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Research article

Technological industry agglomeration, green innovation efficiency, and development quality of city cluster

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Abstract: Technological progress, especially green innovation, is a key factor in achieving sustainable development and promoting economic growth. In this study, based on innovation value chain theory, we employ the location entropy, super-efficiency SBM-DEA model, and the improved entropy TOPSIS method to measure the technological industry agglomeration, two-stage green innovation efficiency, and development quality index in Yangtze River Delta city cluster, respectively. We then build a spatial panel simultaneous cubic equation model, focusing on the interaction effects among the three factors. The findings indicate: (1) There are significant spatial links between the technological industry agglomeration, green innovation efficiency, and development quality in city cluster. (2) The development quality and technological industry agglomeration are mutually beneficial. In the R&D stage, green innovation efficiency, development quality, and technological industry agglomeration compete with each other, while there is a mutual promotion in the transformation stage. (3) The spatial interaction among the three factors reveals the heterogeneity of two innovation stages. The positive geographical spillover effects of technological industry agglomeration, green innovation efficiency, and development quality are all related to each other. This paper can provide a reference for the direction and path of improving the development quality of city clusters worldwide.

Keywords: technological industry agglomeration; green innovation efficiency; development quality; innovation value chain; SBM-DEA model; spatial panel equation

JEL Codes: O18, Q43, R11

1. Introduction

The global economic structure and innovation landscape are undergoing a new technological revolution and industrial change. Many nations have introduced and regularly updated their technological innovation strategies to address this, focusing on fostering economic growth and boosting global competitiveness. Technology innovation centers should be strengthened to aggregate innovation factors, improve innovation efficiency, and achieve development quality. Many developed countries, including the United States, Japan, and the United Kingdom, have made significant strides in establishing scientific and technology innovation hubs with a global impact in recent years. For instance, the San Francisco Bay Area has attracted several well-known businesses like Google, Apple, and Intel, and there are now 20,000 businesses involved in technology (Kemeny and Osman, 2018). A third of the UK's universities and research centers, including Imperial College and the University of London, is located in the London Bay Area, which also attracts a lot of incubators and startups and boasts a solid industrial base and open business environment. Many of the largest multinational corporations in the world, such as Sony, an electronics manufacturer, and Toyota, an automobile manufacturer, are based in the Tokyo Bay Area, which also has excellent R&D capabilities.

One of China's most economically active areas is the Yangtze River Delta (Hou et al., 2021), which benefits from its strong economic base, dense population, and advanced technology. With only 2.1 percent of the country's geographical area, the Yangtze River Delta region accounts for around 25% of the nation's overall economic volume and a quarter of its industrial added value in terms of regional and worldwide economic integration. However, the quest for rapid economic growth has resulted in several issues, including worsening environmental pollution, the exhaustion of available energy sources, and the destruction of ecological habitats (Liu et al., 2022;Ren et al., 2022). The Yangtze River Delta region's economy has grown by around 62 percent over the previous five years, and its carbon emissions make up about 20 percent of the country's total emissions. The Yangtze River Delta's cities continue to be constrained in their ability to build their economies in a high-quality manner by their industrial structure and an imbalance in the amount of green innovation.

Due to the limit of management and production technologies, the traditional industrial development model has resulted in sluggish economic growth. The current "double carbon" goal focuses on modernizing industrial structures and achieving technological empowerment (Zhao et al., 2022). In the meantime, regions have begun implementing traditional industrial transfer policies to balance economic development and ecological improvement (Arbolino et al., 2018;Busch et al., 2018;Nieto et al., 2020). Technological sectors have been expanding quickly and have become firmly ingrained in the country's labor division structure since the twenty-first century (Zhu et al., 2022). Industrial agglomeration and green technological innovation are two ways to express the state of technological industries' development, with the former indicating the integration of resources in the area of industrial development and the latter reflecting the degree of rationalization of resource use (Xu and Li, 2019). Innovation is the heart of technological industry development. If original innovation is not sufficiently robust, issues like the fall of the economic development curve and the slowing of transformation will result. Technological industry agglomeration helps maximize technical empowerment by facilitating the geographical integration of resource factors, including regulations, markets, and capital. The Yangtze River Delta city cluster is currently facing significant problem to its quality of development. Then, what role do industrial agglomeration and green innovation play in developing this knowledge and technology-intensive industry, and how do they support the high-quality growth of the local economy?

The rest of this paper is structured as follows: The literature on technological industry agglomerations, green innovation efficiency, and development quality is introduced in Section 2. The relation among technological industry agglomeration, green innovation efficiency, and development quality is examined in Section 3's theoretical analysis and research hypothesis. The study methodology, index setup, and data sources of this article are introduced in Section 4. The regional variations and driving forces of technological industry agglomeration, green innovation effectiveness, and development quality are examined in Section 5. Section 6 is the conclusion.

2. Literature review

The association between technological industry agglomeration and high-quality economic development has been the subject of many investigations in the literature. Some academics hold a fixed positive relationship between technological industry agglomeration and high-quality economic development. For example, Wu (2022) found that this relation is wavy but always positive. According to some researchers, the relationship between technological industry agglomeration and development quality is no longer straightforwardly positive. For instance, Song et al. (2022) found that only regions with high agglomerations of technological industries will significantly improve the quality of economic growth, indicating that the positive effect is constrained by a "threshold". The relationship between high-quality development and technological industries is no longer a straightforward linear relation, according to Wang et al. (2020c), but rather is more subject to the influence of outside influences like government intervention.

Many studies have been conducted on the green innovation efficiency in technological industries and development quality growth. According to Wang et al. (2021), green innovation in technological industries fosters economic growth by encouraging the modernization and transformation of established businesses. According to Zhou et al. (2020) there is a significant positive association between development quality growth and the development of green technologies over time. In conclusion, studies on the relationship between the technological industry agglomeration, the green innovation efficiency, and development quality have yielded fruitful results; however, few studies have combined these three variables into a single framework for analysis. With the introduction of the innovation value chain theory (Hansen and Birkinshaw, 2007), academics started to separate green technological innovation into two stages: R&D and achievement transformation, to understand the underlying mechanisms of technological innovation activities in technological industries (Zhou et al., 2017). Researchers started looking into the effects of technological industry agglomeration, and development quality on the efficiency of green innovation in both stages since the efficiency of green innovation in the technological industry differs at different stages.

Existing research measured technological industry agglomeration, green innovation efficiency, and high-quality economic development in various methods. For example, many researchers employ locational entropy to measure technological industry agglomeration while accounting for inter-city scale disparities (Wang et al., 2020a). Green innovation efficiency is commonly quantified using the stochastic frontier model (Miao et al., 2017). Still, this approach has drawbacks, such as intense subjectivity and a single input-output variable. Following that, most researchers gradually embrace the SBM model to measure the green innovation efficiency concerning firms (Lv et al., 2021). However, this method cannot totally identify the effective decision-making units for comparison. As a result, this research employs the super-efficient SBM model to overcome the problem of information loss in effective decision units and improve the outcomes' trustworthiness (Zheng et al., 2020;Yao et al., 2021). Development quality should be measured with complete care for the objective of the indicators assigned, and the entropy Topsis approach is commonly employed (Wang et al., 2020b).

The following are the contributions of this paper: First, this paper develops an evaluation index system based on the strategic planning of the future development of the Yangtze River Delta city cluster, and employs the improved entropy TOPSIS method to measure the development quality index, the location entropy to calculate the degree of development quality. It avoids the one-sidedness of a single indicator to measure development quality and green innovation efficiency. Second, current research focuses mainly on the effects of industrial agglomeration or green innovation rather than the heterogeneity of green innovation's stages and the interaction among the three. It is, therefore, more accurate to study the two-way influence and spatial spillover effects of technological industry agglomeration, green innovation efficiency, and development quality by combining the three in a single set of equations. This is because it more closely mirrors the actual development of the Yangtze River Delta region. Through the study above, we seek to clarify the intrinsic relationships among development quality, technological industry agglomeration, and green innovation effectiveness in the Yangtze River Delta city cluster, identify the critical elements of development quality and serve as a guide for high-quality regional economic development decision-making.

