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Driving mechanism and spatial effect of technological potential energy agglomeration promoting the development of high-tech industry

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ABSTRACT

The current technological potential energy agglomeration situation and the driving mechanism for high-tech (HT) industry development can be clarified based on the front view of innovative behaviour. Thus, it can be defined using three dimensions: comprehensive innovation environment, innovation initiative and attraction of innovation factors. This study theoretically investigates the internal mechanism and spatial effect of technological potential energy agglomeration driving the development of the HT industry and establishes an empirical analysis using a general nested space model (GNS). China's regional technological potential energy agglomeration level increases over time, and a 'conduction' development pattern spreading from the northeast to the southwest is observed. The diversified agglomeration of technological potential energy can significantly transform the low- and medium-tech (LMT) industry to the HT industry at the 1% level, with a driving force of 0.5994. The driving force of the specialised agglomeration is 0.2538, less than the diversified agglomeration. The specialised agglomeration of technological potential energy hinders the development of HT industries in neighbouring areas, as core technologies are excusive with limited innovation resources. Therefore, all provinces should promote HT industries by cultivating platforms for technological potential energy agglomeration, encouraging technological innovation, strengthening foreign trade and promoting institutional innovation.

1. Introduction

In recent years, China's high-tech (HT) industry has rapidly expanded. By the end of 2015, its main business income reached nearly 13996.9 billion yuan, of which the export delivery value exceeded 5092.3 billion yuan. The HT industry has become one of the main drivers of sustained and stable economic growth. Given the gradually

apparent shortcomings of the extensive scale expansion growth mode, promoting the HT industry, driven by technological innovation, is crucial for improving the division of labour in the international industrial chain and enhancing international competitiveness. As China's economy enters the 'new normal' stage, new opportunities due to the emerging technological revolution promote technological innovation. This 'new normal' requires balance of the industrial development mode and improvement of the economic development quality through innovation. Therefore, finding an effective way to uncover technological innovation, clarifying the current situation of technological potential energy agglomeration, and exploring the driving mechanism and spatial effects on the HT industry development have considerable theoretical and practical significance. They contribute to strengthening innovation results, promoting the HT industry development, and improving the quality and quantity of regional economies.

Solo ([1951]) first proposed two conditions for technological innovation: the source of new ideas and the development of later stages. Subsequent studies have provided rich theoretical supplements for the connotations and extensions of technological innovation. However, few studies clearly define technological innovation behaviour based on the 'two-step theory'. This study divides technological innovation behaviour into two stages: innovation front end and innovation terminal. The innovation front end refers to the technological potential energy agglomeration stage, which reserves potential energy for technological innovation and provides a powerful guarantee for forming new ideas through knowledge collaboration and the agglomeration of innovative factors. Innovation terminal refers to the stage of innovation kinetic energy conversion, transforming the potential energy of technological innovation into innovation kinetic energy that can directly promote innovation development.

2. Literature review

Few studies have focussed on technological potential energy. Wei and Zhu ([2007]) highlighted that the potential capabilities and motivations of innovation should consist of three aspects: the field, situation, and energy and fully affirmed the importance of environment, initiative, resource adsorption and cohesion to the potential capacity of technological innovation. Regarding technology spill-over effect of foreign direct investment (FDI), several studies have confirmed the 'technological potential energy' hypothesis that it depends on factors such as absorptive capacity and technology gap, regional innovation environment, and enterprise characteristics (Yu & Duan, [2011]; Yu & Wu, [2010]). These studies extend the definition of technological potential energy from physics. However, its refinement is still incomplete. Related research on 'knowledge field' theory effectively supplements the theory of technological potential energy. Nonaka and Takeuchi ([1995]) first proposed the 'knowledge field' theory while researching knowledge creation, formed a theoretical prototype of the 'knowledge field' to study knowledge flow, and simultaneously established the SECI model to elaborate fully. Siemens ([2005]) and Rubin et al. ([2015]) showed the laws and paths of knowledge flow within enterprises using field theory and conducted an empirical analysis using data from Australia and Israel. Many scholars have stated that knowledge

diffusion caused by knowledge potential will not stop until the knowledge level in the entire society improves (Chen & Wang, 1995; Dang et al., 2006).

There is ample research in the literature on technological potential energy and innovation. Some scholars showed that the different degrees of technological innovation diffusion caused inconsistencies in technological innovation capabilities in different regions from the diffusion perspective (Chen et al., 2010). Based on an analysis of the complex characteristics of the technological innovation diffusion system, Ma et al. (2015) studied the dynamic elements of technological innovation transfer between different regions. However, few studies promote the inherent potential of technological innovation and the conversion mechanism between this potential energy and the ability to promote technological innovation. Some scholars introduced the concepts of potential energy and potential differences in physics to analyse the internal mechanism and diffusion path of technical knowledge (Han, 2013; Wang, 2013). Wang, Wang et al. (2015) used the GERT network model to analyse the flow of regional knowledge innovation values.

Studies on innovation that drive the HT industry development have attracted wide attention. Schmitz and Knorringa (2000) showed that knowledge innovation of processes, products and markets is an important approach to upgrading the industrial value chain, and technological innovation is the key force for the HT industry development. Lee et al. (2019) and Szutowski et al. (2019) proved that process innovation significantly impacts radical product innovation and firm performance in HT and low-tech industries. Camisón-Haba et al. (2019) showed that technology-based firms could improve innovation ability under the influence of technical capabilities, management capabilities, and CEO education background, thereby transforming into a technology-based and highly innovative firm. Under the new industrial revolution, digitalisation, intelligence, informatisation and new energy technologies will fully penetrate the production of the HT industry, and technological and institutional innovation would effectively lead to the rapid development of the HT industry (Wang, Ma et al., 2015). Yian (2019) argued that misallocation of human capital could affect productivity through industrial structure upgrading, technological innovation and labour productivity, and the human capital flow to high-tech industries can stimulate the development of emerging economies. Shah et al. (2020) showed that in HT and knowledge-based industries, the leader's technical competence positively impacts the learning and innovation of subordinates. Mohelska et al. (2020) show a correlation between employment and job satisfaction, which affects the development of HT industries and enterprises and economic growth. Caseiro and Coelho (2019) concluded that business intelligence capacities impacted network learning, innovativeness and performance based on a sample of 228 start-ups.

Existing literature does not define technological potential energy uniformly. Some studies have expanded its definition from physics, but the concept is not fully refined. As the definition of technological potential energy has not been proposed accurately, there is currently no relevant research on the mechanism of technological potential energy in the HT industry development. Therefore, this study proposes a definition of technological potential energy agglomeration from the front view of innovative behaviour. Accordingly, it analyses the internal mechanism and spatial effect of

diversified and specialised agglomerations of technological potential energy to promote the HT industry development.

