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The Evolution and Driving Factors of China's Green Technology Transfer Network

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Abstract

Using a sample of 297 prefecture-level cities in China from 2010 to 2022 and drawing on green patent transfer data, this study constructs a directed weighted network and applies social network analysis, a modified gravity model, and quadratic assignment procedure (QAP) regression to examine the spatial structural evolution, node topology characteristics, and driving factors of China's green technology transfer (GTT) network. The results show that: (1) From 2010 to 2022, the number of nodes grew from 249 to 292, network coverage increased from 83.8% to 98.3%, and the number of edges expanded by a factor of 14.47. Network density and average degree also rose markedly. The spatial structure evolved from an initially sparse and fragmented configuration into a polycentric complex network centered on the Beijing–Tianjin–Hebei region, the Yangtze River Delta, and the Chengdu–Chongqing economic circle. (2) In terms of node topology, the intermediary and control capacities of cities exhibit dynamic changes, with central and western cities gaining growing influence within the network. (3) Cohesive subgroup analysis identifies four functional blocks, revealing a multi-level technology spillover path of "core—secondary—regional—peripheral." (4) QAP regression further identifies the digital economy, geographic location, high-speed rail mileage, industrial structure, and government environmental concern as key drivers of network formation and evolution. This study offers a new perspective on understanding cross-regional green technology transfer and provides theoretical grounding and policy references for promoting regional collaborative innovation and green low-carbon development.

Keywords: green technology transfer; social network analysis; topology characteristics; driving factors

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1. Introduction

The scientific community widely regards global climate change as one of the most severe environmental challenges facing human society in the 21st century [1]. Against the backdrop of climate governance restructuring and low-carbon economic transition, green technology transfer (GTT) has emerged as a key policy focus in achieving the dual-carbon goals, owing to its central role in promoting low-carbon and high-quality development [2] and its function as a critical mechanism for breaking carbon lock-in, alleviating ecological pressure, and facilitating a paradigm shift toward sustainable development [3]. The International Energy Agency (IEA) projects that by 2050, approximately 50% of global carbon emission reductions will depend on innovative technologies not yet fully mature, underscoring the urgency of advancing green technology R&D and diffusion systems.

In response to this global governance challenge, while also improving the institutional framework for ecological civilization and achieving greenhouse gas emission reduction and synergistic governance, China has continuously strengthened its top-level design in recent years. Both the *Green Technology Promotion Catalogue* (2020) and the white paper *China's Policies and Actions on Climate Change* (2021) explicitly emphasize the need to establish an efficient and systematic green technology transfer mechanism to support the comprehensive green transformation of the economy and society and the realization of the dual-carbon strategic goals. As spatial carriers of knowledge spillovers and innovation factor flows, the topological structure and network efficiency of green technology transfer directly influence the quality and pace of low-carbon transformation [4]. Under the binding constraints of the dual-carbon strategy, an in-depth exploration of the optimal pathways for the green technology transfer network holds strategic significance and far-reaching policy value for driving the paradigm shift of economic development from traditional factor-driven growth to green innovation-driven growth [5].

As the world's largest developing country, China faces pronounced regional development disparities. Specifically, the eastern coastal region, benefiting from a strong economic foundation and innovation capacity, leads in green technology development [6]. In contrast, the central and western regions lag behind due to their industrial structure and energy endowment constraints [7]. This gradient disparity theoretically creates conditions for green technology transfer [8], yet in practice gives rise to numerous obstacles [9]. Existing studies further indicate that the highly uneven spatial distribution of innovation factors impedes the formation of collaborative mechanisms for green technology transfer, leading to marked heterogeneity across regions and a lack of effective pathways for coordinated development [10]. Against this backdrop, constructing a systematic intercity green technology transfer network holds strategic value. By thoroughly analyzing the spatial evolution patterns and regional interaction mechanisms of technology transfer across cities, and identifying key driving factors, this study can help optimize network pathways and improve regional innovation systems. Such efforts not only enhance the efficiency of science and technology resource allocation and deepen the integration of green technologies with industrial development, but also provide theoretical support for addressing regional imbalances and inadequacies in green development, ultimately advancing the integrated process of green technology transfer nationwide.

