can collect real-time energy consumption data, which, combined with AI algorithms for intelligent analysis and optimization control, can promote a reduction in carbon emissions from manufacturing processes by approximately 15% to 30%. Cloud computing platforms play a core role in data integration and value mining. By aggregating and analyzing environmental data from various segments of the industrial chain, they provide decision-making support for enterprises to identify key emission reduction points and formulate precise emission reduction strategies. Most importantly, digital market platforms break down traditional barriers to the diffusion of green technologies. By accurately matching the needs of both supply and demand sides, they accelerate the large-scale implementation of green technologies, generating significant scale and demonstration effects.

(3) Industrial Structure Upgrading. The digital economy is profoundly reshaping the industrial landscape, driving traditional industries towards greener and smarter directions. In this process, the digital economy has spawned diverse new green business models, such as block chain-based carbon asset trading systems, which ensure the security and traceability of carbon credit flows; and big-data-driven new energy power dispatching systems, which enable precise analysis and optimal allocation of power supply and demand. Within industrial clusters, digital technology serves as the core engine driving the synergistic upgrading of the green industry chain. Taking the “digital carbon footprint tracking system” as an example, it conducts real-time monitoring and precise accounting of carbon emissions throughout the entire product life cycle (from raw material procurement to finished product delivery), helping enterprises accurately identify key emission reduction points, thereby driving the green synergy and efficiency improvement of the entire industrial chain. Based on this, the following hypotheses are proposed:

H2: The digital economy in Fujian Province has a significant positive promoting effect on green technology innovation.

H3: The digital economy in Fujian Province positively moderates the relationship between high-tech industry agglomeration and green innovation.

4. Research Design and Model Construction

4.1 Variable Selection

4.1.1 Dependent variable

Regarding the quantitative measurement of green technology innovation (GTI), the academic community has primarily developed two main paradigms: The first is the input-output efficiency paradigm, which typically constructs an evaluation system by selecting indicators such as R&D personnel input, R&D expenditure, and new product sales revenue. The second is the innovation output paradigm, which often uses green patent data as a proxy variable for innovation activities. Considering that green technology innovation itself is characterized by complex processes, long cycles, and high uncertainty, relying solely on input-output efficiency indicators makes it difficult to fully capture its true level. In contrast, patent data can more directly reflect the actual output of innovation activities. Based on this, this study selects the number of green patent applications as the core measurement indicator and processes it by taking the logarithm after adding one to measure the green technology innovation level of high-tech industries in each province.

4.1.2 Independent variable

The calculation formula for high-tech industry agglomeration is as follows: $LQ_i = \frac{m_i/\sum_{i=1}^{n} m_i}{M_i/\sum_{i=1}^{n} M_i}$

Here, the level of innovative talent agglomeration in the i-th prefecture-level city of Fujian Province is denoted as LQ_i.

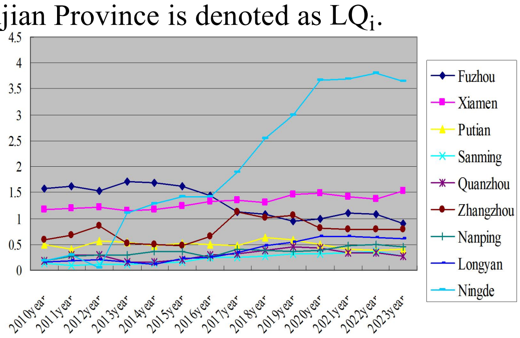

Figure 1. Agglomeration Degree of High-Tech Industries in Fujian's Cities from 2010 to 2023

The full-time equivalent of R&D personnel in the high-tech industry of the ith prefecture-level city is represented by m_i, while $\sum_{i=1}^{n} m_i$ represents the total full-time equivalent of R&D personnel in the high-tech industry across all prefecture-level cities in Fujian Province. Furthermore, Mi represents the total full-time equivalent of R&D personnel across all prefecture-level cities in Fujian Province.

When $LQ_i>1$, it can be determined that the level of high-tech industry agglomeration in region i is higher than the average level of other regions. When $LQ_{it}<1$, it is considered that the agglomeration advantage of this industry is not significant. The calculation results are shown in Figure 1.

4.1.3 Moderating variable

Currently, there is no unified paradigm in academia for measuring the level of digital economy development. Drawing on the research approach of scholars such as Zhao Tao et al., this paper constructs a comprehensive evaluation index system for the digital economy (Table 1) by selecting five indicators from the dimensions of internet infrastructure, industrial application, and digital finance development: internet penetration rate, number of internet-related employed persons, internet-related output, number of mobile internet users, and the digital inclusive finance index. To avoid biases introduced by subjective weighting and to ensure the objectivity and robustness of the measurement results, this study employs the entropy weight method to assign weights to each indicator, thereby calculating the digital economy development level for each province, denoted as Dige.