The study's contributions are as follows. First, based on the innovation front end, the theory of technological potential innovation is expanded appropriately, and the definition of technological potential energy agglomeration is proposed by introducing the theory of gravitational potential energy in physics. Second, based on dividing the specialised and diversified agglomerations, the production function, including the two major sectors of the HT and low- and medium-tech (LMT) industries, is used to analyse the internal mechanism of technological potential energy agglomeration driving the HT industry. Third, an indicator system of regional technological potential energy agglomeration is established based on physics. Then we explore its spatial and temporal distribution. Finally, an empirical analysis is conducted to investigate its mechanism and spatial effects in different regions on the HT industry development with the general nested space model (GNS) containing spatial effects.

3. Mechanism analysis

3.1. Definitions

3.1.1. Technological potential energy

The definition of technological potential energy in previous research is still uncertain. Its definition is proposed based on three dimensions by extending the concept of gravitational potential energy in physics to the 'knowledge field' theory: comprehensive innovation environment, innovation initiative and attraction of innovation factors. In physics, the gravitational potential energy of an object is the product of its mass, gravitational acceleration and height, where mass represents its characteristics, gravitational acceleration represents the environmental characteristics, and height represents the potential capability. Hence, this study defines technological potential energy as the maximum technological improvement achieved by independent, collaborative, and other forms of innovations under the three constraints, innovation initiative, internal and external innovation environment and attraction of innovation factors. Additionally, it refers to the maximum achievable innovation capability or the upper limit of technological progress under the corresponding conditions. Technological potential energy cannot be fully transformed into actual innovation power in complex innovation activities, and conversion losses exist.

3.1.2. Technological potential energy agglomeration

Technological potential energy agglomeration refers to the degree of concentration of three dimensions (the technological innovation environment, technological innovation initiative and the attraction of innovative factors) of technological upgrading potential in a specific spatial area. It can be decomposed further into diversified and specialised agglomeration of technological potential energy.

The diversified agglomeration of technological potential energy refers to the degree of its concentration in the space area. Diversified technological innovation is achieved through three dimensions and generates comprehensive innovation and various integrative industrial development objectives.

The specialised agglomeration of technological potential energy refers to the degree of concentration of specialised technological potential energy in the space area. This results in greater technological progress and effective breakthrough by resolving single or closely related technological problems. Additionally, specialised agglomeration can cultivate the core competitiveness of the industry.

3.2. Theoretical analysis[1]

Suppose the economy consists of two sectors: HT and LMT industries. Among them, as a technology-intensive industry, the HT industry has relatively higher research and development (R&D) and investment ratios and more advanced production methods than the LMT industry. In the LMT industry, a labour-intensive industry, imitation innovation is the main approach to knowledge accumulation. Without the impact of technological potential energy, there is no technological spill-over between the HT and LMT industries. According to the fundamental framework of the new economic growth theory (Romer, 1990), the production function is constructed as follows:

$$Y = K^{\alpha}[AH_p]^{1-\alpha}. \tag{1}$$

Accordingly, the industrial knowledge production function is derived as:

$$\dot{A} = [H_p K]^{\beta}[H_r A]^{\theta}. \tag{2}$$

Here Y, K, A and $\dot{A}$ represent the total output, capital input, knowledge stock, and industrial knowledge output during the industrial production process, respectively. β and θ indicate the output elasticity of collaborative innovation and independent R&D on industrial knowledge accumulation, respectively. H_p and H_r are the human capital invested in production and R&D, respectively. $H(t) = L(t)G(E)$ is the human capital in period t, where $L(t)$ is the total labour force in the economy and the growth rate of the labour force is a fixed value n. $G(E)$ is the human capital function of employees, and E, an exogenous variable, represents the average education level. When $\beta + \theta < 1$, industrial knowledge production diminishes and returns to scale. Meanwhile, when the savings rate is exogenous, and the influence of technological potential energy is not considered, the HT and LMT industries have the same steady-state knowledge growth rate as follows:

$$g_{h0}^{*} = g_{l0}^{*} = \frac{2\beta + \theta}{1 - \beta - \theta} \cdot n. \tag{3}$$

The knowledge stock of the HT industry is higher than that of the LMT industry, and the knowledge growth rates of the two industries are equal. Additionally, the balanced growth paths of the two industries appear as parallel growth paths.

3.2.1. The diversified agglomeration of technological potential energy and transformation in the LMT industry

The differences in technology intensity between different industries and the technological difference between the HT and LMT industries significantly impact the flow and diffusion of knowledge (Hauknes & Knell, 2009). As the diversified agglomeration level of technological potential energy increases, more LMT industries can find suitable technology reserves that match their development and internalise these technologies through imitation innovation. Thus, the knowledge production function of the LMT industry is

$$\dot{A}_l = [H_{lp}K_l]^\beta [H_{lr}A_l]^\theta A_h^\phi. \tag{4}$$

Here, the subscripts h and l denote that the subordinate departments are the HT and LMT industries, and the other symbols have the same meanings as discussed earlier. A_h^ϕ represents the knowledge output achieved by the transformation of the LMT industries to the HT industry by imitation innovation, where knowledge growth is generated by the diversified agglomeration of technological potential energy. ϕ represents the output elasticity of the diversified agglomeration, promoting the knowledge growth of the LMT industry. Thus, we obtain the steady-state knowledge growth rate of the LMT industry as:

$$g_{l1}^* = \frac{n(2\beta + \theta)}{1 - \beta - \theta} \cdot \left(1 + \frac{\phi}{1 - \beta - \theta}\right). \tag{5}$$

In Equation (5), the change in g_{l1}^* is related to β, θ and ϕ. As the diversified agglomeration of technological potential energy can promote knowledge accumulation in the LMT industry, $\phi > 0$. When $\beta + \theta < 1$ and $n \neq 0$, the knowledge growth rate in the LMT industry is higher than that in the HT industry. As a result, the knowledge gap between the two industries gradually narrows, and the LMT industry shows a clear trend towards the HT industry. Based on this analysis, the following assumptions were made:

> **Hypothesis H1:** Diversification of diversified agglomeration of technological potential energy positively impacts knowledge dissemination and technology diffusion, leading to the realisation of 'embedded' development of the LMT industry by imitating and innovating like the HT industry, and the transformation to a HT industry.