2. Literature Review

The academic literature currently defines green technology transfer as the systematic transfer of green innovation technologies and related intellectual property rights from technology holders through institutionalized transfer mechanisms [11]. Existing research primarily focuses on the following dimensions.

Regarding research methods, as a specialized branch of urban innovation networks in the environmental technology field, GTT networks are typically studied following the paradigm of urban innovation networks. Scholars employ social network analysis to systematically characterize the roles and positions of cities in knowledge production, diffusion, and application, primarily by constructing networks, quantifying structures, identifying mechanisms, and testing effects [12]. Concerning influencing factors, GTT is widely regarded as a socio-economic process with complex system characteristics, shaped by the synergistic effects of multiple dimensions [13]. A substantial body of empirical evidence indicates that key variables—such as market demand intensity, regional technology gradients, technological heterogeneity, absorptive capacity, institutional environment, and social capital—significantly affect GTT efficiency [14–16]. In terms of research value, numerous studies have demonstrated that GTT plays a crucial role in enhancing regional carbon

emission reduction performance, optimizing industrial structures, driving economic development model transformation, and promoting high-quality economic growth [17–20]. Regarding evolutionary pathways, focusing on specific Chinese urban agglomerations or economic circles, scholars have generally found that regional technology transfer networks tend to evolve from simple, loose configurations toward complex, orderly structures [21]. The spatial structure typically transitions from initial dispersed or random flows to single-center or polycentric agglomeration, eventually forming hub-and-spoke or multi-core synergistic patterns [22]. This evolutionary process exhibits the coexistence of path dependence and path creation, reflecting the deepening and restructuring of technology diffusion alongside regional development [23].

The emerging literature on urban innovation networks has provided important theoretical complements for understanding GTT. For example, one study constructs a two-layer framework connecting collaborative innovation structures and energy technology knowledge flows, finding that a city's network position affects energy intensity through three pathways: knowledge openness, technological complexity, and knowledge connectivity [24]. Such research suggests that general knowledge flows between cities and green technology transfer are not separate but rather nested and mutually conditional systemic processes [25]. Conceptually, the GTT network can be viewed as a special subset of the broader urban innovation network: both share general patterns of network structural evolution and are jointly influenced by factors such as absorptive capacity and institutional environment [26]. However, the GTT network also has distinct characteristics; its flow objects are environmentally friendly technologies, making it more susceptible to specific drivers such as environmental regulation intensity and carbon reduction policies [27].

Nevertheless, a systematic review of the literature reveals certain theoretical gaps and methodological limitations. First, most studies on GTT networks focus on the structural evolution of developed urban agglomerations, lacking systematic comparisons of the spatial patterns of GTT networks across cities at different development stages in China. Second, as core carriers of innovation factor agglomeration and technology flows, cities' positions and interactive relationships within the GTT network directly determine the quality and pace of regional green development. However, existing research has largely concentrated on general innovation networks, paying insufficient attention to the intercity network evolution mechanisms in the specific field of green technology. Third, although some scholars have systematically depicted GTT from a network perspective, they mostly treat it as a relatively independent phenomenon and fail to conduct cohesive subgroup clustering analysis of cities with similar functions within the network, thereby neglecting an in-depth examination of the specific roles assumed by each subgroup. This omission may lead to an underestimation of how subgroups' relative positions within the network shape cities' capacity to acquire green technologies and their transformation efficiency.