3. Theoretical analysis and research hypothesis

3.1. The interplay of technological industry agglomeration and development quality

Industrial agglomeration is not only geographically concentrated but also a reflection of sharing and integrating different resources. Technological industries are primarily knowledge-intensive industries with high technological content, low pollution output, and significant benefits in energy conservation, emission reduction, and efficiency improvement. Due to the need for more specialized products and services and quick access to information resources, related industries will congregate in the same area (Lu et al., 2016). The scale of the industry is growing as a result of the development of industrial agglomeration, allowing businesses to gather advanced knowledge and production experience, develop specialized and standard production techniques, increase production efficiency, boost export competitiveness, and utilize the "dry learning" and "student learning" effects (Arrow, 1971), all of which contribute to the gradual formation of one or more core businesses. Technological industries, gradually emerging as new industries, play a significant role in supporting economic development. In the context of development quality, economic output is tilted to help the technological industry agglomeration. These two factors are inextricably linked to achieving development quality. Industrial agglomeration creates a "trickle-down effect" when economic development is high. Technological industries are characterized by their high-end, high efficiency, and high radiation, which help the radiation effect grow. In contrast, more developed areas stimulate the growth of less developed ones through employment and consumption, fostering economic growth and creating a positive feedback loop (Akinci, 2018). Therefore, the first hypothesis is proposed in this paper.

H1: *Technological industry agglomeration and development quality are mutually beneficial.*

3.2. The Interplay of green innovation efficiency and development quality

Green technological innovation is an endless source of energy for business development, and development quality is a requirement for sound industrial development. In the R&D stage, enterprises must contend with the challenges of technology level and production cost, and they must share some of the funds to provide economic support for green innovation activities. However, developing green technologies is lengthy, it is challenging to turn inputs into outputs immediately, and the difficulties of scientific and technological research and development will surely drive-up economic expenses (Du and Li, 2019). The fundamental strategy for consistently raising the development standard is to optimize and innovate on core technologies. The awareness of and demand for green innovation rises when economic development is prioritized on high quality. Yet, scientific and technological research and development outcomes typically remain at the theoretical stage. The speed of research and development for green innovations will also speed up with excessive economic growth, which will result in a decline in the quality of research and development outcomes and an increase in the associated costs to assess further the quality of the products of the R&D stage. Additionally, the production process must take intellectual property rights protection into account, and how those rights are currently protected will obstruct some of that process (Greco et al., 2022). The physicalizing of products beginning with the output of the R&D phase to attain practical utility and generate income, is referred to as the transformation phase of results. Increasing the investment of capital, human resources, and other resources can promote the transformation of scientific research results to generate new products. The development quality of the economy will result. If the trend of making new products is good, it creates a strong force of attraction and brings good economic returns. When green innovation has a positive effect on the quality of economic development, it also positively affects the trend of making new products. At the back end of the R&D knowledge leading to the transformation of results, the longtime effort and payment are urgently needed for the output of results (Peng et al., 2020). As a result, the second hypothesis is suggested in this work.

H2: *Green innovation efficiency and development quality compete each other during the R&D stage, but they support each other during the outcome transformation stage.*

3.3. The interplay of technological industry agglomeration and green innovation efficiency

The “competition effect” is one of the critical relations between technological industry agglomeration and green innovation efficiency. The growth of industrial agglomeration increases business competitiveness, strengthens the protection of intellectual property rights, is detrimental to the exchange of ideas and technologies, and impedes the advancement of green innovation (Song et al., 2022). However, unlike the front end of green innovation in the R&D stage, the gradual development of green innovation is also not conducive to drawing related industries to gather. The “attraction effect” is the second. Enterprises increasingly understand the need to encourage the gathering and sharing of external knowledge when green innovation progresses slowly or when collaboration among innovation elements declines. Only when industrial clustering reaches a certain scale can it foster R&D practices and the exchange of scientific and technological information to achieve the complementary benefits of resources and foster green innovation (Poon et al., 2013), and the gathering of R&D resources fosters green innovation to form an innovative force to foster industrial transformation and upgrading, and to direct new enterprises and supporting facilities to move in, as well as the strong development of the cluster (Yin and Guo, 2021). The two are mutually reinforcing, as is often the case at the back end of green innovation. As a result, the third hypothesis is suggested in this work.

H3: *Technological industry agglomeration and green innovation efficiency support each other at the transformation stage while competing at the R&D stage.*

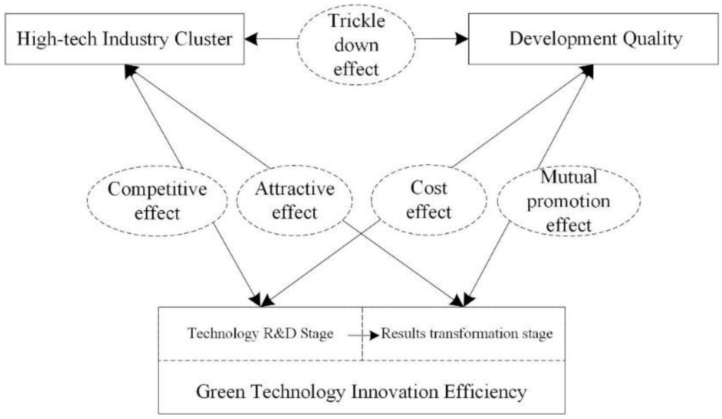

Figure 1. Structural model of the three parties' interactions from the perspective of the innovation value chain.

3.4. Spatial interaction of high technology industry agglomeration, green innovation efficiency and development quality

Technological industry agglomeration has advantageous spatial spillover effects. The agglomeration aims to achieve the spatial clustering of related companies, making it convenient for information sharing and exchange. It also encourages group learning and upstream motivation through interaction, which promotes deeper technological industry agglomeration. Innovation in green technology has a beneficial spatial spillover effect. Local enterprises will re-integrate innovation factors and accelerate the output of products through learning and emulating each other in the two-stage green innovation process (Liu et al., 2020). Additionally, the improved R&D capability and the increased output of neighboring regions will promote green innovation in the area. Because economic development doesn't happen in a vacuum, the different sectors have been linked for a long time. Interregional cooperation and exchange, which strengthens economic ties even more, also positively affect the quality of economic growth (Sun et al., 2015;Liu et al., 2021). The fourth hypothesis is thus put out in this study.

H4: *Technological industry agglomeration, the green innovation efficiency, and development quality have spatial spillover effects.*

Economic growth, industrial agglomeration, and technological innovation are not independent, and the crossover among the three variables is determined by a line of information sources generated by the vertical and horizontal networks across regions (Xu and Li, 2021). The development of green technologies and the process of industrial agglomeration in neighboring areas can be influenced by the development quality of a region, which can draw in a lot of talent, money, and businesses as well as absorb the corresponding factor resources of the neighboring regions. The higher degree of industrial agglomeration in the surrounding areas suggests that the area's development trend and potential are favorable. The site has more resources, talents, and other elements for green innovation. As a result, the overall innovation process is accelerated to support the development quality. In contrast, the neighboring areas may experience a delay in development due to the resources being drawn from them (Hong et al., 2022). Efficiency in green technology development can operate as both a technical barrier and a hub for communication and interaction, which impacts the quality of economic growth and the concentration of industries in surrounding areas. It is clear that the spatial interaction influence among the three always occurs, and this study suggests the fifth hypothesis in light of the development characteristics of green innovation effectiveness.

H5: *There is heterogeneity in the direction of influence and geographical solid interaction effects of technological industry agglomeration, green innovation efficiency, and development quality.*

4. Research methodology and data

4.1. Study area

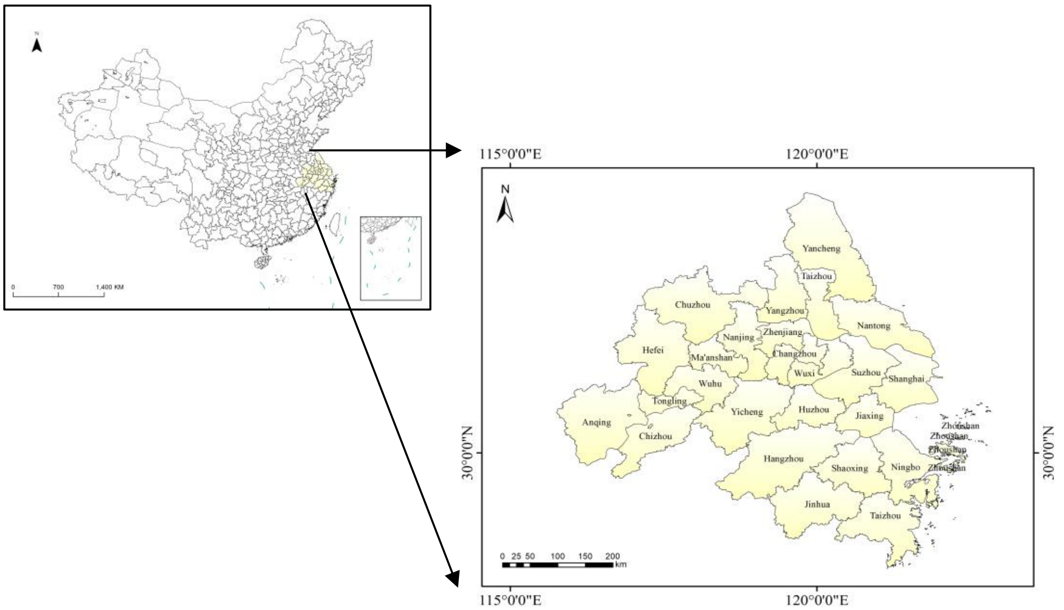

Figure 2. Yangtze river delta region location map.