3.2.2. The specialised agglomeration of technological potential energy and the high end of the HT industry

Regarding the agglomeration effect, Marshall (1890) showed that specialised agglomeration resulted in the 'reservoir' effect of original inputs, the scale effect of intermediate inputs, and the spill-over effect of knowledge output, called Marshall's externalities. In the process of specialised agglomeration of technological potential energy, labour productivity in the HT industry further increases because of Marshall's externalities. Assuming that the output elasticity of the impact of specialised agglomeration of technological potential energy on knowledge accumulation in the HT

industry is ω, the knowledge production function of the HT industry can be rewritten as

$$\dot{A}_h = [H_{hp}K_h]^\beta [H_{hr}A_h]^\theta A_h^\omega. \tag{6}$$

A corresponding steady-state knowledge growth rate can be obtained as:

$$g_{h1}^* = \frac{n(2\beta + \theta)}{1 - \beta - \theta} \cdot \left(1 + \frac{\omega}{1 - \beta - \theta}\right). \tag{7}$$

Comparing (7) and (3), the specialised agglomeration of technological potential energy increases the steady-state knowledge growth rate and furthers technological advancement of the HT industry. When $\beta + \theta < 1$ and $n \neq 0$, the HT industry breaks through the technological bottleneck at a rate of $\omega/(1-\beta-\theta)$. Thus, the following assumption is proposed:

> **Hypothesis H2:** The specialised agglomeration has a significant strengthening effect on the knowledge accumulation and technological progress in the HT industry, which can realise the 'leapfrog' development and the high end of the HT industry during independent innovation.

3.2.3. Spatial effect of technological potential energy agglomeration

Jacobs (1969) states that diversified agglomeration can effectively promote the spatial spill-over of knowledge. When the technological potential difference is within a reasonable range, the spatial effect of technological potential energy appears as a positive feedback effect, and its intensity depends on the collaborative cooperation among the HT industries (Santamaría et al., 2009). However, if the technological potential difference is too large, achieving technological breakthroughs is difficult through collaborative innovation for the regions with high technological potential energy, and will be accompanied by negative spatial effects.

For the convenience of analysis, this study sets the elasticity of the spatial effect of diversified agglomeration of technological potential energy as ϕ. Then, we set the positive and negative feedback levels of the spatial effects of specialised agglomeration of technological potential energy to ω_1 and $-\omega_2$, respectively, and ϕ, ω_1 and ω_2 are all positive. $\phi + \omega_1 - \omega_2$ represents the feedback strength of the spatial spill-over effect of region j to region i. Under the spatial effect of technological potential energy agglomeration in region j, the knowledge production function in region i is

$$\dot{A}_i = [H_{ip}K_i]^\beta [H_{ir}A_i]^\theta A_j^{\phi + \omega_1 - \omega_2}, \tag{8}$$

and the corresponding steady-state knowledge growth rate is:

$$g_i^* = \frac{n(2\beta + \theta)}{1 - \beta - \theta} \cdot \left(1 + \frac{\phi + \omega_1 - \omega_2}{1 - \beta - \theta}\right). \tag{9}$$
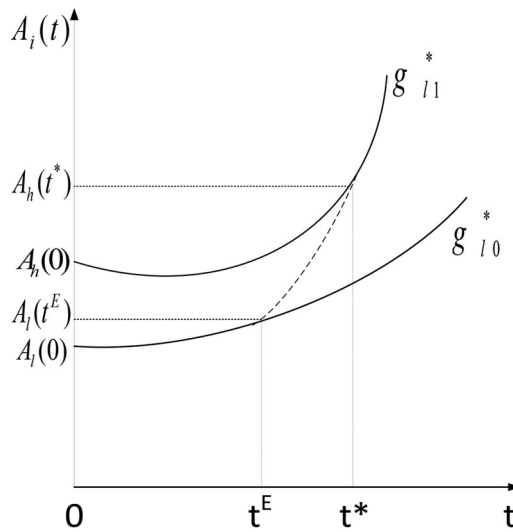
Figure 1. Transformation of the LMT industry.
Source: Authors.

Equations (5) and (7) represent the steady-state knowledge growth rate of the LMT industry transformation process to the HT industry under the effect of diversified agglomeration, and the high-end process of the HT industry under the effect of specialised agglomeration. Equation (9) shows that the spatial effect of technological potential energy agglomeration on the HT industry development is uncertain. When $\beta + \theta < 1$ and $n \neq 0$, the spatial spill-over effect of the agglomeration of technological potential energy significantly affects the transformation of the LMT industries and the high-end of the HT industry when $\phi + \omega_1 > \omega_2$. In contrast, the spatial effect will hinder the high end of HT industries when $\phi + \omega_1 < \omega_2$. Therefore, this study proposes the following hypothesis:

Hypothesis H3: When the specialised agglomeration of technological potential energy is in the appropriate range, the spatial effect of technological potential energy agglomeration on the HT industry development is significantly positive, but the spatial effect is negative when the difference in the specialised agglomeration of technological potential energy is too large.

Consequently, technological potential energy agglomeration promotes the HT industry through the transformation of the LMT industry and the high-end of the HT industry, as shown in Figures 1 and 2.

3.3. Mechanism of technological potential energy agglomeration promoting the development of HT industry

Under the impacts of the diversified and specialised agglomeration, there are two paths for the technological potential energy agglomeration to drive the HT industry development (see Figure 3).

1. The technological level of the LMT industry gradually approaches the HT industry and eventually transforms into the HT industry.
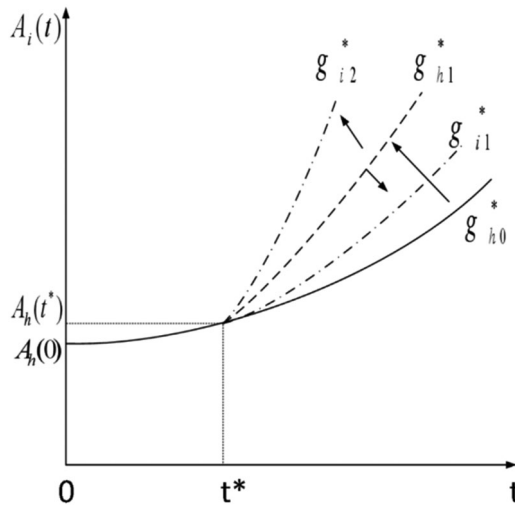
Figure 2. High-end of the HT industry.
Source: Authors.
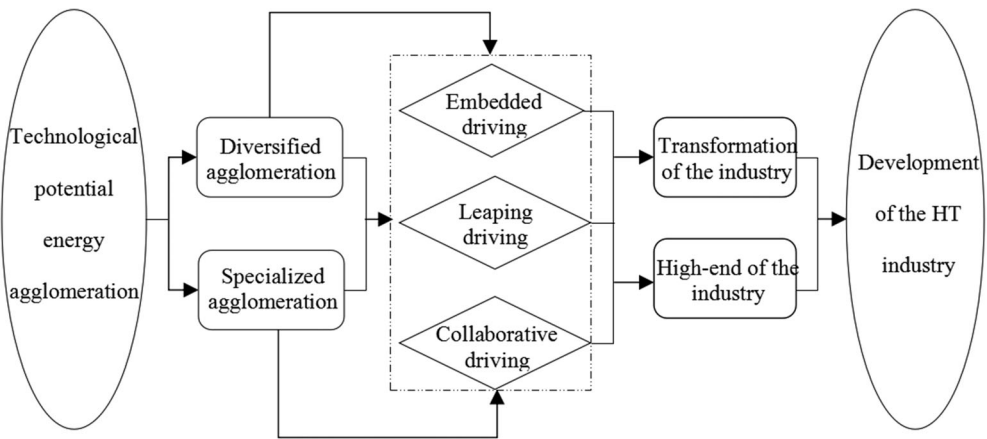
Figure 3. The mechanism of technological potential energy agglomeration promoting the HT industry.
Source: Authors.