To address these gaps, this study takes 297 prefecture-level cities and municipalities in China from 2010 to 2022 as the research sample. Using directed green patent transfer data and social network analysis, we construct an intercity green technology transfer network. The study reveals spatiotemporal evolution patterns from both the overall network structure and node topology characteristics, and empirically tests the driving factors of network formation using quadratic assignment procedure (QAP) regression. The contributions of this study are threefold: it systematically uncovers the evolutionary mechanisms and intrinsic driving laws of China's GTT network; introduces an analytical framework for studying innovation networks to integrate the structure, function, and drivers of the GTT network in a co-evolutionary analysis, revealing the simultaneous occurrence of network densification and functional flattening, as well as the shift in driving factors from a dominance of geographical proximity to a coexistence of institutional and

technological forces; and performs cohesive subgroup analysis on cities within the GTT network to identify the roles and functions assumed by different subgroups.

3. Methodology and Analysis

3.1. Data Sources and Processing

3.1.1. Data Sources

The measurement of green technology transfer relies principally on patent-based metrics, a method widely recognized as an effective indicator of technological knowledge output. Patents are routinely employed as a direct proxy for technology transfer due to their capacity to capture knowledge production and interregional innovation interactions [28]. Patent assignment transactions not only reflect the mechanisms of technology exchange and sharing between regions, but also serve as a vital vehicle for tracing technological knowledge flows and diffusion, thus constituting the most immediate quantitative foundation for measuring technology transfer [29]. Under the International Patent Classification (IPC) system, all technological fields are systematically divided into eight sections encompassing over 70,000 subclass codes, forming a standardized taxonomy that enables patents to be precisely assigned to specific technological domains. To measure urban green technology diffusion, this study adheres to the standardized measurement approach of the World Intellectual Property Organization (WIPO) and adopts the IPC Green Inventory as the identification criterion for green patents. Ensuring data continuity and availability, the study selects relevant data from 297 cities spanning the period 2010–2022 for systematic analysis. Patent transfer data were sourced from the Chinese Research Data Services Platform (CNRDS); data on spatial contiguity relationships among prefecture-level cities were obtained from the National Platform for Common Geospatial Information Services (NPCGIS); and city-level indicators required for the gravity model as well as socioeconomic data for regression analysis were drawn from the China City Statistical Yearbook. Minor data gaps were supplemented by consulting the statistical yearbooks of the corresponding cities for the respective years (Table 1).

Table 1. Description of Core Data Sources.

Data Category	Core Indicators and Contents	Data Sources
Green Patent Transfer Data.	Patent application number, legal status change items, registration effective date, names and addresses of transferors/transferees, patent type.	China Research Data Services Platform.
Geospatial Data.	Prefecture-level city administrative boundaries, inter-city spatial adjacency relationships, inter-city geographical distances.	National Platform for Common Geospatial Information Services.
Urban Socioeconomic Data.	Number of internet users, number of mobile phone users, Digital Inclusive Finance Index, high-speed railway operating mileage, proportion of secondary industry output value in GDP, total population at year-end, built-up area.	China City Statistical Yearbook, Institute of Digital Finance, Peking University.
Government Environmental Attention Data.	Word frequency of environment-related keywords in local government work reports.	Official websites of the people's governments of all cities.

3.1.2. Data Processing Description

The data processing procedure comprised three principal steps.

First, basic patent information was acquired. All patent transfer records for 297 cities spanning 2010 to 2022 were retrieved from the Chinese Research Data Services Platform (CNRDS), each entry containing the patent application number, legal status changes (primarily the assignment of patent rights and patent application rights), the effective registration date, the legal status announcement date, and the names and addresses of both the assignor and the assignee.

Second, green patents and their transaction years were identified. Using Python 3.13.1, patent classification codes were matched against the WIPO IPC Green Inventory to extract green patent samples, with the effective registration year taken as the transaction year. Given that invention patents and utility model patents embody greater technological sophistication and transaction value than design patents, only these two categories were retained. Furthermore, to concentrate strictly on domestic inter-city technology transfer, transactions involving assignors or assignees located outside mainland China (including Hong Kong, Macao, and Taiwan) were excluded.