The Yangtze River Delta is one of the areas in China with the most robust ability for innovation, the highest level of openness, and the most active economic development. The Yangtze River Delta, with a population of 235 million people (in 2021) and a regional area of 358,000 square kilometers, is situated in the lower sections of the Yangtze River in China, bordering the Yellow Sea and the East China Sea. The Yangtze River Delta has an urbanization rate of nearly 60% and a gross regional product of 24.5 trillion yuan in 2020. The Yangtze River Delta region includes Shanghai; Nanjing, Wuxi, Changzhou, Suzhou, Nantong, Yancheng, Yangzhou, Zhenjiang, and Taizhou in Jiangsu Province; Hangzhou, Ningbo, Jiaxing, Huzhou, Shaoxing, Jinhua, Zhoushan, and Taizhou in Zhejiang Province; and Hefei, Wuhu, Ma'anshan, Tongling, Anqing, Chuzhou, Chizhou, and Xuancheng in Anhui Province. The location map is shown below (Figure 2).

4.2. Research methods

4.2.1. Super-efficient SBM model

The most significant benefit of the super-efficient SBM-DEA model is that can solve the input-output slackness problem and the efficiency decomposition problem without the need to estimate the parameters or make weighting assumptions, minimizing the impact of human subjectivity and enlarging the range of constraints that the model can be applied to (Su et al., 2021;Wang et al., 2022).

$$min\,\rho = \frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1-\frac{1}{s}\sum_{i=1}^{m}\frac{s_r^+}{y_{rk}}}, s.t. \left\{ \begin{array}{c} \sum_{j=1,j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq x_{ik} \\ \sum_{j=1,j\neq k}^{n} y_{rj}\lambda_j + s_r^+ \leq y_{rk} \\ \sum_{j=1,j\neq k}^{n} \lambda_j = 1 \\ \lambda, s_i^-, s_r^+ \geq 0 \\ i = 1,2,\cdots,m; r = 1,2,\cdots,q; j = 1,2,\cdots,n(j \neq k) \end{array} \right\} \quad (1),$$

in Equation 1, ρ is the efficiency evaluation value, and when $\rho \geq 1$, it indicates that the decision unit is effective; λ denotes the weight vector; S_r^+, S_i^- denotes the input and output slack variables, respectively; n is the number of decision units evaluated, denoted as DMU_j (j=1,2,..., n); m and q are the input and output types of the decision unit, and the input and output of the kth decision unit are denoted as x_{ik} (i=1,2,..., m) and y_{rk} (r=1,2,..., q) (Demirtas and Kececi, 2020;Kolia and Papadopoulos, 2020).

4.2.2. *Location entropy method*

The following calculation formula for the location entropy model, which can reduce scale differences across cities to more accurately reflect the degree of industrial agglomeration, has the qualities of high explanation and convenience.

$$hia_{ij} = (htec_{ij}/iads_{ij}) \,/\, (htec_i/iads_i) \quad (2),$$

in Equation 2, the variables i, j, hia, $htec$, and $iads$ stand for the year, region, and the technological industry agglomeration, technological industry output value, and total industrial output value above the scale, respectively. If hia_{ij} is larger than 1, the city's industry concentration is greater than the national average, indicating a clear trend toward technological sector concentration.

4.2.3. *Improved entropy-weighted TOPSIS method*

The entropy method, which has reasonable impartiality, can weigh several solutions according to information entropy. The ranking method of approximating ideal solutions, or the TOPSIS method, is frequently used in analyzing systems' multi-program, multi-attribute problems. It can thoroughly evaluate complex issues and is an objective evaluation method by calculating how closely each solution approaches the ideal solution. Consequently, the outcomes of the development quality index calculation can be improved by employing the entropy-TOPSIS technique. Assuming that there are *t* years, *n* regions, and *m* indicators, the formula, and calculation steps are as follows.

Step 1: Data standardization: $f_{\lambda ij}$ and f_{ij} are the unstandardized raw data, while $r_{\lambda ij}$ is the normalized value of the *i*th indicator for the *j*th region in the λth year.

Positive indicators:

$$r_{\lambda ij} = \frac{(f_{\lambda ij} - min\, f_{ij})}{(max\, f_{ij} - min\, f_{ij})} \quad (3),$$

Negative indicators:

$$r_{\lambda ij} = \frac{(max\, f_{ij} - f_{\lambda ij})}{(max\, f_{ij} - min\, f_{ij})} \quad (4),$$

Step 2: Calculating the indicator's entropy value:

$$e_i = -k \sum_{\lambda} \sum_{j} H_{\lambda ij}\, ln(H_{\lambda ij}), H_{\lambda ij} = \frac{r_{\lambda ij}}{\sum_{\lambda} \sum_{j} r_{\lambda ij}}, k = [ln(tn)]^{-1}, k > 0 \quad (5),$$

Step 3: Establishing indicator weights: The symbol g_i stands for the *i*th indicator's information utility value, where g_i=1-e_i.

$$\omega_i = \frac{g_i}{\sum_i g_i} \quad (6),$$

Step 4: Construction of evaluation matrix with entropy weights: The entropy weight ω_i is used to create a weighted evaluation matrix Y, which further increases objectivity.

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} \quad (7),$$

In Equation 7, $y_{11} = r_{12} \cdot \omega_1$, $y_{21} = r_{21} \cdot \omega_2$,..., $y_{m1} = r_{m1} \cdot \omega_m$; $y_{1n} = r_{1n} \cdot \omega_1$, $y_{2n} = r_{2n} \cdot \omega_2$,..., $y_{mn} = r_{mn} \cdot \omega_m$.

Step 5: Determining positive and negative ideal solutions: Let Y^+ represent the highest value of the *i*th indicator in the evaluation data after weighting across all regions and all years, which is a positive ideal solution; let Y^- represent the lowest value of the *i*th indicator in the evaluation data after weighting across all regions and all years, which is a negative ideal solution.

$$Y^+ = \{max(1 \le j \le n)\, y_{ij} | i = 1,2,\cdots,n\} = \{y_1^+, y_2^+, \cdots, y_n^+\} \quad (8),$$

$$Y^- = \{min(1 \le j \le n)\, y_{ij} | i = 1,2,\cdots,n\} = \{y_1^-, y_2^-, \cdots, y_n^-\} \quad (9),$$

Step 6: Distance calculation: The greatest distance (X) and the shortest distance (Y) between the value vector of assessment indicators and the index of development quality growth in each region, respectively the formula for the computation is as follows.

$$D_j^+ = \sqrt{\sum_{i=1}^{n} (y_i^+ - y_{ij})^2} \quad (10),$$

$$D_j^- = \sqrt{\sum_{i=1}^{n}\left(y_i^- - y_{ij}\right)^2} \tag{11},$$

In Equations 10 and 11: y_{ij} is the weighted normalized value of the ith indicator for each region; y_i^+ and y_i^- are the greatest and lowest program values of the ith indicator selected for each region, which respectively reflect the development quality index.

Step 7: Evaluation of the target development index's proximity: Let there be closeness T_j indicates that the development quality index for the jth region is approaching the minimum, and its value lies between [0,1]. The region's development quality index decreases as T_j decreases. The article makes use of proximity to emphasize the high development quality index. The formula for the computation is as follows.

$$T_j = \frac{D_j^-}{D_j^+ + D_j^-} \tag{12}.$$

4.2.4. *Spatial panel equation*

This paper builds a spatial simultaneous cubic equation model with the three endogenous variables to examine the relationships among technological industry agglomeration, green innovation efficiency, and development quality. The spatial lag term coefficients are incorporated into the model while taking into account the spillover effects among the three, avoiding the drawbacks of traditional simultaneous cubic equation models that ignore spatial effects and employing the generalized spatial three-stage least squares (GS3SLS) method proposed by Kelejian and Prucha (2004) was used for estimation based on testing the significant spatial clustering and spatial dependence characteristics of among technological industry agglomeration, green innovation efficiency, and development quality. All data variables are logarithm zed to reduce the effect of heteroscedasticity.