Table 1. Evaluation Index System for the Level of Digital Economy Development

Secondary Indicators	Tertiary Indicators
Internet Penetration Rate	Number of Internet Users per 100 People
Number of Internet-Related Employees	Proportion of Employees in Computer Services and Software
Internet-Related Output	Per Capita Total Telecommunications Business Volume
Number of Mobile Internet Users	Number of Mobile Phone Subscribers per 100 People
Digital Inclusive Finance Index	China Digital Inclusive Finance Index

4.1.4 Control variables

To mitigate potential endogeneity bias caused by omitted variables as much as possible, this study, based on a review of relevant literature on factors influencing green technology innovation, selects control variables from the following five dimensions (specific measurement methods are shown in Table 2):

(1) Economic Development Level (GDP). An increase in the overall economic aggregate helps enhance enterprises' R&D investment capacity and stimulates market consumer demand for green products, thereby positively driving green innovation.

(2) Degree of Openness to the Outside World (OPEN). Opening up to the outside world injects external momentum into green innovation by promoting the cross-regional flow of factors such as resources, technology, and talent.

(3) Human capital level (ER), which represents a reservoir of high-quality talent serving as a crucial foundation for green technology R&D and knowledge spillovers, is measured by the proportion of students enrolled in regular institutions of higher education to the resident population.

(4) The intensity of environmental regulation (HC) is measured by the proportion of words in sentences containing environmental protection keywords to the total word count of a city's government work report. An appropriate level of this regulatory pressure can create an "innovation compensation effect", thereby forcing enterprises to engage in green technological innovation.

(5) The regional scientific and technological foundation, which provides underlying technical support and a guarantee for the transformation of achievements in green technology innovation, is measured by the proportion of scientific and technological expenditure to total fiscal expenditure in each prefecture-level city, denoted as scientific and technological level (STL).

Table 2. Variable Names

Variable	Variable Names
Dependent Variable	*GIT*
Independent Variable	*LQ*
Moderating Variable	*Dige*
Control Variable	*GDP*
	OPEN
	ER
	HC
	STL

4.2 Model Construction

This study employs provincial-level panel data for stepwise regression analysis. To mitigate estimation bias potentially caused by heteroscedasticity, the green technology innovation indicator, measured in absolute quantities, is subjected to logarithmic transformation. Regarding model specification, a two-way fixed effects model is adopted to control for disturbances from individual heterogeneity and time trends. Based on this, the following regression models are constructed sequentially to test the core hypotheses: First, a baseline regression model is established to examine the effect of high-tech industry agglomeration on green innovation efficiency. Subsequently, the level of digital economy and its interaction term with industrial agglomeration are introduced respectively to investigate the direct effect and moderating effect of the digital economy on green innovation. The baseline model is specified as follows:

$$lnGIT_{it}=\alpha+\beta_1 LQ_{it} \quad (1)$$

$$lnGIT_{it}=\alpha+\beta_1 LQ_{it}+\gamma X_{it}+\varepsilon_{it} \quad (2)$$

The digital economy and the interaction term between the digital economy and high-tech industry agglomeration are then incorporated, as shown below:

$$lnGIT_{it}=\alpha+\beta_1 LQ_{it}+\beta_2 Dige_{it}+\gamma X_{it}+\varepsilon_{it} \quad (3)$$

$$lnGIT_{it}=\alpha+\beta_1 LQ_{it}+\beta_2 Dige_{it}+\beta_3 LQ_{it}\times Dige_{it}+\gamma X_{it}+\varepsilon_{it} \quad (4)$$

Where ii and tt denote the individual province and year, respectively; α, β, and γ are coefficients to be estimated; ϵ represents the random error term; and XX denotes the vector of control variables.

5 Empirical Analysis

5.1 Data Collection and Processing

Based on the principles of data availability and completeness, this study selects panel data from various prefecture-level cities in Fujian Province covering the period 2010–2023 as the research sample. The primary data sources include authoritative statistical publications such as the Fujian Statistical Yearbook on Science and Technology, Fujian Social and Technological Statistics, China Statistical Yearbook on High Technology Industry, and Fujian Statistical Yearbook. To address missing data for specific years or regions, methods including mean imputation, linear interpolation, and moving average imputation were employed to supplement the dataset, ensuring sample continuity and the robustness of the empirical analysis.