Third, the cities of the transacting parties were identified. Based on the 293 prefecture-level cities and four municipalities recorded in the Brochure of Administrative Divisions of the People's Republic of China, the Python library CPCA mapper was employed to automatically extract and match city information from the addresses of patent assignors and assignees; records with missing or unidentifiable city data were removed. After cleaning, consolidation, and aggregation, an adjacency list was produced, containing the effective registration date, assignor city, assignee city, and the volume of green technology transfers.

Finally, because social network analysis is inherently designed to examine inter-agent relationships and cannot capture intra-city green technology transfers, records in which the assignor and assignee cities were identical were discarded to remain within the method's analytical boundaries.

3.2. Methodology

3.2.1. Social Network Analysis

This study adopts Social Network Analysis (SNA) as its primary methodology [30]. Drawing on graph theory, a directed and weighted network model is constructed to capture the directional and quantitative heterogeneity of intercity green technology transfer (GTT). In this model, the 297 prefecture-level cities engaged in GTT serve as network nodes, and the volume of patent transfers between them is quantified as edge weights. By constructing a 297 $\times$ 297 directed, weighted, and asymmetric adjacency matrix, the model comprehensively delineates the network's topological structure while preserving the critical weight information that encodes connection strength. The network thus embodies two defining characteristics: directed edges represent the spatial flow orientation of GTT, and edge weights capture its intensity. Accordingly, from the dual perspectives of overall network architecture and nodal topological attributes, this study selects samples from 2010, 2016, and 2022 to map the structural topology of the GTT spatial correlation network and employs visualization methods to examine its evolutionary dynamics across multiple dimensions. The matrix is shown below.

$$R = \begin{bmatrix} 0 & R_{1,2} & \cdots & R_{1,296} & R_{1,297} \\ R_{2,1} & 0 & \cdots & R_{2,296} & R_{2,297} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ R_{296,1} & R_{296,2} & \cdots & 0 & R_{296,297} \\ R_{297,1} & R_{297,2} & \cdots & R_{297,296} & 0 \end{bmatrix} \quad (1)$$

where R_{ij} denotes the number of green patents transferred from city i to city j.

The network metrics encompass the number of nodes, number of edges, density, average weighted degree, betweenness centrality, closeness centrality, and degree centrality, defined as follows.

Number of nodes: the total count of individual entities within the network. A greater number of nodes signifies broader participation.

Edges: an edge denotes a connection between two nodes. The number of edges captures the total actual connections among nodes, reflecting the aggregate volume of interrelationships and serving as a fundamental measure of network connectivity richness. In the green technology transfer network, each edge represents an instance of green technology transfer. When the number of nodes is N, the theoretical maximum number of edges is N(N−1).

Density: network density is the ratio of the actual number of edges to the maximum possible number of edges, acting as a core indicator of the network's overall cohesion. It ranges from 0 to 1. A density approaching 1 indicates tighter connectivity and higher network interrelatedness; conversely, a density approaching 0 signals sparser connections and an increasingly fragmented structure. Its calculation formula is:

$$Density = \frac{E}{N(N-1)} \tag{2}$$

where E denotes the number of edges and N the number of nodes in the network.

Average weighted degree captures the mean total number of green patent transfers each city participates in within the network. It is calculated as follows:

$$s = \frac{1}{N}\sum_{i=1}^{N} s_i = s^{out} + s^{in} \tag{3}$$

$$s^{out} = \frac{1}{N}\sum_{i=1}^{N} s_i^{out} = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1,j\neq i}^{N} W_{ij} \tag{4}$$

$$s^{in} = \frac{1}{N}\sum_{i=1}^{N} s_i^{in} = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1,j\neq i}^{N} W_{ji} \tag{5}$$

where s_i denotes the aggregate volume of green patent transfers involving city i; N is the total number of nodes in the network; s^{out} represents the average weighted out-degree, i.e., the mean number of green patents transferred outward per city, and s_i^{out} the weighted out-degree of node i, namely the total outward transfers from city i; s^{in} signifies the average weighted in-degree the mean number of green patents received per city and s_i^{in} the weighted in-degree of node i, or the total inward receipts of city i; and W_{ij} indicates the volume of green patents transferred from city i to city j.