2. The technological level will be further improved in the HT industry by breaking through technological bottlenecks.

In the embedded driving process, the technological innovation environment in the three dimensions of technological potential energy plays a leading role. With the increase in the diversified agglomeration of technological potential energy, the technological types and knowledge that regional industries can contact become diversified, further enriching the knowledge and technologies obtained by regional industries, especially the LMT industry. As the main body, structure, organisation, or system and other elements of the LMT industry innovation systems are embedded in the HT industry innovation systems and interaction between the two industries, the technological level of the LMT industry gradually approaches the HT industry and is finally transformed.

In the leaping driving process, the attractiveness of innovative factors plays a key role. As the specialised agglomeration of technological potential energy increases, technological behaviour ensures that the regional innovation factors are attractive enough to closely match the characteristics of industrial development. When the HT industry has accumulated technological capabilities, this matching will gradually modify the current innovation support structure, strengthening the R&D in the HT industry. It will break the constraints of bottlenecks while maintaining existing advantages and finally achieving the high end of the HT industry.

In the collaborative driving process, the technological innovation initiative plays a leading role. Under the influence of diversified agglomeration and its spatial spill-over effect, after the regional innovation system is impacted by external factors, a new balance between the internal and external systems is formed by continuously adjusting innovation behaviour. In this balance, the motivation and intention to innovate will improve, and collaborative innovation cooperation among regions will increase.

This section theoretically analyses the internal mechanism of the diversified agglomeration, specialisation agglomeration, and spatial spill-over effects of technological potential energy and accordingly proposes hypotheses H1, H2 and H3. The following section establishes an empirical analysis using the GNS model to test the theoretical analysis and the proposed hypotheses.

4. Measurement of the technological potential energy agglomeration

This section quantitatively measures technological potential energy, according to the definition in previous articles, to explore its agglomeration level and temporal and spatial evolution.

4.1. Measurement method

Referring to the formula of gravitational potential energy calculation, the formula for calculating the technological potential energy is $TPE = TI \times TE \times AIF$. TPE represents the potential technological energy level. TI represents the technological innovation initiative, reflecting the characteristics of the main body of innovation. TE is the technological innovation environment, indicating the environmental characteristics of technological innovation. AIF is the attraction of innovation factors, reflecting the potential level of technological innovation. The regional technological potential energy measurement can be completed only if the three dimensions of technological potential energy are quantified separately.

4.1.1. Technological innovation initiative (*TI*)
Technological innovation initiative refers to the choices made by the subject to external or internal innovation incentives. Its manifestation is the initiative of the subject, directly affected by the incentives made by the decision-maker. Zhang et al. (2008) showed that a good incentive mechanism is beneficial for improving the efficiency of knowledge exchange in an organisation, but an unfair incentive mechanism is not

Table 1. All the used indicators of technological innovation environment (*TE*).

First-level indicators	Second-level indicators	Third-level indicators
Soft environment	Talent introduction institution	The intensity of talent introduction
	Intellectual property protection institution	Number of lawsuits related to intellectual property
	Industrial supporting policy	The intensity of industry support
Hard environment	Higher education resources	Number of college teachers in the region
	Distribution of scientific research institutions	Number of research institutions in the region
	Science and technology infrastructure	The proportion of science and technology expenditure in total regional expenditure
	Technology industry scale	The proportion of the output value of the HT industry in the gross regional product

Source: Authors.

conducive to knowledge transfer. Therefore, the award amount of regional invention patents is used as an indicator of innovation initiatives.

4.1.2. Technological innovation environment (*TE*)

The technological innovation environment, consisting of soft and hard environments, is where various technological innovation activities are carried out.

This study employs the Principal Component Analysis (PCA) method to quantify the technological innovation environment. Fan et al. (2003) studied the marketisation index using PCA. The biggest advantage of PCA is that the weight used is determined by the characteristics of the data itself. The comprehensive indicators of the technological innovation environment established by the PCA method are presented in Table 1.

4.1.3. The attraction of innovation factors (*AIF*)

The attraction of innovation factors determines the region's ability to absorb foreign innovation factors and the cohesion of innovation factors in the region. Hence, the agglomeration level of regional innovation factors is used to represent the attraction of innovation factors.

The agglomeration of innovative factors is quantified by referring to the EG agglomeration indicator proposed by Ellison and Glaeser (1997). Suppose there are N regions, M types of innovation elements in the economic system, and the time span is T. RF_{ijt} represents the intensity of the agglomeration of innovation factors j in area i in year t:

$$RF_{ijt} = \frac{GN_{ijt} - \left[1 - (x_{ijt})^2\right]H_{ijt}}{\left[1 - (x_{ijt})^2\right](1 - H_{ijt})}, \ x_{ijt} = \frac{F_{ijt}}{\sum_i F_{ijt}}, \ H_{ijt} = \frac{F_{ijt}}{\sum_t F_{ijt}}$$

Here, GN_{ijt} represents the Gini coefficient, referring to Wen (2004). The formula is as follows:

$$GN_{ijt} = \frac{1}{2N^2 \bar{x}_t} \sum_{k=1}^{N} \sum_{l=1}^{N} \left| F_{ljt}/\sum_i F_{ijt} - F_{kjt}/\sum_i F_{ijt} \right|, \ \bar{x}_t = \sum_t x_{ijt}/n$$

Here, $i = 1, 2, 3, ..., N; j = 1, 2, 3, ..., M; t = 1, 2, 3, ..., T,$ and F_{ijt} represent the number of innovation factors j in region i in year t.