5.2 Descriptive Statistical Analysis

Descriptive statistics for each variable, including basic statistics such as mean and standard deviation, were calculated using Stata 17 software. The specific results are presented in Table3. The statistical results indicate: The minimum value of high-tech industry agglomeration is 0.04, while the maximum value is 3.813. This suggests, on one hand, that prefecture-level cities in Fujian Province have preliminarily formed a spatial agglomeration trend in high-tech industries; on the other hand, it reflects significant disparities in the level of specialized agglomeration among different regions. The mean value of the digital economy level is 0.088, indicating that the current development of the digital economy in Fujian Province remains at a relatively low level, suggesting considerable room for future improvement in areas such as digital infrastructure construction and industrial digital integration.

Table 3. Descriptive Statistics of Variables

Variable	Sample Size	Mean	Standard Deviation	Minimum	Maximum
GIT	126	5.6	1.334	2.944	7.929
LQ	126	0.791	0.751	0.04	3.813
Dige	126	0.088	0.099	0.002	0.525
GDP	126	7.87	3.231	2.412	15.304
OPEN	126	0.329	0.408	0.042	1.874
ER	126	1.05	0.287	0.498	2.185
HC	126	0.017	0.013	0.003	0.057
STL	126	0.019	0.011	0.005	0.057

5.3 Regression Analysis

Prior to conducting the formal regression analysis, a multicollinearity test was performed on the model. The diagnostic results of the Variance Inflation Factor (VIF) show that the VIF values for all variables are less than 10, indicating that there is no severe multicollinearity problem in the model. Subsequently, the Hausman test was employed to select between the random effects and fixed effects models. Based on the p-value of the test result, the final model form was determined. The specific results are presented in Table 4.

(1) The Direct Impact of High-Tech Industry Agglomeration on Green Technology Innovation

The regression results from Model (1) reveal a significant positive correlation between high-tech industry agglomeration and green technology innovation in Fujian Province, with a regression coefficient of 0.266. This indicates that for each unit increase in the level of high-tech industry agglomeration, the level of green technology innovation correspondingly increases by 26.6%. After incorporating control variables, the regression coefficient in Model (2) decreases slightly to 0.196 but remains statistically significant. This outcome supports Hypothesis H1, confirming that high-tech industry agglomeration in Fujian Province has a positive promoting effect on green technology innovation. A possible explanation is that, on one hand, industrial agglomeration strengthens knowledge spillover and technology diffusion effects within the region, accelerating the dissemination and application of green technologies among enterprises, thereby enhancing overall innovation efficiency. On the other hand, the agglomeration effect attracts more high-quality talent and R&D resources, fostering economies of scale and collaborative innovation networks, which provide solid factor support for green technology R&D.

(2) The Direct and Moderating Effects of the Digital Economy

The regression results from Models (3) and (4) reveal the complex mechanism of the digital economy's role. Viewed in isolation, the level of digital economy exhibits a positive impact on green technology innovation (Model 3), thus validating Hypothesis H2. However, upon introducing the interaction term between high-tech industry agglomeration and the digital economy (Model 4), the coefficient for the interaction term is -2.405 and is significantly negative at the 1% level. This finding indicates that, contrary to expectations, the digital economy does not strengthen the promoting effect of industrial agglomeration on green innovation; instead, it generates a significant negative moderating effect, leading to the rejection of Hypothesis H3. This phenomenon can be explained from the following four dimensions: First, regional development imbalance. Digital economy resources in Fujian Province are highly concentrated in core cities like Xiamen and Fuzhou. Peripheral areas, due to weak digital infrastructure, struggle to effectively absorb the positive spillovers from industrial agglomeration and instead face the dilemma of outflows of innovation resources.

Second, factor competition effect. The rapid development of the digital economy may divert funds, talent, and policy support originally intended for the high-tech industry sector, leading to a relative contraction in green R&D investment, thereby weakening the green innovation capacity of industrial clusters. Third, corporate behavior bias. Some high-tech enterprises tend to leverage digital technologies for short-term efficiency gains while adopting an avoidant attitude towards the high investment, long cycles, and outcome uncertainty required for green innovation, causing green innovation activities to be marginalized in corporate strategies. Fourth, crowding-out effect of virtual agglomeration. The rise of digital economy platforms enables enterprises to overcome geographical limitations and achieve virtual agglomeration. To some extent, this diminishes face-to-face communication and deep industry-university-research cooperation within traditional geographical clusters, even though breakthroughs in green innovation still heavily rely on knowledge exchange and joint problem-solving within physical spaces.