The following is how the equation for the R&D stage of technology is put together.

$$ln\,h\,st_{it} = \alpha_0 + \alpha_1 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,st_{it} + \alpha_2\, ln\,h\,qe_{it} + \alpha_3 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,qe_{it} + \alpha_4\, ln\,h\,ia_{it} + \alpha_5 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,ia_{it} + \alpha\, ln\, Z_{it} + \varphi_{it} + \nu_{it} \tag{13'}$$

$$ln\,h\,qe_{it} = \beta_0 + \beta_1 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,qe_{it} + \beta_2\, ln\,h\,st_{it} + \beta_3 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,st_{it} + \beta_4\, ln\,h\,ia_{it} + \beta_5 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,ia_{it} + \beta\, lnX_{it} + \sigma_{it} + \varepsilon_{it} \tag{14'}$$

$$ln\,h\,ia_{it} = \delta_0 + \delta_1 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,ia_{it} + \delta_2\, ln\,h\,qe_{it} + \delta_3 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,qe_{it} + \delta_4\, ln\,h\,st_{it} + \delta_5 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,st_{it} + \delta\, lnY_{it} + \eta_{it} + \theta_{it} \tag{15'}$$

The following are the equations that are constructed for the results transformation phase.

$$ln\,h\,at_{it} = \alpha_0 + \alpha_1 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,at_{it} + \alpha_2\, ln\,h\,qe_{it} + \alpha_3 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,qe_{it} + \alpha_4\, ln\,h\,ia_{it} + \alpha_5 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,ia_{it} + \alpha\, ln\, Z_{it} + \varphi_{it} + \nu_{it} \tag{16'}$$

$$ln\,h\,qe_{it} = \beta_0 + \beta_1 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,qe_{it} + \beta_2\, ln\,h\,at_{it} + \beta_3 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,at_{it} + \beta_4\, ln\,h\,ia_{it} + \beta_5 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,ia_{it} + \beta\, lnX_{it} + \sigma_{it} + \varepsilon_{it} \tag{17'}$$

$$ln\,h\,ia_{it} = \delta_0 + \delta_1 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,ia_{it} + \delta_2\, ln\,h\,qe_{it} + \delta_3 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,qe_{it} + \delta_4\, ln\,h\,at_{it} + \delta_5 \sum_{j=1}^{n} \omega_{ij}\, ln\,h\,at_{it} + \delta\, lnY_{it} + \eta_{it} + \theta_{it} \quad (18)'$$

Whereas hqe, hia, hst, and hat denote green innovation efficiency at the stages of development quality, high technology industrial agglomeration, R&D, and transformation, respectively; i and j denote regions, and $i \neq j$, n denotes sample size, and t denotes time. Control variables Z, X, and Y, respectively, influence the green innovation efficiency, development quality, and high technology industrial agglomeration.

The constant term is α_0, β_0 and δ_0; the estimated explanatory variable parameter is α_2, α_4,β_2, β_4, δ_2 and δ_4; the estimated spatial lagged variable parameter is α_1, α_3, α_5, β_1, β_3, β_5, δ_1 δ_3 and δ_5; the estimated control variable parameter is α, β and δ; the regional individual effect is φ_{it}, σ_{it} and η_{it}, the random error disturbance term is ν_{it}, ε_{it}, θ_{it}; and the spatial weight matrix is ω_{ij}. Three different weight matrices are built in this study to verify the reliability of the results: a spatial adjacency matrix ($W1$), a geographical distance matrix ($W2$), and an economic distance matrix ($W3$).

4.3. Indicator selection

4.3.1. Development quality

Development quality is characterized in terms of economic growth and social consequences based on a reference to the indicator settings of Ma and Xu (2022) and Lin et al. (2022). Social outcomes include human and ecological capital, and economic growth provides intensity, stability, rationalization, and outward orientation. From these six dimensions, the evaluation index system of development quality is created by integrating economic, social, and environmental dimensions. The improved entropy TOPSIS method is used to measure the level of development quality by fully utilizing the benefits of the objective assignment of the entropy method. The specific index descriptions are shown in Table 1 concerning the applicability and accuracy of the measurement method and the research results of Huang et al. (2022) and Ren (2020).

Table 1. Development quality evaluation index system.

Target layer	System layer	Element layer	Indicator layer	Unit	Code	Symbol
Development quality (hqe)	Economic Growth	Strength	Per capita GDP	Yuan	$rgdp$	+
		Stability	Coefficient of variation of GDP growth rate	-	$cvgr$	-
		Reasonableness	Percentage of employees in the tertiary industry	%	$peti$	+
		Extroversion	Export amount/GDP	%	$prop$	+
	Social Achievement	Human Capital	Number of college students in school	10,000 people	$ncsp$	+
		Ecological Capital	GDP/CO2 emissions	%	$emis$	+

4.3.2. Technological industry agglomeration

Since location entropy has the qualities of high explanation and convenience and can eliminate the scale difference among cities, this paper examines the degree of association of technological industries in various geographic spaces to more accurately reflect the degree of technological industry agglomeration. So, the level of technological industry agglomeration is determined using location entropy concerning the studies of Wu et al. (2022). Relevant indicators are high technology industry output value and total industrial output value.

4.3.3. Green innovation efficiency

To set up a two-stage green innovation index system to measure the two-stage efficiency values of green innovation. We combined the existing research concept of green innovation efficiency (Zhu et al., 2021), took into account all resources like people, money, and products, and used the super-efficient SBM model to calculate the two-stage green innovation efficiency (Wu et al., 2020;Wu et al., 2021), precisely the R&D stage (hst) and the transformation stage (hat). The indicators were chosen as shown in Table 2.

Table 2. Evaluation index system of green innovation efficiency in technological industry.

Indicator type	Evaluation Indicators	Variable	Unit
Technology R&D investment index	Capital input	R&D internal expenses	10,000 yuan
	Manpower input	R&D personnel full-time equivalent	Person
Technology R&D output indicators and results transformation input indicators	Intermediate output	Total Patent Applications	piece
		Invention Patent Grant	piece
		Total new product development projects	piece
	Additional input	Cost of introducing technology	10,000 yuan
		Cost of purchasing domestic technology	10,000 yuan
Results transformation output indicators	Economic output	New product sales revenue	10,000 yuan

4.3.4. Control variables

Population agglomeration ($poag$), fiscal expenditure level ($expe$), and environmental regulation indicators ($envi$), which are expressed by population density, fiscal expenditure as a proportion of GNP, and pollution control investment amount as a proportion of GDP, respectively, are the control variables for development quality.

The criteria used to choose the control variables for technological industry agglomeration are regional living environment quality ($lieq$), financial development level ($fina$), and marketization level ($mark$), which are each measured by per capita green space, the ratio of deposits and loans made by local financial institutions to regional GDP, and the retail sales of social consumer goods to regional GDP.

The industrial structure upgrading ($stru$), the transportation level ($tran$), and the construction of communication infrastructure ($pote$) are chosen as the control variables for the green innovation efficiency in technological industries. The variable data are calculated by the ratios of regional tertiary industry to secondary industry output value, total passenger transportation to total population, and total post and telecommunications infrastructure to total population.

4.3.5. Data sources and descriptive statistics of variables

The China Urban Statistical Yearbook, the China Environmental Statistical Yearbook, and the China Technological Industry Statistical Yearbook are used to collect data on development quality, green innovation efficiency, and control variables from 2008 to 2019. The provincial technology statistical yearbooks are used to collect data on technological industry agglomeration. Table 3 shows the descriptive statistics.

Table 3. Descriptive statistics of variables.

Items	Abbr.	Mean	Std.	Max	Min
Development quality	hqe	0.414	0.117	0.758	0.079
Green innovation efficiency	hst	0.150	0.167	1.895	0.022
	hat	0.195	0.192	1.107	0.009
Technological industry agglomeration	hia	0.954	0.923	4.856	0.022
Control variables	$poag$	6.383	0.507	7.746	4.769
	$expe$	2.601	0.551	4.476	0.632
	$envi$	0.672	0.709	3.655	0.046
	$lieq$	3.176	0.838	4.983	1.523
	$fina$	5.568	0.575	7.633	3.801
	$mark$	3.656	0.400	5.689	2.813
	$stru$	4.452	0.348	5.596	3.442
	$tran$	8.017	0.576	9.752	6.666
	$pote$	2.487	2.068	25.891	0.232

5. Empirical Analysis

5.1. *Stability test*

Because the method used to calculate spatial factors can accurately reflect the level of interaction among regions, it is necessary to do the spatial estimation first to assume that each variable's data is smooth. Therefore, the smoothness test of the variables is performed in this study using LLC, IPS, and Hadri (Strauss and Yigit, 2001) (Table 4). The findings demonstrate that all the variables are smooth and can be submitted to the estimate analysis.

Table 4. Stability test results.