Degree centrality captures the extent of interconnectivity among nodes, effectively delineating their positional significance and prominence within the network. A higher out-degree centrality for node i indicates a greater capacity to establish connections with other nodes, while a higher in-degree centrality signifies that node i is more readily accessible from others. The standardized calculation formula is:

$$DC(i) = DC^{out}(i) + DC^{in}(i) \tag{6}$$

$$DC^{out}(i) = \frac{\sum_{j=1,j\neq i}^{N} W_{ij}}{(N-1)\cdot W_{max}} \tag{7}$$

$$DC^{in}(i) = \frac{\sum_{j=1,j\neq i}^{N} W_{ji}}{(N-1)\cdot W_{max}} \tag{8}$$

where $DC^{\mathrm{out}}(i)$ is the weighted out-degree centrality, which is the sum of the weights of all directed edges from node i to all other nodes; $DC^{in}(i)$ is the weighted in-degree centrality,

which is the sum of the weights of all directed edges from all other nodes to node i; N is the total number of nodes in the network; W_{max} is the maximum weight of all edges in the network; and W_{ij} is the number of green patents transferred from city i to city j.

Betweenness centrality quantifies the extent to which a node lies on the shortest paths between other nodes, capturing its intermediary or brokerage role. A higher value indicates that the node serves as an obligatory passage for numerous node pairs, functioning as a critical hub that underpins network connectivity and flow efficiency. The standardized calculation formula is:

$$BC(i) = \frac{\sum_{s=1}^{N} \sum_{t=1, s \neq t \neq i}^{N} \frac{\sigma_{st}(i)}{\sigma_{st}}}{(N-1)(N-2)} \tag{9}$$

where N denotes the total number of nodes in the network; σ_{st} represents the total number of shortest paths from node s to node t; and $\sigma_{st}(i)$ indicates the number of those shortest paths that traverse node i.

Closeness centrality quantifies a node's proximity to all other nodes within the network. A larger value signifies shorter average shortest paths and a position nearer the network's core. The standardized formula is:

$$C(i) = \frac{N-1}{\sum_{j=1, j \neq i}^{N} d_{ij}} \tag{10}$$

where N denotes the total number of nodes in the network, and d_{ij} represents the geodesic distance from node i to node j, measured by the number of edges traversed along the shortest path.

3.2.2. Cohesive Subgroup Analysis

Cohesive Subgroup Analysis, introduced by social network scholars Breiger, Boorman, and Arabie, is a positional analysis technique grounded in the principle of structural equivalence [31]. By computing a Pearson correlation coefficient matrix, this method identifies clusters of nodes exhibiting similar connectivity patterns, thereby systematically uncovering latent substructures within the network. Its core logic lies in iteratively assessing the degree of similarity in nodes' connection profiles and aggregating structurally equivalent nodes into coherent subgroups, thus revealing functional differentiation. In this study, we employ this approach to partition China's urban green technology transfer network into distinct subgroups, with the aim of rigorously elucidating its spatial clustering characteristics and the relational spillover pathways operating between subgroups.