The weighted sum of the agglomeration intensity of each innovation factor in region i is used to quantify the attraction of innovation factors to measure the comprehensive agglomeration level of all innovation factors in particular regions. Among them, the contribution of each innovation factor to innovation CD_j is weight.

CD_j can be derived from an innovative production process. Suppose that each innovation factor has an endogenous impact on innovation output during innovation production, and its elasticity is α_j. Then, the innovation output is obtained as follows:

$$C = \prod_{j=1}^{M} F_j^{\alpha_j}.$$

The contribution of innovation factors j to innovation is

$$CD_j = \alpha_j \ln F_j / \sum_j \alpha_j \ln F_j.$$

In summary, the attraction of innovative factors is:

$$AIF_i = \sum_{j=1}^{M} CD_j RF_{ij}.$$

The technological potential energy of the region i is $TPE_i = TI_i \times TE_i \times AIF_i$.

4.1.4. The level of technological potential energy agglomeration

This study uses modified Getis-Ord statistics to measure the technological potential energy agglomeration. The measurement results are obtained by replacing the economic growth index in the traditional Getis-Ord statistics with the technological potential energy measurement results.

$$G_i = \frac{\left(\sum_j w_{ij} TPE_j - W_i TPE^* \right) - (TPE_i - TPE^*)}{s \left\{ \left[(nS_i) - W_i^2 \right] \Big/ (n-1) \right\}^{1/2}} \tag{10}$$

Here, w_{ij} is an element of the spatial weight matrix, and its value is the reciprocal of the distance between the two regions; $W_i = \sum_{i \neq j} w_{ij}; S_i = \sum_j w_{ij}^2;$ s is the variance of technological potential energy; TPE^* is the average value of technological potential energy.

Larger the value of G_i, higher the agglomeration level of technological potential energy in the region i, and greater the impact on the surrounding areas. This is consistent with the characteristic that greater the potential energy of a node, greater the possibility of potential energy flow to other nodes.

Table 2. Measurement results of technological potential energy agglomeration.

	2001	2003	2005	2007	2009	2011	2013	2015	Ranking
Beijing	0.3901	0.4197	0.5410	0.5466	0.6417	0.6776	0.7704	0.8012	1
Tianjin	0.4009	0.4440	0.5225	0.5238	0.6113	0.6317	0.7346	0.7463	3
Hebei	0.2255	0.2348	0.2934	0.3099	0.3500	0.3727	0.4272	0.5082	25
Shanxi	0.2386	0.2447	0.2801	0.2848	0.3399	0.3608	0.4293	0.5278	19
Inner Mongolia	0.2421	0.2630	0.3269	0.3688	0.4268	0.4472	0.5357	0.5707	15
Liaoning	0.2596	0.3063	0.3479	0.3972	0.4461	0.4540	0.5735	0.6190	9
Jilin	0.2444	0.2498	0.2895	0.3020	0.3513	0.3774	0.4284	0.5715	14
Heilongjiang	0.2210	0.2579	0.3046	0.3326	0.3926	0.4101	0.4717	0.5441	17
Shanghai	0.3778	0.4493	0.5262	0.5486	0.6199	0.6363	0.7106	0.7670	2
Jiangsu	0.2550	0.2704	0.3214	0.3522	0.4246	0.4789	0.5414	0.6546	4
Zhejiang	0.3315	0.3445	0.3947	0.4044	0.4718	0.4928	0.5545	0.6474	6
Anhui	0.2164	0.2208	0.2589	0.2925	0.3402	0.3601	0.4048	0.5333	18
Fujian	0.2438	0.2694	0.3199	0.3335	0.3757	0.3906	0.4586	0.6344	8
Jiangxi	0.2562	0.2706	0.3361	0.3591	0.4155	0.4214	0.5021	0.5152	23
Shandong	0.2085	0.2551	0.2997	0.3692	0.4816	0.4873	0.5508	0.6140	10
Henan	0.2788	0.2885	0.3332	0.3500	0.4088	0.4182	0.4886	0.5273	20
Hubei	0.2490	0.2895	0.3566	0.3714	0.4229	0.4450	0.5440	0.6014	12
Hunan	0.2236	0.2407	0.3214	0.3330	0.3861	0.4217	0.4910	0.5561	16
Guangdong	0.2205	0.2353	0.3238	0.3304	0.4322	0.4839	0.5586	0.6501	5
Guangxi	0.2152	0.2175	0.2734	0.2844	0.3308	0.3597	0.4362	0.4987	27
Hainan	0.2202	0.2570	0.2980	0.3008	0.3504	0.3702	0.4534	0.5034	26
Chongqing	0.2063	0.2298	0.2813	0.2958	0.4359	0.4585	0.5450	0.6046	11
Sichuan	0.2238	0.2888	0.3473	0.3734	0.4419	0.4577	0.5601	0.5822	13
Guizhou	0.2223	0.2598	0.3100	0.3357	0.3839	0.3954	0.4437	0.4609	30
Yunnan	0.2217	0.2387	0.2976	0.3235	0.3678	0.3950	0.4623	0.4922	28
Shaanxi	0.3454	0.3569	0.4144	0.4199	0.5398	0.5423	0.6274	0.6395	7
Gansu	0.2461	0.2583	0.3093	0.3212	0.3863	0.3988	0.4592	0.5146	24
Qinghai	0.2220	0.2512	0.2853	0.3098	0.3540	0.3771	0.4360	0.5153	22
Ningxia	0.2265	0.2378	0.3156	0.3215	0.3608	0.3910	0.4556	0.5176	21
Xinjiang	0.2227	0.2329	0.2669	0.2709	0.3208	0.3613	0.4259	0.4649	29

Source: Authors.

4.2. Data source

The study uses the corresponding data for each indicator in 30 provinces, municipalities, and autonomous regions of China (except Hong Kong, Macao, Taiwan, and Tibet) from 2001 to 2015. The missing data of several indicators are filled using the moving average method. Considering 2001 as the base period, the intermediate data that does not include the price factor are obtained using its conversion price index. The original data are collected from the China Statistical Yearbook on the HT industry, China Statistical Yearbook on Science and Technology, China Statistical Yearbook on Judicial Administration, China Economic Net Statistical Database, EPS Database and the corresponding statistical yearbooks of various provinces and cities.

4.3. Measurement results

The measurement results of the technological potential energy agglomeration in various regions of China from 2001 to 2015 are shown[2] in Table 2.