Items	LLC	IPS	HADRI	Stability
hqe	-5.9618^{***}	-3.032^{***}	10.978^{***}	Stable
hia	-8.273^{***}	-3.551^{***}	11.464^{***}	Stable
hst	-12.509^{***}	-5.712^{***}	10.634^{***}	Stable
hat	-11.447^{***}	-3.944^{***}	10.862^{***}	Stable
$poag$	-14.272^{***}	-9.083^{***}	12.333^{***}	Stable
$expe$	-6.809^{***}	-2.967^{***}	9.426^{***}	Stable
$envi$	-8.357^{***}	-4.346^{***}	11.780^{***}	Stable
$lieq$	-7.425^{***}	-3.370^{***}	9.867^{***}	Stable
$fina$	-6.482^{***}	-2.649^{***}	13.194^{***}	Stable
$mark$	-6.695^{***}	-3.101^{***}	11.881^{***}	Stable
$stru$	-2.266^{**}	-0.869	10.650^{***}	Stable
$tran$	-7.034^{***}	-3.832^{***}	9.575^{***}	Stable
$pote$	-9.003^{***}	-4.701^{***}	10.415^{***}	Stable

5.2. *Analysis of regression results*

Before the spatial equation calculation, the core variables need to be tested for spatial correlation. The global Moran's I plot for development quality, technological industry agglomeration, and green innovation efficiency is calculated with the help of Stata 14.0, and the results are shown in Figure 3. The results show that Moran's I of the three variables are positive during the study period. All of them are significant at the 10% level, indicating that they have a significant positive spatial correlation. The fluctuation of the curve also indicates that the degree of spatial correlation of each variable has changed during the study period. Still, the spatial influence always exists, which can be analyzed by subsequent spatial methods.

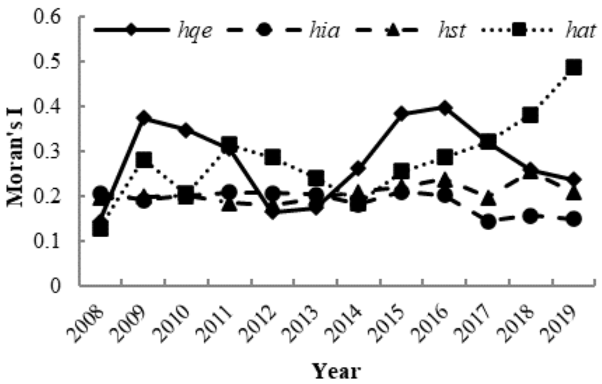

Figure 3. Trend of global moran's I.

An important factor contributing to the improper estimation of model parameters is the endogeneity among technological industry agglomeration, green innovation effectiveness, and development quality. This paper uses generalized spatial three-stage least squares (GS3SLS) estimation to address this issue. It is based on creating a spatial panel simultaneous equation model of the three, which considers both the correlation that already exists among the random disturbance terms and any potential spatial correlation among the endogenous variables (Long et al., 2020). The three cross-sectional spatial weight matrices used in the general spatial weight matrices are converted into panel matrices using Stata14.0 software because this paper uses panel data instead of the cross-sectional data used in the available spatial weight matrices. Next, GS3SLS is used to derive the estimation results for the R&D stage and the transformation of the results stage.

5.2.1. Technology development stage

From the equation for development quality in Table 5. First, under the three spatial weight matrices, the spatial lag terms of development quality coefficients are 1.518, 2.096, and 2.605, and they are significant at the 5%, 1%, and 1% levels, respectively. This shows that the neighboring regions are positively pulling the local economy toward development quality, which supports hypothesis H4. The Yangtze River Delta urban agglomeration has long relied too heavily on conventional energy sources, resulting in the formation of a rough economy that is unsuitable for the current steps of ecological civilization construction. Economic development urgently needs to transform into a green and sustainable economy. Second, the estimated coefficients of green innovation efficiency are significantly negative for all three weight matrices, and the significance is increased when geographic and economic distance is taken into account. This indicates that green innovation efficiency significantly inhibits development quality, and the spatial association is substantial. The development of green innovation in the Yangtze River Delta city cluster under the crude economic growth model requires significant economic input. Still, the output of scientific and technological achievements has a time lag, especially in the front-end of green innovation costs are not proportional to the benefits. This indicates that the R&D stage plays a "cost effect". The high standard of economic development necessitates using green innovation both to accomplish benefit innovation and concentrate on green innovation, which raises the bar for innovation. Third, under the three matrices, the coefficient of the spatial lag term of the efficiency of green innovation on the high-quality development of the economy is significantly positive, indicating that R&D in nearby regions will promote the high-quality development of the local economy; the impact of high technology industry agglomeration on the high-quality development of the economy is not significant, indicating that the contribution o Fourth, the level of fiscal expenditure has a significant positive impact on high-quality economic development at the 1% level, according to the results of exogenous variable estimation. This finding shows that the level of fiscal expenditure in the Yangtze River Delta city cluster is directly related to high-quality economic development and is a significant factor influencing economic growth. Environmental regulation is significantly positive at the 5% level, indicating that during development quality, ecological constraints are conducive to the greenness of economic development, in line with the Porter hypothesis. From a global perspective, it is essential to accurately grasp the proportion of fiscal expenditure and determine the focus of economic development. However, the impact of environmental control needs to be further enhanced based on the predicted coefficients and importance.

Table 5. Regression results of R&D stages (hqe).

Items	Development quality equation		
	$W1$	$W2$	$W3$
hqe	-	-	-
hia	0.046	0.037	0.033
hst	-0.444^{*}	-0.574^{**}	-0.612^{***}
$W \cdot hqe$	1.518^{**}	2.096^{***}	2.605^{***}
$W \cdot hia$	-0.002	-1.117	-0.543
$W \cdot hst$	1.010^{**}	2.720^{***}	2.509^{***}
$poag$	0.002	0.008	0.010
$expe$	0.012^{***}	0.015^{***}	0.022^{***}
$envi$	0.019^{**}	0.019^{**}	0.020^{**}
$lieq$	-	-	-
$mark$	-	-	-
$fina$	-	-	-
$tran$	-	-	-
$stru$	-	-	-
$pote$	-	-	-
Cons	0.154	0.324^{***}	0.336^{***}
R^2	0.0767	0.0925	0.1279

Note: The symbols ***, **, and * indicate significant at the 1%, 5%, and 10% levels, respectively.

From the standpoint of the technological industry agglomeration equation in Table 6, firstly, the three spatial weight matrices' coefficients for the spatial lags of technological industry agglomeration are 1.044, 4.928, and 3.163, respectively. They are significant at 10%, 1%, and 1% levels, showing that the technological industry agglomeration in nearby areas is advantageous to the growth of related sectors, further supporting hypothesis H4. Similar development structures and geographic environments successfully drive the aggregation of sectors in the surrounding areas. Secondly, the estimated coefficients of high-quality economic development under the three spatial weight matrices derived from endogenous variables are 4.196, 4.502, and 4.489, respectively, and are all significant at the 10% level. This confirms hypothesis H1 because it shows a significant positive driving effect on technological industry agglomeration. When the level of environmental pollution caused by reliance on traditional energy consumption is too high, the concentration of traditional enterprises is reduced through industrial transfer, which is conducive to the technological industry agglomeration with low energy consumption, low emission, and high added value. The investment of superior resources is raised, whereas industrial transformation is prioritized to support the construction of technological industry agglomerations as economic development moves toward a high-quality stage. According to the estimated coefficients of green innovation efficiency under the three spatial weight matrices, −4.977, −4.221, and −4.352, all of which are significant at the 1% level and demonstrate the competition effect, developmental enterprises are more competitive at the R&D stage and have strengthened the secrecy of R&D and intellectual property protection, ignoring the advantageous side. Thirdly, the coefficients of the spatial lag term of the efficiency of green innovation are 0.173, 1.823, and 2.456, respectively. They are significant at 10%, 5%, and 1% levels, showing that the advancement of R&D in neighboring regions positively affects the local technological industry agglomeration and fosters the local industry agglomeration process. Fourth, when it comes to exogenous factors, the degree of opening up to the outside world significantly affects the technological industry agglomeration, which boosts the export volume of luxury goods and draws in foreign investment. At the same time, it strengthens information exchange among enterprises and the outside world, enables companies to learn cutting-edge production technology and management techniques, and promotes local industrial growth.

Table 6. Regression results of R&D stages (hia).

Items	Technological industry agglomeration equation		
	$W1$	$W2$	$W3$
hqe	4.196^{*}	4.502^{*}	4.489^{*}
hia	-	-	-
hst	-4.977^{***}	-4.221^{***}	-4.352^{***}
$W \cdot hqe$	-1.044^{*}	-5.649^{***}	-2.310^{**}
$W \cdot hia$	1.044^{*}	4.928^{***}	3.163^{***}
$W \cdot hst$	0.173^{*}	1.823^{**}	2.456^{***}
$poag$	-	-	-
$expe$	-	-	-
$envi$	-	-	-
$lieq$	0.014^{**}	0.017^{*}	0.024^{**}
$mark$	0.004	0.005	0.007
$fina$	−0.001	−0.001	-0.001^{*}
$tran$	-	-	-
$stru$	-	-	-
$pote$	-	-	-
Cons	−1.372	1.642^{***}	1.64^{***}
R^2	0.8780	0.8286	0.8618

Note: The symbols ***, **, and * indicate significant at the 1%, 5%, and 10% levels, respectively.