3.2.3. Modified Gravity Model

The modified gravity model offers a robust approach for gauging spatial association intensity by synthesizing multidimensional determinants. As a vital analytical instrument in spatial econometrics, it captures intercity connectivity potential through an integrated assessment of urban economic mass, population, built-up area, and geographic distance—aligning more closely with the spatial interaction dynamics of green technology transfer than simple difference or similarity matrices. To illuminate the spatial association mechanisms driving the green technology transfer network, the model is specified as follows, enabling a precise characterization of its dynamic evolutionary features.

$$F_{ij} = K_{ij} \frac{\sqrt[3]{X_i POP_i AREA_i} \sqrt[3]{X_j POP_j AREA_j}}{(D_{ij})^2} \tag{11}$$

$$K_{ij} = \frac{X_i}{X_i + X_j} \tag{12}$$

where F_{ij} represents the gravitational strength of X between city i and city j; K_{ij} captures city i's contribution to the X linkage between the two cities; and X denotes the vector of driving factors for each city, encompassing the digital economy, high-speed rail mileage, industrial structure, and governmental environmental attention detailed below. These factors are derived from city-wide annual averages over the full study period and standardized to eliminate dimensional discrepancies. POP denotes total urban population; $AREA$ signifies the built-up area of the city; and D_{ij} is the spatial distance between the two cities.

3.2.4. QAP Regression

The Quadratic Assignment Procedure (QAP) regression is a widely employed technique in social network analysis. Grounded in permutation testing, it computes correlation coefficients by examining the relationships between matrix elements and assesses their statistical significance through nonparametric inference. Compared with conventional regression, QAP offers two distinct advantages: first, matrix permutation effectively resolves the inherent autocorrelation problem in network data; second, its unique testing mechanism circumvents the influence of multicollinearity on analytical outcomes. These properties render QAP particularly well-suited for investigating the driving factors of green technology transfer networks. This study conducts the regression using the average matrix over the entire research period, with the model specification following Yao et al. [32].

$$Y = \beta_0 + \beta_1 X + U \tag{13}$$

where Y denotes the dependent variable, namely the GTT matrix. To mitigate the impact of magnitude differences, the number of green patent transfers is increased by one before taking the natural logarithm. β_0 and β_1 represent the estimated parameters. X denotes the independent variable, namely the attraction matrices of the five selected driving factors described below. U denotes the residual term.

4. Results

4.1. Evolution of Overall Network Characteristics

4.1.1. Temporal Evolution of Network Topology

Using data from 2010, 2016, and 2022, this study employs Gephi 0.10.1, a social network analysis tool, to calculate overall network structure indicators and visualize the evolution of the green technology transfer network (see Table 2 and Figure 1). As shown in Table 2, from 2010 to 2022, the number of nodes increased from 249 to 292, and network coverage rose from 83.8% to 98.3%, indicating that nearly all prefecture-level cities have become integrated into the green technology transfer network, with isolated nodes virtually disappearing. The most striking growth occurred in the number of edges, which jumps from 680 in 2010 to 9844 in 2022—a 14.47-fold increase over the 12-year period—reflecting an explosive rise in intercity green technology transfer interactions. Network density climbs from 0.011 to 0.116 (a 10.54-fold increase), signaling progressively tighter network cohesion; technological linkages among cities are no longer sporadic or accidental but have gradually formed normalized interaction mechanisms. Average degree grows from 2.751 to 33.712, meaning the average number of technology transfer partners per city has multiplied by 12.25. Meanwhile, average weighted degree rises from 67.12 to 585.045, indicating that the intensity of individual green technology transfers has also increased in tandem, deepening the technological collaboration between cities.

Table 2. Overall Structural Characteristic Indicators of Green Technology Transfer Network.

Indicators	2010	2016	2022
Number of nodes	249	290	292
Number of edges	680	3165	9844
Network density	0.011	0.038	0.116
Average degree	2.751	10.914	33.712
Average weighted degree	67.12	259.483	585.045