Only the measurement results in odd-numbered years are given due to space limitations, and the last column contains the ranking of each region's technological potential energy agglomeration in 2015.

Table 2 shows the measurement results of the technological potential energy agglomeration of the 30 regions over the years and their rankings in 2015. From

2001 to 2015, China's regional technological potential energy agglomeration increased by more than 120%, of which the average annual growth rate for the first five years of the 21st century was 5.69%, and for the subsequent two 5-year periods were 5.07% and 6.10%, respectively.

From the spatial distribution perspective, coastal areas such as Shanghai, Jiangsu, Zhejiang and Tianjin have always been leaders, while the inland areas – Beijing and Shaanxi Provinces – play the same role as agglomeration centres. Additionally, only Beijing, Shanghai, Jiangsu, Zhejiang and other regions experienced remarkable growth in the first five years. From 2005 to 2010, due to rapid development of technological potential energy in coastal areas, the externalities and spatial spill-over effects also began to radiate to the surrounding areas.

China's regional technological potential energy agglomeration continues to grow and shows different characteristics at different stages of economic development. From the perspective of space, it shows the east, north coastal areas, Beijing and Shaanxi as the agglomeration centres, along the 'conduction' development pattern spreading from northeast to southwest.

5. Empirical analysis

A spatial model is constructed to empirically test the direct and indirect effects of technological potential energy agglomeration on the HT industry development using the panel data of indicators.

5.1. Spatial model

The study uses the GNS to empirically test the spatial spill-over effect of technological potential energy agglomeration on the HT industry development. The GNS model with all interaction effects are shown as follows (Elhorst, 2014; LeSage & Fischer, 2008):

$$Y = \rho WY + X\beta + XW\theta + \alpha \iota_N + u$$
$$u = \lambda Wu + \varepsilon \tag{11}$$

Here, WY represents the endogenous interaction effect between the explained variables, XW represents the exogenous interaction effect between the explanatory variables and Wu represents the interaction effect between different disturbance terms. Endogenous and exogenous interaction effects are the main sources of spatial spill-over effects, but the interaction effects between disturbance terms do not contain information on spill-over effects (Vega & Elhorst, 2015). ρ is the spatial autoregressive coefficient, θ and β both represent k by one unknown parameter vector and W is a spatial weight matrix. Simplifying the above formula, we obtain:

$$Y = (1 - \rho W)^{-1}(X\beta + XW\theta) + R, \tag{12}$$

where, $R = (1 - \rho W)^{-1}(\alpha \iota_N + u)$ includes the redundant terms of the intercept term and error term. The difference in indirect effects is reflected in the difference between the main diagonal elements of the matrix $W(\rho \neq 0, \ \theta_k \neq 0)$ and $(I_N - \rho W)^{-1}$. The

indirect effect in this expression indicates the space overflow effect. By imposing certain constraints on the spatial autoregressive coefficients and parameters to be estimated, GNS can be transformed into various spatial measurement models such as SAR, SDM, SLX and SDEM.

5.2. Variables

5.2.1. Explained variable

The HT industry development level (*HIL*) is represented by the ratio of the main business income[3] of HT industries in each province (or city) to the number of people employed in HT industries. The increase in income from the number of employees per unit can effectively reflect the production efficiency of regional HT industries.

5.2.2. Core explanatory variables

Compared with other industries, the HT industry development is more dependent on technology. Therefore, the potential of regional technological progress, that is, technological potential energy, is the primary factor affecting HT industry development. The core explanatory variable is the regional technological potential energy agglomeration level *G*, and its data are obtained from the measurement results in Table 2.

5.2.3. Control variables

Considering that the technological potential energy reflects the technical level that the region may reach, financial support is indispensable for enterprises to use regional technological potential energy to achieve their own technological breakthroughs. Therefore, financial support (*Fin*) was introduced as a control variable in the model. Additionally, factors such as regional economic development level (*Eco*), government behaviour (*Gov*), industrial structure (*Is*) and degree of dependence on foreign trade (*Dft*) also play an irreplaceable role in the HT industry development. Therefore, this study introduces these variables as control variables.

The variables involved in this part are shown in Table 3.

Table 3. Variable calculation method.

Variable classification	Variable name	Variable calculation method
Explained variable	HT industry development level (*HIL*)	Main business income (or number of employees) of the HT industry
Threshold variable	Technological potential energy agglomeration level (*G*)	Calculation results shown in Table 2
Control variable	Financial support (*Fin*)	Number of employees in financial institutions as a percentage of total population
	Economic development level (*Eco*)	GDP per capita in the region
	Government behaviour (*Gov*)	The proportion of regional science and technology expenditure in total expenditure
	Industrial structure (*Is*)	The proportion of the output value of the secondary and tertiary industries to the total output value
	Degree of dependence on foreign trade (*Dft*)	The proportion of total regional import and export trade to GDP

Source: Authors.

Table 4. The indicators of institution quality.

Variable	Indicators
Government support	The proportion of government funds in R&D funds in the amount of science and technology funds raised
Non-state economic development	The proportion of non-state-owned economy employment in total urban employment
Factor market development	Imported foreign investment (FDI to GDP ratio)
	The ratio of turnover in technology market to the number of regional technology employees
Market legal regulation	The ratio of the number of three patent applications accepted to the number of scientific and technological personnel
	The ratio of the number of three types of patent applications approved to the number of scientific and technological personnel

Source: Authors.

5.3. Spatial correlation test

Prior to spatial econometric analysis, $Moran'I$ is employed to examine the spatial relevance of the regional HT industry development. Referring to the method of Hou et al. (2015), the following comprehensive weight matrix based on geographic location and institutional association is constructed using the gravity model:

$$W_{ij} = \begin{cases} 0 & i = j \\ (S_i \times S_j)/d_{ij}^2 & i \neq j \end{cases}. \tag{13}$$

Here, S_i and S_j represent the institution quality of the two regions.

Institutional quality refers to the degree of perfection of a regional institution, expressed by the marketisation process of the region in the market mechanism. Institutional variables are difficult to quantify, but institutional quality directly influences innovation-driven effects on regional economic growth. This paper selects the following indicators to measure institutional quality: government support, non-state economic development, factor market development and market legal regulation. The constituent factors of each indicator are listed in Table 4.

The factor analysis method of maximum variance rotation measures the weight of the factor market development degree, the market legal standardisation degree, and the detailed indicators of institutional HT. The weighted sum method is employed to integrate each indicator.

Using the related data of the development level of the HT industry in 30 provinces and cities in China from 2001 to 2015, the $Moran'I$ statistics are calculated and shown in Table 5.