From the green innovation efficiency equation in the technological sector in Table 7, firstly, according to the three spatial weight matrices, the spatial lag term coefficients of green innovation efficiency are 0.944, 5.245, and 3.988, respectively. They are significant at 10%, 1%, and 1% levels, showing that the neighboring regions' technological advancements positively influence local R&D, supporting hypothesis H4. Green innovation is a critical component of industrial transformation and upgrading. Innovation ideas continue to be exported, and the surrounding regions learn from the development model and invest in innovation factors and technologies. The Yangtze River Delta city cluster's proportion of high energy-consuming industries and its crude development mode gradually do not adapt to the current sustainable development and urgently need to change the status quo. Secondly, the calculated coefficients of development quality on green innovation efficiency from the endogenous factors are −0.677, −0.664, and −0.759, all significant at the 5% level and acting as a cost impact, supporting hypothesis H2. R&D is a long-term process that requires the accumulation and cooperation of various factors. In contrast to low output, high capital input can easily cause a period of economic input fatigue, which can reduce investment in technology. On the one hand, the high level of development quality makes it easy to ignore the importance of green innovation factor resource allocation and reduce the proportion of R&D investment. The calculated coefficients of the technological industry agglomeration on the green innovation efficiency are −0.140, −0.135, and −0.139, all of which are significant at the 1% level, playing the role of competitiveness effect and supporting hypothesis H3. Enterprises concentrate on encouraging technology research and development in the production technology development stage and secrecy because the larger the agglomeration of the technological industry, the more competition among similar businesses. The too-closed manner of cooperation among firms during this time is not favorable for the quick advancement of scientific and technological breakthroughs. Thirdly, the spatial lag term of development quality's coefficient is negative at the 5% level under the geographic and economic distance matrix, showing that the expansion of economic quality in nearby regions reduces the effectiveness of local green innovation. The growth of adjacent economies brings in foreign capital and favorable resources from nearby cities. Still, the decline in local talent employment and information access harms the green innovation efficiency. Fourth, regarding exogenous factors, building communication infrastructure significantly improves the green innovation efficiency, and the ease of information access makes R&D easier.

Table 7. Regression results of R&D stages (*hst*).

Items	Green innovation efficiency equation		
	$W1$	$W2$	$W3$
hqe	-0.677^{**}	-0.664^{**}	-0.759^{**}
hia	-0.140^{***}	-0.135^{***}	-0.139^{***}
hst	-	-	-
$W \cdot hqe$	−0.031	-5.595^{**}	-4.706^{**}
$W \cdot hia$	−0.001	−0.513	−0.448
$W \cdot hst$	0.944^{*}	5.245^{***}	3.988^{***}
$poag$	-	-	-
$expe$	-	-	-
$envi$	-	-	-
$lieq$	-	-	-
$mark$	-	-	-
$fina$	-	-	-
$tran$	0.002	0.005	0.008
$stru$	0.001	0.002	0.004
$pote$	0.013^{***}	0.010^{**}	0.009^{**}
Cons	0.577	0.513^{***}	0.549^{***}
R^2	0.7873	0.6331	0.6593

Note: The symbols ***, **, and * indicate significant at the 1%, 5%, and 10% levels, respectively.

5.2.2. Transformation stage

Table 8. Regression results of transformation stage (hqe).

Items	Development quality equation		
	$W1$	$W2$	$W3$
hqe	-	-	-
hia	0.015	0.009	0.033
hat	0.325**	0.323**	0.362**
$W \cdot hqe$	0.024	0.885	0.605
$W \cdot hia$	−0.005	−0.974	−0.543
$W \cdot hst$	1.022*	4.098***	4.714***
$poag$	0.005	0.008	0.009
$expe$	0.021***	0.028***	0.030***
$envi$	0.024***	0.023**	0.013
$lieq$	-	-	-
$mark$	-	-	-
$fina$	-	-	-
$tran$	-	-	-
$stru$	-	-	-
$pote$	-	-	-
Cons	0.325	0.400***	0.393***
R^2	0.1010	0.1160	0.1279

Note: The symbols ***, **, and * indicate significant at the 1%, 5%, and 10% levels, respectively.

Considering the equation for development quality in Table 8, firstly, the positive but negligible spillover impact of development quality suggests that the local economy is favorably tugged in a positive direction by the bordering regions, albeit weakly. With consistent outcomes, development quality growth creates a more stable development system that is less influenced by the surrounding areas. Secondly, in terms of endogenous variables, the estimated coefficients of green innovation efficiency are significantly positive under all three weight matrices, indicating that green innovation efficiency shows a significant positive promoting effect on the high-quality development of the economy, which supports hypothesis H2. It also demonstrates the significance of development quality with the power of technology innovation. The transformation of knowledge achievements into new products brings economic benefits. It encourages the high-quality development of the economy, gradually forming a virtuous circle, accelerating technology transfer, and promoting economic and environmental benefits simultaneously. Thirdly, based on the coefficient of the spatial lag term of the endogenous variables, the efficiency of green innovation is significantly positive, indicating that the transformation of outcomes in bordering regions is advantageous to the high-quality development of the region's economy. The Yangtze River Delta city cluster's continuing regional integration accelerates the flow of new products, which boosts the quantitative level of green innovation and expands the prospects for local learning and learning, supporting the high-quality development of the economy. Fourth, the exogenous variable estimate findings show that the level of fiscal expenditure has a considerable beneficial impact on development quality, suggesting that budgetary expenditure control is feasible at this point and that maintaining the current expenditure share is crucial. Environmental regulation under the adjacency and geographic distance matrix show a significant positive driving effect on high-quality economic development. The various degrees of implementation of environmental policies and environmental protection behaviors of cities within the Yangtze River Delta city cluster produce significant differences in ecological governance effects, resulting in some cities not achieving the expected governance effects, an important finding. Consequently, economic development quality is controlled. The findings above show that the Yangtze River Delta urban agglomeration's degree of economic development is primarily controlled by local variables and has minimal impact on the nearby regions. The "center-periphery" theory more effectively explains this phenomenon, showing how inter-regional resources and policies cause the central cities to dominate the peripheral cities and how their dependence on neighboring regions' development is much less potent than their development forerunners.

Table 9. Regression results of transformation stage (hia).

Items	Technological industry agglomeration equation		
	$W1$	$W2$	$W3$
hqe	1.936**	2.222**	4.489***
hia	-	-	-
hat	3.610***	3.862**	3.765***
$W \cdot hqe$	−0.050	−2.557***	−1.310***
$W \cdot hia$	0.030	1.777***	1.258**
$W \cdot hst$	−0.101	−2.698***	−1.456**
$poag$	-	-	-
$expe$	-	-	-
$envi$	-	-	-
$lieq$	0.002	0.001	0.001
$mark$	0.020	0.033*	0.033*
$fina$	0.003	0.005	0.006
$tran$	-	-	-
$stru$	-	-	-
$pote$	-	-	-
Cons	0.054	−0.272	−0.555
R^2	0.9881	0.9691	0.9034

Note: The symbols ***, **, and * indicate significant at the 1%, 5%, and 10% levels, respectively.

From the equation for technological industry agglomeration in Table 9, firstly, under both the geographic and economic distance matrices, the technological industry spatial lag term coefficient is significantly positive, demonstrating that the technological industry agglomeration in the region is encouraged by the technological industry agglomeration in the neighboring regions, supporting hypothesis H4. The region's geographic area is constrained, and the initial stage of fruit transformation draws many businesses to a location known as an agglomeration. The pressure of growing business competitiveness constrains this area and the Yangtze. While newly emerging companies adhere to the principle of results proximity to choose the location, driving industrial agglomeration in the surrounding areas, the policy convergence of urban agglomeration compels the unstable development and high energy consumption type firms to migrate away. Secondly, the development quality has a strong positive driving effect on endogenous factors, consistent with the paper's hypothesis H1, showing that it significantly promotes the clustering of technological industries. The Yangtze River Delta region's integrated development model has aided in the scale effect of development quality growth, which attracts numerous outside businesses to form an agglomeration. The sharing superposition of resources also supports industrial agglomeration. In all three matrices, the green innovation efficiency makes a considerable contribution, supporting hypothesis H3. Enterprises are paying more and more attention to the benefits of resource sharing and the export of results as knowledge accumulation and R&D innovation drive the transformation of results—a concentration of industry. Thirdly, the neighboring regions' development quality and green innovation efficiency have a negative inhibitory effect on the technological industry agglomeration in the area, and the direction of influence is different from that of the R&D stage, which is consistent with hypothesis H5. Fourth, the spatial lags of the endogenous variables under the geographic distance matrix and the economic distance matrix have a positive inhibitory effect on the technological industry agglomeration in the region. The growth restriction of the industrial agglomeration in this location is raised to some extent by the expansion of bordering areas during the accomplishment transformation stage. Fourth, the level of marketization has a sizable positive effect on technological industry agglomeration in terms of exogenous variables, showing that the current market environment is advantageous to industrial agglomeration. The Yangtze River Delta city cluster, one of China's more open regions, focuses on developing green technologies and benefits from access to capital, talent, information, and other resources. At the moment, marketization should be fostered and maintained for its beneficial effects.