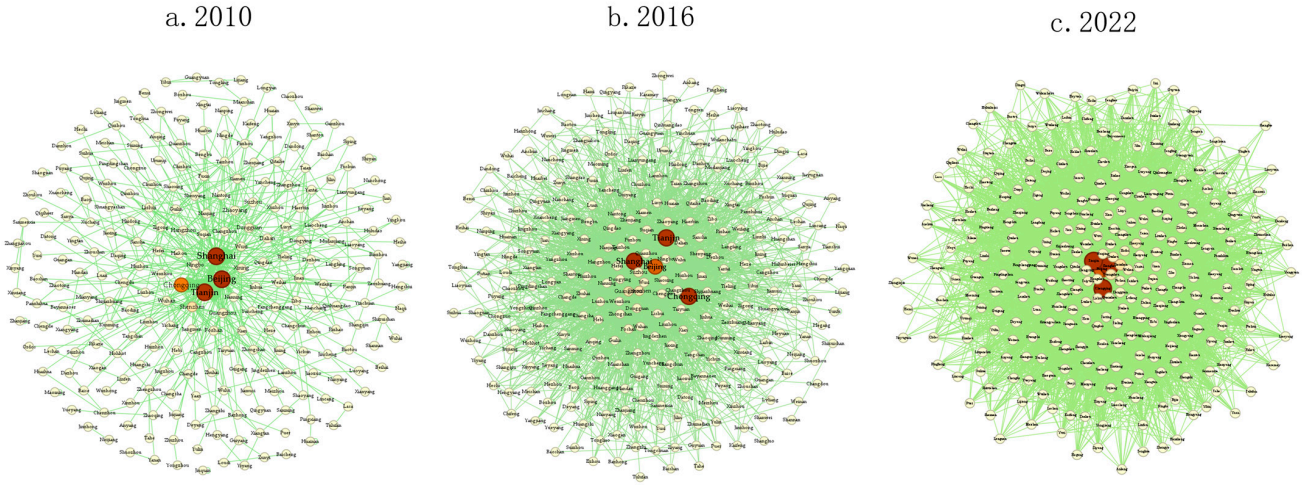


Figure 1. Topology of the GTT network in 2010, 2016, and 2022. Note: Darker color of a node indicates a larger number of edges connected to it.

Figure 1 illustrates the topological structure of the green technology transfer network in 2010, 2016, and 2022. From an evolutionary perspective, the network exhibits significant trends between 2010 and 2022: the number of connections continues to increase, and the topology becomes increasingly dense. This reflects steadily strengthening technological linkages among cities, a growing number of cities integrated into the network, substantially enhanced intercity interaction intensity, a gradual overcoming of geographical proximity constraints, and an increasingly prominent role of core cities—ultimately forming a four-core driven network with a "core–periphery" structure.

Specifically, in 2010, the network comprised 249 city nodes. The overall structure was relatively sparse, with low connection density; cities mainly maintained simple "one-to-one" and "many-to-one" association patterns, and a "core–periphery" structure had just begun to emerge. At this stage, Beijing, Shanghai, and Chongqing stood out as core nodes, establishing green technology transfer links with 84 cities—accounting for 39.25% of all nodes. By 2016, the network structure had changed markedly: the number of nodes increased significantly, and network density rose substantially. Tianjin joined the core, forming a four-core driven network pattern. The diffusion of green technology transfer connections from core to peripheral nodes expanded considerably; the number of linkages between peripheral and core cities, as well as among peripheral cities themselves, grew noticeably, and the network began to take on a complex "many-to-many" connection pattern. Over time, the number of participating cities continued to rise. By 2022, the network had achieved near-full coverage, with 292 participating cities and markedly fewer isolated nodes. At this point, the network exhibits a highly integrated configuration: core cities form clusters, their connections extend across almost the entire network, and network density reaches a high level. This indicates that technological transfer linkages among cities have achieved comprehensive coverage, forming a mesh-like synergistic structure. Not only have deep linkages been established among core cities, but peripheral cities have

also achieved deep network embeddedness, thereby maximizing the overall network's synergistic effect.

4.1.2. Evolution of Spatial Structural Characteristics

To further investigate the four-core driven pattern of the green technology transfer network, Figure 2 presents its spatial distribution. Overall, from 2010 to 2022, the network's spatial pattern gradually expanded from "highly concentrated in the east and relatively sparse in the central and western regions" toward the central and western areas, indicating that the number of cities participating in GTT has steadily increased and the network has become increasingly national in scope.