In Table 5, all $Moran'I$ indexes of the HT industry development level are significant at the 5% confidence level (statistic Z value is greater than 1.96), indicating that the development of the HT industries has a significant spatial dependence (positive autocorrelation). In other words, China's HT industry development level has a strong spatial correlation, and regions with similar HT industry development levels tend to agglomerate spatially.

5.4. Empirical results

We focus on SAR, SEM, SLX, SDEM and SDM models and select the optimal estimation model. To obtain consistent parameter estimates, the maximum likelihood

Table 5. Results of spatial correlation tests.

Time	Moran-I	Z statistic	Time	Moran-I	Z statistic
2001	0.340	2.290	2009	0.274	2.194
2002	0.249	2.422	2010	0.269	2.374
2003	0.300	2.130	2011	0.274	2.216
2004	0.382	2.398	2012	0.331	2.141
2005	0.285	2.213	2013	0.283	2.165
2006	0.307	2.422	2014	0.364	2.421
2007	0.342	2.257	2015	0.330	2.097
2008	0.272	2.104	–	–	–

Source: Authors.

Table 6. Regression results of spatial models.

	SDM	SDEM	SLX	SAR	SEM	OLS
ln G	0.8697***	0.8516***	0.7722***	0.8591***	0.8132***	0.8549***
	(3.142)	(2.988)	(3.014)	(2.875)	(3.179)	(3.066)
ln Fin	0.6178**	0.6254*	0.5842**	0.5983*	0.6143*	0.6365*
	(2.225)	(1.816)	(1.975)	(1.682)	(1.674)	(1.852)
ln Eco	0.1162***	0.1401**	0.1179***	0.1410***	0.1443**	0.1336***
	(4.219)	(2.037)	(3.221)	(2.735)	(2.101)	(4.109)
ln Gov	−0.0312*	−0.0261	−0.0299**	−0.0342*	−0.0257*	−0.0326*
	(−1.725)	(−1.630)	(−2.005)	(−1.789)	(−1.895)	(−1.855)
ln Is	0.0040	−0.0050	0.0460	−0.0059	−0.0454	0.0448
	(0.115)	(−0.106)	(−0.099)	(−0.108)	(−0.113)	(0.102)
ln Dft	0.2162***	0.1798**	0.1896**	0.1956***	0.1853**	0.2098***
	(2.912)	(1.969)	(2.223)	(2.594)	(2.018)	(2.725)
ρ	0.2284***			0.2617***		
	(3.003)			(2.923)		
λ		0.3052***			0.2904***	
		(3.904)			(4.010)	
$W \times$ ln G	2.0284***	1.9807***	2.1383***			
	(6.247)	(6.176)	(6.615)			
$W \times$ ln Fin	1.5897**	1.7248*	1.6342*			
	(2.204)	(1.958)	(1.894)			
$W \times$ ln Eco	0.2353***	0.3775***	0.3928**			
	(3.258)	(2.642)	(2.847)			
$W \times$ ln Gov	−0.0639**	−0.0550	−0.1047*			
	(−2.061)	(−1.313)	(−1.694)			
$W \times$ ln Is	0.0089	−0.0144	0.0183			
	(0.339)	(−0.317)	(−0.428)			
$W \times$ ln Dft	0.6816**	0.0.4831*	0.5189*			
	(2.020)	(1.955)	(1.843)			
R^2	0.8293	0.7851	0.7015	0.7144	0.7428	0.6907
Log-like	1232.27	1219.22	984.18	1051.85	1208.90	901.62

The values of t are in parentheses; *, ** and *** indicate that the results are significant at the 10%, 5% and 1% levels, respectively, and Log-like is log-likelihood.
Source: Authors.

method for model estimation is used. The model estimation results are presented in Table 6.

The results show that the goodness of fit and log-likelihood of the SDM model are the largest, and the significance of the parameters is optimal. Therefore, the SDM model is the optimal model for the empirical research in this study.[4] The spatial autoregression coefficient ρ and the spatial autocorrelation coefficient λ of each model in Table 6 are significantly positive at the 1% level, indicating that under the spatial influence of endogenous interaction effects and random shocks, the development level of HT industries in various regions has obvious spatial dependence. By further comparison of the estimated values of the spatial

Table 7. Spatial spill-over effect (based on SDM model).

	ln G	ln Fin	ln Eco	ln Gov	ln Is	ln Dft
Space spill-over effect	−0.2174**	0.1759***	0.0083**	0.0528**	0.0013	0.1802
	(−2.107)	(3.211)	(2.101)	(2.391)	(0.095)	(0.590)

The values of t are in parentheses. *, ** and *** denote that the results are significant at the 10%, 5% and 1% levels, respectively.
Source: Authors.

autoregressive coefficients ρ of the SDM and SAR models, the estimated values in the SDM model are significantly smaller than the SAR model, indicating that ignoring the spatial lag term of the explanatory variables will cause the endogenous spatial interaction effects to be overestimated. To determine accurately the spatial spill-over effects of various variables on the development of HT industries, the study further estimates the indirect effects in the SDM model. The results are presented in Table 7.

Table 7 shows the spatial spill-over effects of all explanatory variables on the development of HT industries. The industrial structure and the degree of dependence on foreign trade in neighbouring areas have no significant space spill-over effects. Economic growth in neighbouring areas can significantly improve the development of regional HT industries, but the effect is not significant. The promotion effect of financial institutions on the HT industry is not restricted by the location of the space. A 1% increase in financial support in neighbouring areas can promote the growth of HT industries in the region by 0.1759%. Under the demonstration effect, local government behaviour is adjusted and revised according to the surrounding area's government behaviour to reduce or avoid unnecessary government intervention. Therefore, the spatial effect of government behaviour on the development of HT industries is not as insignificant or negative as expected, but has a significant positive spatial spill-over effect. Moreover, the spatial spill-over effect of technological potential energy agglomeration on HT industries development is inconsistent with expectations. For every 1% increase in the level in the neighbouring areas, decreases the total income of HT industries in the region by 0.2174%. The reasons for this phenomenon may be as follows:

1. Each province-level region in China has stricter management of its core technology, and the willingness to share technology in various regions is not high.
2. High-end technological innovation depends on independent innovation, and imitation is not the source of technological innovation.

5.5. Impact of different modes of technological potential energy agglomeration on the development of HT industries

To analyse further the effect mode and spatial effect of regional diversified and specialised agglomeration of technological potential energy on the development of HT industries, the technological potential energy agglomeration in Equation (10) is decomposed into two parts. The diversified agglomeration of technological potential energy is (the meaning of each variable is the same as described earlier):

Table 8. Estimation results under different agglomeration modes.