Table 10. Regression results of transformation stage (*hat*).

Items	Green innovation efficiency equation		
	$W1$	$W2$	$W3$
hqe	1.616***	1.506***	1.391***
hia	0.271***	0.234***	0.226***
hat	-	-	-
$W \cdot hqe$	−0.094	−2.476***	−1.697***
$W \cdot hia$	−0.009	−1.012	0.857
$W \cdot hst$	2.024***	2.126***	1.910***
$poag$	-	-	-
$expe$	-	-	-
$envi$	-	-	-
$lieq$	-	-	-
$mark$	-	-	-
$fina$	-	-	-
$tran$	0.005	0.007	0.010
$stru$	−0.013***	−0.022***	−0.023***
$pote$	0.005	0.005	0.006
Cons	0.752	−0.258	−0.193
R^2	0.7719	0.7207	0.7115

Note: The symbols ***, **, and * indicate significant at the 1%, 5%, and 10% levels, respectively.

According to the high technology industry's green innovation efficiency equation in Table 10, firstly, at a 1% confidence level, the coefficients of the spatial lag term of green innovation efficiency are 2.024, 2.126, and 1.910, all of which are significant. This shows that the green innovation efficiency of this region is positively influenced by the green innovation efficiency of its neighbors. Scientific and technological information is converted into output. Regional production is sped up with the mobility of people and goods, and interregional technology exchange is made more accessible. Secondly, the calculated coefficients of development quality from the endogenous factors are 1.616, 1.506, and 1.391, all of which are significant at the 1% level, supporting hypothesis H2. The growth of industrial clusters encourages the pile-up layout of green innovation elements, and this result is consistent with hypothesis H3, which is following the attraction impact. Industrial clustering has a strong beneficial effect. Thirdly, the development quality of nearby regions hinders the green innovation efficiency in this area. Economic development also attracts resources from nearby regions to join, allows the main components of innovation to leave for nearby cities, and slows down green innovation through businesses. Fourthly, it is important to speed up the process of technologically changing the industrial structure, fully utilize the ability of technological industries to manage pollution emissions, and lessen the intensity of energy consumption of traditional industries because upgrading the industrial structure has a significant inhibitory effect on the efficiency of green innovation.

6. Conclusions and discussion

This study establishes a spatial panel simultaneous model to analyze the relationship among technological industry agglomeration, green innovation efficiency, and development quality in the Yangtze River Delta city cluster. The results show the following conclusions: (1) There is a considerable positive spatial link between the technological industry agglomeration, the green innovation efficiency, and development quality. Although green innovation efficiency, development quality, and technological industry agglomeration are all mutually suppressed during the R&D stage, there are positive effects during the transformation stage. Development quality and technological industry agglomeration in neighboring regions have adverse inhibitory effects on the other two variables; green innovation efficiency in neighboring regions positively promotes high-quality local economic development in both stages. (2) Technological industry agglomeration, green innovation efficiency, and development quality have positive spillover effects. There are positive impacts in R&D stage and the negative impacts in transformation stage both on the local industrial agglomeration. (3) There is apparent heterogeneity in the exogenous variables of high technology industry agglomeration and green innovation efficiency, and all of the exogenous elements of development quality growth favorably influence it.

Admittedly, there are no comparative analysis of other industries in this study, which focuses only on the technological industry. Additionally, the chosen research area has a limited scope and a tendency toward one-sidedness. The research area should be further broadened in the following study so that comparisons with the Beijing-Tianjin region, the Pearl River Delta region, even city cluster in United States and Japan, etc., can be made. The research objectives can also include businesses like manufacturing and service industries.

The following policy recommendations are made in light of the findings above: (1) It is valuable to exploit the mutual promotion effect among technological industry agglomeration, green innovation efficiency, and development quality, maximize the release of the positive driving force, and reduce negative inhibition. Local government need to increase financial spending, accelerate the technology development stage of knowledge accumulation and the transformation stage of the output of technology research and development, create a social environment of innovation for all, attract the gathering of high-end large and medium-sized enterprises, and create a technological industry. These steps will help to strengthen the market supervision mechanism and guide and control the development stage of green innovation and the flow direction of production factors. (2) Central Government should coordinate and support the high-quality development of the technological industry and economy among regions, as well as the synergistic development of technological industry agglomeration, green innovation efficiency, and development quality. The new paradigm will boost collaborative innovation, deepens government, business, academia, and research, and supports concurrent economic quality improvement. (3) Policy maker can take into account the current development situation, grasp the stage of green innovation, expand the opening to the outside world, broaden the channels of communication with the outside world, actively absorb knowledge elements and innovative ideas, strengthen environmental protection, and reduce the entry barrier for technology industry.

Conflict of interest

All authors declare no conflicts of interest in this paper.

References

Akinci M (2018) Inequality and economic growth: Trickle-down effect revisited. *Dev Policy Rev* 36: O1–O24. https://doi.org/10.1111/dpr.12214

Arbolino R, De Simone L, Carlucci F, et al. (2018) Towards a sustainable industrial ecology: Implementation of a novel approach in the performance evaluation of Italian regions. *J Clean Prod* 178: 220–236. https://doi.org/10.1016/j.jclepro.2017.12.183

Arrow KJ (1971) *The economic implications of learning by doing.* Readings in the Theory of Growth, 131–149. https://doi.org/10.1007/978-1-349-15430-2_11

Busch J, Foxon TJ, Taylor PG (2018) Designing industrial strategy for a low carbon transformation. *Environ Innov Soc Transitions* 29: 114–125. https://doi.org/10.1016/j.eist.2018.07.005

Demirtas YE, Kececi NF (2020) The efficiency of private pension companies using dynamic data envelopment analysis. *Quant Financ Econ* 4: 204–219. https://doi.org/10.3934/qfe.2020009

Du KR, Li JL (2019) Towards a green world: How do green technology innovations affect total-factor carbon productivity. *Energy Policy* 131: 240–250. https://doi.org/10.1016/j.enpol.2019.04.033

Greco M, Cricelli L, Grimaldi M, et al. (2022) Unveiling the relationships among intellectual property strategies, protection mechanisms and outbound open innovation. *Creat Innov Manage* 31: 376–389. https://doi.org/10.1111/caim.12498

Hansen MT, Birkinshaw J (2007) The innovation value chain. *Harvard Bus Rev* 85: 121.

Hong Y, Liu W, Song H (2022) Spatial econometric analysis of effect of New economic momentum on China's high-quality development. *Res Int Bus Financ* 61: 101621. https://doi.org/10.1016/j.ribaf.2022.101621

Hou YX, Zhang KR, Zhu YC, et al. (2021) Spatial and temporal differentiation and influencing factors of environmental governance performance in the Yangtze River Delta, China. *Sci Total Environ* 801: 149699. https://doi.org/10.1016/j.scitotenv.2021.149699

Huang CX, Zhao X, Deng YK, et al. (2022) Evaluating influential nodes for the Chinese energy stocks based on jump volatility spillover network. *Int Rev Econ Financ* 78: 81–94. https://doi.org/10.1016/j.iref.2021.11.001

Kelejian HH, Prucha IR (2004) Estimation of simultaneous systems of spatially interrelated cross sectional equations. *J Econometrics* 118: 27–50. https://doi.org/10.1016/s0304-4076(03)00133-7

Kemeny T, Osman T (2018) The wider impacts of high-technology employment: Evidence from US cities. *Res Policy* 47: 1729–1740. https://doi.org/10.1016/j.respol.2018.06.005

Kolia DL, Papadopoulos S (2020) The levels of bank capital, risk and efficiency in the Eurozone and the U.S. in the aftermath of the financial crisis. *Quant Financ Econ* 4: 66–90. https://doi.org/10.3934/Qfe.2020004

Lin BQ, Zhou YC (2022) Does energy efficiency make sense in China? Based on the perspective of economic growth quality. *Sci Total Environ* 804: 149895. https://doi.org/10.1016/j.scitotenv.2021.149895