Table 4. Regression Results

variable	(1)	(2)	(3)	(4)
lq	0.266***	0.196***	0.202***	0.286***
	(5.212)	(3.418)	(3.551)	(4.780)
gdp		0.074*	0.092**	0.060
		(1.768)	(2.136)	(1.419)
open		0.637**	0.624**	0.464*
		(2.287)	(2.259)	(1.734)
er		-0.286***	-0.295***	-0.294***
		(-2.692)	(-2.791)	(-2.928)
hc		-9.668	-15.280	-8.711
		(-0.723)	(-1.116)	(-0.661)
stl		-1.441	-4.801	-6.130
		(-0.363)	(-1.082)	(-1.444)
dige			-0.812	2.722**
			(-1.640)	(2.329)
lq×dige				-2.405***
				(-3.306)
cons	4.099***	4.066***	4.167***	4.190***
	(47.203)	(12.798)	(12.983)	(13.702)
Time Effects	Yes	Yes	Yes	Yes
Individual Effects	Yes	Yes	Yes	Yes
N	126	126	126	126
R^2	0.922	0.933	0.935	0.942
F	87.258	71.921	69.638	73.631

***p<0.01, **p<0.05, *p<0.10

(3) Analysis of Control Variables

Examining the regression results for the control variables, the estimated coefficient for the degree of openness to the outside world on green technology innovation is significantly positive. This positive effect may stem from two mechanisms: first, the spillover effect of green technologies, whereby cross-border cooperation and international trade directly introduce advanced foreign environmental technologies and knowledge; second, the forcing mechanism of market competition, where export-oriented high-tech enterprises are compelled to strengthen their green R&D investments to meet the environmental access standards of international markets.

Notably, the estimated coefficient for the level of human capital is significantly negative. This seemingly counterintuitive result requires careful interpretation. The likely reason is not that human capital itself is detrimental to green innovation, but rather that structural obstacles exist in the current transformation pathway from human capital to effective innovation resources in Fujian Province. First, specialization mismatch. The proportion of graduates majoring in fields related to green technology within the university education system is relatively low, creating a significant gap between the supply of graduates and the demands of the industrial green transformation. Second, regional talent outflow. Highly qualified talents cultivated within Fujian Province tend to concentrate in core cities such as Xiamen and Fuzhou, leaving peripheral areas facing a net outflow of talent. Third, timeliness lag. The cultivation cycle in higher education is relatively long, making it difficult for the human capital of enrolled students to respond quickly to the immediate demands of industrial green innovation. This may even generate short-term negative shocks by crowding out existing R&D resources. In summary, this negative coefficient reveals a shortcoming in the human capital transformation mechanism within Fujian Province, rather than negating the value of human capital itself.

5.4 Robustness and Endogeneity Tests

To verify the reliability of the empirical results, this study conducts robustness checks from the following two aspects. First, substitution of core variables. The full-time equivalent of R&D personnel is replaced with the number of R&D personnel, and simultaneously, the number of green patent applications is replaced with the number of granted green patents. The regression results show that the signs and significance levels of the core variables do not change substantially, indicating that the conclusions remain robust. Second, addressing endogeneity issues. Considering the potential endogeneity bias arising from bidirectional causality between high-tech industry agglomeration and green technology innovation, the core explanatory variable lagged by one period is used as an instrumental variable for regression estimation. The results still support the original conclusions. The results of the above tests are detailed in Table 5.

Table 5. Robustness Tests

variable	Original Regression Results	Replacement of Independent Variable	Replacement of Dependent Variable	Independent Variable Lagged by One Period
lq	0.286***	0.277***	0.256***	
	(4.780)	(4.966)	(3.991)	
llq				0.340***
				(5.299)
gdp	0.060	0.069	0.064	0.054
	(1.419)	(1.638)	(1.429)	(1.218)
open	0.464*	0.496*	0.423	0.505
	(1.734)	(1.859)	(1.479)	(1.639)
er	-0.294***	-0.302***	-0.124	-0.296***
	(-2.928)	(-3.007)	(-1.155)	(-2.928)
hc	-8.711	-8.195	-22.251	0.670
	(-0.661)	(-0.621)	(-1.576)	(0.049)
stl	-6.130	-7.351*	-6.470	-4.841
	(-1.444)	(-1.711)	(-1.424)	(-1.153)
dige	2.722**	2.210**	3.013**	2.744**
	(2.329)	(2.091)	(2.409)	(2.199)
lq×dige	-2.405***	-2.146***	-2.373***	
	(-3.306)	(-3.229)	(-3.047)	
llq×dige				-2.539***
				(-3.104)
cons	4.190***	4.172***	3.783***	4.128***
	(13.702)	(13.698)	(11.557)	(11.835)
Time Effects	Yes	Yes	Yes	Yes
Individual Effects	Yes	Yes	Yes	Yes
N	126	126	126	117
R^2	0.942	0.942	0.950	0.933
F	73.631	74.287	91.960	60.858