Variable	Regression coefficients	Spatial effect	Variable	Regression coefficients	Spatial effect
ln DG	0.5994***	0.0043*	ln SG	0.2538**	−0.2181***
	(3.083)	(1.937)		(2.533)	(−3.577)
ln Fin	0.6113*	0.1467**	ln Fin	0.5928**	0.1539**
	(1.716)	(2.110)		(2.026)	(1.971)
ln Eco	0.1204***	0.0459**	ln Eco	0.1358***	0.0491**
	(3.855)	(1.986)		(3.162)	(2.019)
ln Gov	−0.0325**	0.0279*	ln Gov	−0.0291*	0.0503**
	(−2.237)	(1.704)		(−1.923)	(2.140)
ln Dft	0.1834***	0.1286	ln Dft	0.2088***	0.1421
	(2.889)	(0.411)		(2.803)	(0.428)
ρ	0.2523***		ρ	0.2259***	
	(2.971)			(2.946)	
R^2	0.7415		R^2	0.7107	
Log-like	902.95		Log-like	963.41	

The values of t are in parentheses; *, ** and *** denote that the results are significant at the 10%, 5% and 1% levels, respectively, and Log-like is log-likelihood.
Source: Authors.

$$DG_i = \frac{\sum_j w_{ij}TPE_j - TPE_i}{s\{[(nS_i) - W_i^2]/(n-1)\}^{1/2}} \tag{14}$$

The specialised agglomeration of technological potential energy is:

$$SG_i = \frac{TPE^* - W_iTPE^*}{s\{[(nS_i) - W_i^2]/(n-1)\}^{1/2.}} \tag{15}$$

Similar to the previous analysis, the SDM model is used for the following empirical analysis. First, we replace the core explanatory variables in the model with the diversified or specialised agglomeration of technological potential energy. Meanwhile, the industrial structure is eliminated from the model because its impact is not significant. The main regression results of the SDM model are presented in Table 8.

Comparing the regression coefficients in Table 8 with the estimated results of the OLS model in Table 6, the results show that the regional technological potential energy agglomeration has a significant impact on driving the development of HT industries.

The diversified agglomeration regression coefficient of technological potential energy is significantly positive at the 1% level, indicating that diversified agglomeration can effectively promote knowledge dissemination and technology diffusion, thereby promoting the high-tech LMT industry. The LMT industry is embedded in the HT industry's development model through imitation innovation. The driving force for the diversified agglomeration of technological potential energy to promote high-tech in the LMT industry is 0.5994. Therefore, hypothesis H1 holds.

The specialised agglomeration regression coefficient of technological potential energy is also significantly positive at the 1% level, indicating that specialised agglomeration can significantly enhance the knowledge accumulation and technological progress of the HT industry, thereby promoting the high-end of the HT industry.

Through the independent innovation activities of regional industrial technologies, the specialised agglomeration of technological potential energy has a driving force of 0.2538 for the HT industries' development. The driving force of imitation innovation is much greater than that of independent innovation, indicating that under technological potential agglomeration, HT industries in China have strong imitation innovation capabilities and weak independent innovation capabilities. Therefore, hypothesis H2 holds.

Regarding spatial effects, the spatial effect of the diversified agglomeration of technological potential energy on HT industries development in neighbouring areas is significant only at the 10% level, and the spatial effect level is 0.0043. The specialised agglomeration of technological potential energy is significant at the 1% level, and the level of spatial effect is −0.2181. This shows that specialised agglomeration has a significant hindering effect on the HT industries development in neighbouring areas. Thus, China's HT industry does not focus on collaborative innovation between regions and adopts a relatively closed technology strategy.

6. Conclusion

According to previous research, technological innovation is divided into two processes: front-end technological potential energy agglomeration and terminal innovation kinetic energy conversion. Based on the front view of innovative behaviour, the definition of technological potential energy agglomeration is proposed from three dimensions: the comprehensive innovation environment, innovation initiative and attraction of innovation factors. This study theoretically investigates the internal mechanism and spatial effects of technological potential energy agglomeration driving the HT industry development and empirically analyses the theoretical mechanism and spatial effects using a GNS model.

The results reveal that the impact of technological potential energy on the HT industry development has two aspects: the transformation of the LMT industry to an HT industry and the further improvement of the HT industry. Through empirical analysis, China's technological potential energy is centred on the eastern coastal region and the Beijing-Tianjin-Hebei region, and its overall average increases with time. From a spatial perspective, a 'conduction' development pattern shows the spread from northeast to southwest. Additionally, excessive government intervention negatively impacts the sustained and stable development of the HT industry. Financial support, foreign trade and regional economic growth bring capital accumulation, effectively promoting the regional HT industries.

Furthermore, diversified and specialised agglomerations contribute to avoiding the limitations of existing technologies and cultivating core innovative technologies in the HT industry, thereby promoting the HT industry. Under the demonstration effect, government behaviour has a significantly positive spatial spill-over effect on the HT industry development. Given the exclusivity of core technologies and the limited innovation resources, there exists a natural competitive relationship among different regions concerning technological potential energy. The specialised agglomeration of technological potential energy is a significant obstacle to the HT industry

development in neighbouring areas. The actual reason behind this phenomenon is that China's HT industry does not focus on collaborative innovation across regions, but adopts a relatively closed technology strategy.

Based on these conclusions, several policy recommendations are proposed. All provinces should actively cultivate platforms for technological potential energy agglomeration and encourage technological innovation to promote China's HT industry development. The regional HT industry's technological innovation capabilities will improve by increasing investments in HT personnel and R&D funds, strengthening foreign trade and vigorously promoting institutional innovation.

Additionally, this study analyses from a macro perspective, and there are slight deficiencies in data collection and research scope, which can be microcosmic. Our next step of research can be from the macro to micro perspective by collecting relevant micro-data for further analysis, making the research scope more precise and in-depth.

Notes

1. Due to space limitations, the intermediate derivation process of the mathematical model is not listed.
2. Due to space limitations, the specific measurement results of the three subdivision dimensions of technological potential energy are not listed.
3. The total output value of the HT industry has not been calculated since 2012 in China. So, this paper uses the main business income of the HT industry as a substitute variable.
4. In addition to the goodness of fit and natural logarithm, there are some reasons why we consider the SDM model as the optimal model. SAR, SEM and SLX models have asymmetric requirements for spatial weight matrices and restrictions on parameters such as spatial regression coefficients, making the parameter estimation process of the model particularly complicated and easily affecting the accuracy of its variance estimation. The assumptions of the OLS model are too strict, affecting the reliability of parameter estimates.

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