Liu CY, Gao XY, Ma WL, et al. (2020) Research on regional differences and influencing factors of green technology innovation efficiency of China's high-tech industry. *J Comput Appl Math* 369: 112597. https://doi.org/10.1016/j.cam.2019.112597

Liu H, Lei H, Zhou Y (2022) How does green trade affect the environment? Evidence from China. *J Econ Anal* 1: 1–27. https://doi.org/10.12410/jea.2811-0943.2022.01.001

Liu Y, Liu M, Wang GG, et al. (2021) Effect of Environmental Regulation on High-quality Economic Development in China-An Empirical Analysis Based on Dynamic Spatial Durbin Model. *Environ Sci Pollut Res* 28: 54661–54678. https://doi.org/10.1007/s11356-021-13780-2

Long RY, Gan X, Chen H, et al. (2020) Spatial econometric analysis of foreign direct investment and carbon productivity in China: Two-tier moderating roles of industrialization development. *Resour Conserv Recy* 155: 104677. https://doi.org/10.1016/j.resconrec.2019.104677

Lu R, Ruan M, Reve T (2016) Cluster and co-located cluster effects: An empirical study of six Chinese city regions. *Res Policy* 45: 1984–1995. https://doi.org/10.1016/j.respol.2016.07.003

Lv CC, Shao CH, Lee CC (2021) Green technology innovation and financial development: Do environmental regulation and innovation output matter? *Energy Econ* 98: 105237. https://doi.org/10.1016/j.eneco.2021.105237

Ma XW, Xu JW (2022) Impact of Environmental Regulation on High-Quality Economic Development. *Front Env Sci* 10: 896892. https://doi.org/10.3389/fenvs.2022.896892

Miao CL, Fang DB, Sun LY, et al. (2017) Natural resources utilization efficiency under the influence of green technological innovation. *Resour Conserv Recy* 126: 153–161. https://doi.org/10.1016/j.resconrec.2017.07.019

Nieto J, Carpintero O, Lobejon LF, et al. (2020) An ecological macroeconomics model: The energy transition in the EU. *Energy Policy* 145: 111726. https://doi.org/10.1016/j.enpol.2020.111726

Peng BH, Zheng CY, Wei G, et al. (2020) The cultivation mechanism of green technology innovation in manufacturing industry: From the perspective of ecological niche. *J Clean Prod* 252: 119711. https://doi.org/10.1016/j.jclepro.2019.119711

Poon JP, Kedron P, Bagchi-Sen S (2013) Do foreign subsidiaries innovate and perform better in a cluster? A spatial analysis of Japanese subsidiaries in the US. *Appl Geogr* 44: 33–42. https://doi.org/10.1016/j.apgeog.2013.07.007

Ren S, Liu Z, Zhanbayev R, et al. (2022). Does the internet development put pressure on energy-saving potential for environmental sustainability? Evidence from China. *J Econ Anal* 1: 81–101. https://doi.org/10.12410/jea.2811-0943.2022.01.004

Ren ZL (2020) Evaluation Method of Port Enterprise Product Quality Based on Entropy Weight TOPSIS. *J Coastal Res* 766–769. https://doi.org/10.2112/si103-158.1

Song Y, Yang L, Sindakis S, et al. (2022) Analyzing the Role of High-Tech Industrial Agglomeration in Green Transformation and Upgrading of Manufacturing Industry: the Case of China. *J Knowl Econ,* 1–31. https://doi.org/10.1007/s13132-022-00899-x

Strauss J, Yigit T (2001) Present value model, heteroscedasticity and parameter stability tests. *Econ Lett* 73: 375–378. https://doi.org/10.1016/S0165-1765(01)00506-7

Su Y, Li Z, Yang C (2021) Spatial Interaction Spillover Effects between Digital Financial Technology and Urban Ecological Efficiency in China: An Empirical Study Based on Spatial Simultaneous Equations. *Int J Environ Res Public Health* 18: 8535. https://doi.org/10.3390/ijerph18168535

Sun CZ, Yang YD, Zhao LS (2015) Economic spillover effects in the Bohai Rim Region of China: Is the economic growth of coastal counties beneficial for the whole area? *China Econ Rev* 33: 123–136. https://doi.org/10.1016/j.chieco.2015.01.008

Wang L, Xue YB, Chang M, et al. (2020a) Macroeconomic determinants of high-tech migration in China: The case of Yangtze River Delta Urban Agglomeration. *Cities* 107: 102888. https://doi.org/10.1016/j.cities.2020.102888

Wang MY, Li YM, Li JQ, et al. (2021) Green process innovation, green product innovation and its economic performance improvement paths: A survey and structural model. *J Environ Manage* 297: 113282. https://doi.org/10.1016/j.jenvman.2021.113282

Wang S, Yang C, Li Z (2022) Green Total Factor Productivity Growth: Policy-Guided or Market-Driven? *Int J Environ Res Public Health* 19: 10471. https://doi.org/10.3390/ijerph191710471

Wang SJ, Hua GH, Yang LZ (2020b) Coordinated development of economic growth and ecological efficiency in Jiangsu, China. *Environ Sci Pollut Res* 27: 36664–36676. https://doi.org/10.1007/s11356-020-09297-9

Wang Y, Pan JF, Pei RM, et al. (2020c) Assessing the technological innovation efficiency of China's high-tech industries with a two-stage network DEA approach. *Socio-Econ Plan Sci* 71: 100810. https://doi.org/10.1016/j.seps.2020.100810

Wu HT, Hao Y, Ren SY (2020) How do environmental regulation and environmental decentralization affect green total factor energy efficiency: Evidence from China. *Energy Econ* 91: 104880. https://doi.org/10.1016/j.eneco.2020.104880

Wu HT, Hao Y, Ren SY, et al. (2021) Does internet development improve green total factor energy efficiency? Evidence from China. *Energy Policy* 153: 112247. https://doi.org/10.1016/j.enpol.2021.112247

Wu MR (2022) The impact of eco-environmental regulation on green energy efficiency in China-Based on spatial economic analysis. *Energy Environ*. https://doi.org/10.1177/0958305x211072435

Wu XX, Huang Y, Gao J (2022) Impact of industrial agglomeration on new-type urbanization: Evidence from Pearl River Delta urban agglomeration of China. Int Rev Econ Financ 77: 312–325. https://doi.org/10.1016/j.iref.2021.10.002

Xu J, Li JS (2019) The impact of intellectual capital on SMEs' performance in China Empirical evidence from non-high-tech vs. high-tech SMEs. *J Intellect Capital* 20: 488–509. https://doi.org/10.1108/jic-04-2018-0074

Xu JH, Li Y (2021) Research on the Impact of Producer Services Industry Agglomeration on the High Quality Development of Urban Agglomerations in the Yangtze River Economic Belt. World Congress on Services, Springer, Cham, 12996: 35–52. https://doi.org/10.1007/978-3-030-96585-3_3

Yao Y, Hu D, Yang C, et al. (2021) The impact and mechanism of fintech on green total factor productivity. *Green Financ* 3: 198–221. https://doi.org/10.3934/gf.2021011

Yin XB, Guo LY (2021) Industrial efficiency analysis based on the spatial panel model. *Eurasip J Wireless Commun Netw* 2021: 1–17. https://doi.org/10.1186/s13638-021-01907-5

Zhao BY, Sun LC, Qin L (2022) Optimization of China's provincial carbon emission transfer structure under the dual constraints of economic development and emission reduction goals. *Environ Sci Pollut Res,* 1–17. https://doi.org/10.1007/s11356-022-19288-7

Zheng Y, Chen S, Wang N (2020) Does financial agglomeration enhance regional green economy development? Evidence from China. *Green Financ* 2: 173–196. https://doi.org/10.3934/GF.2020010

Zhou B, Zeng XY, Jiang L, et al. (2020) High-quality Economic Growth under the Influence of Technological Innovation Preference in China: A Numerical Simulation from the Government Financial Perspective. *Struct Change Econ Dyn* 54: 163–172. https://doi.org/10.1016/j.strueco.2020.04.010

Zhou J, Wang G, Lan S, et al. (2017) Study on the Innovation Incubation Ability Evaluation of High Technology Industry in China from the Perspective of Value-Chain An Empirical Analysis Based on 31 Provinces. *Procedia Manuf* 10: 1066–1076. https://doi.org/10.1016/j.promfg.2017.07.097

Zhu L, Luo J, Dong QL, et al. (2021) Green technology innovation efficiency of energy-intensive industries in China from the perspective of shared resources: Dynamic change and improvement path. *Technol Forecasting Soc Change* 170: 120890. https://doi.org/10.1016/j.techfore.2021.120890

Zhu M, Song X, Chen W (2022) The Impact of Social Capital on Land Arrangement Behavior of Migrant Workers in China. *J Econ Anal* 1: 52–80. https://doi.org/10.12410/jea.2811-0943.2022.01.003