***p<0.01, **p<0.05, *p<0.

6 Conclusions and Recommendations

6.1 Main Research Conclusions

Based on panel data from prefecture-level cities in Fujian Province spanning 2010 to 2023, this paper empirically investigates the impact mechanism of high-tech industry agglomeration on green technology innovation, as well as the moderating effect of the digital economy, using a two-way fixed effects model. The main findings are as follows:

First, high-tech industry agglomeration in Fujian Province has a significant positive promoting effect on green technology innovation. This indicates that the knowledge spillover, talent concentration, and collaborative innovation effects generated by industrial agglomeration have become important forces driving breakthroughs in green technology.

Second, the development level of the digital economy has a direct positive impact on green technology innovation, but its moderating effect is negative. That is, as the level of digital economy increases, the promoting effect of high-tech industry agglomeration on green technology innovation is instead weakened. This finding reveals a potential competitive relationship between the digital economy and traditional agglomeration in the allocation of innovation resources, or suggests that virtual agglomeration has, to some extent, substituted for physical agglomeration.

Third, analysis of control variables shows that the level of human capital has a significantly negative impact on green technology innovation, reflecting a structural mismatch between the supply side of human capital and the demand side of the industry in Fujian Province. Conversely, the level of openness to the outside world has a significantly positive impact, indicating that international technology spillovers and the forcing mechanism of market competition have effectively empowered green innovation.

6.2 Policy Recommendations

Based on the above conclusions, the following four recommendations are proposed to enhance the level of green technology innovation in Fujian Province's high-tech industry and promote regional green and sustainable development:

(1) Optimize the spatial layout of the high-tech industry and strengthen inter-regional factor mobility. Due to differences in economic foundations, locational conditions, and policy support among cities within Fujian Province, the level of high-tech industry agglomeration is uneven, and the agglomeration effects in some areas have not been fully realized. Therefore, it is necessary to coordinate the planning of industrial spatial distribution, implement differentiated policy support for regions with relatively lagging development, smooth the channels for cross-regional flow of innovation factors such as talent, capital, and technology, and optimize resource allocation efficiency, thereby unleashing the green innovation potential of industrial agglomeration.

(2) Establish a policy system for the synergistic development of the digital economy and green innovation. Addressing the negative moderating effect of the digital economy on the green innovation impact of industrial agglomeration, local governments need to adopt proactive intervention measures. Specifically, this could involve establishing special funds for green technology innovation to broaden financing channels for corporate green R&D; increasing financial support for green technology R&D centers and strengthening intellectual property protection; formulating special plans for green industry development; and establishing a cultivation mechanism for exemplary green innovation enterprises. Through systematic policy arrangements, guide the formation of a positive interaction between the digital economy and industrial agglomeration, amplifying synergistic effects.

(3) Deepen openness to the outside world and strengthen the spillover effects of green technology. Fujian Province should fully leverage its advantages as a hometown for overseas Chinese and its geographical proximity to Taiwan to build a multi-level, wide-ranging open cooperation system for green technology. Key actions include promoting joint research and development and achievement transformation of green technologies between Fujian and Taiwan, establishing a green industry investment fund for overseas Chinese entrepreneurs, and actively participating in the mutual recognition of international green standards. Concurrently, relying on the institutional innovation advantages of the Pilot Free Trade Zone, align with high-standard international economic and trade rules, promote cross-border green R&D cooperation, and create an open green innovation ecosystem with Fujian characteristics.

(4) Implement targeted policies to break the bottleneck in human capital transformation. Addressing the issue of insufficient contribution of human capital to green innovation, efforts should be coordinated on the supply side, allocation side, and transformation side. First, optimize the structure of academic disciplines. Increase the number of applied majors such as green technology and digital environmental protection in universities, and establish university-enterprise joint training mechanisms to achieve a precise match between talent cultivation and industrial demands. Second, improve the mechanism for regional talent allocation. In secondary agglomeration areas like Sanming and Nanping, leverage characteristic industries to build green innovation platforms, supported by talent subsidies and housing security policies, to attract local university graduates to stay and develop. Third, strengthen the skill upgrading of in-service talent. Collaborate with universities and research institutions to conduct special training programs in green technology, enhancing the practical capabilities of existing corporate R&D teams. Fourth, reform the evaluation orientation of human capital. Reduce the reliance on single measures centered on the size of the enrolled student population, and steer resources towards segments that facilitate

the effective transformation of human capital.

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