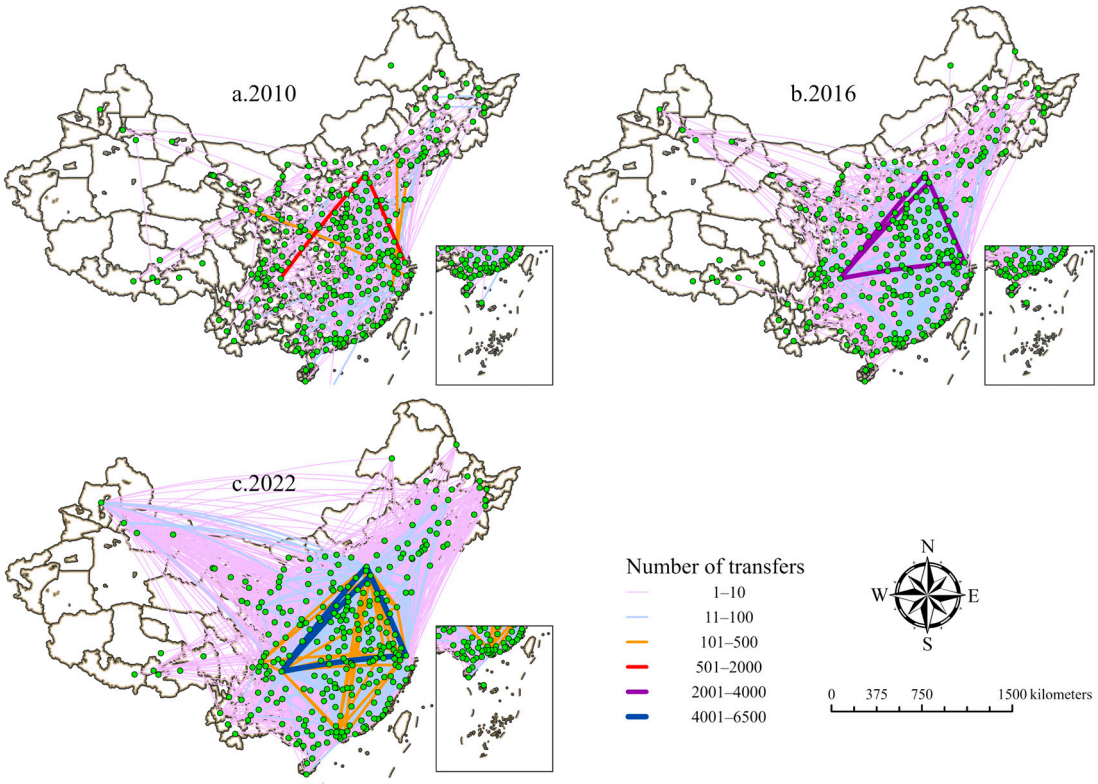


Figure 2. Spatial distribution of the GTT network. The original map is sourced from the National Platform for Common Geospatial Information Services (NPCGIS). Note: Green dots represent the locations of the people's government of each city.

In 2010, network connections were mainly concentrated in the eastern coastal region, while links in the central and western regions were extremely limited, exhibiting a pronounced "strong east, weak west" spatial differentiation that reflects significant regional imbalance in GTT development. This disparity can likely be attributed to the eastern cities' stronger economic foundation, favorable geographic location, well-developed industrial base, and efficient transport infrastructure, which give them a leading edge in green technology adaptability and absorptive capacity, thereby enabling them to play a pioneering role in GTT.

By 2016, the network began to extend into the central and some western areas, while connections in the east became even denser, and cross-regional penetration started to emerge. At this stage, the network structure gradually formed a triangular, four-core driven configuration centered on the Beijing–Tianjin–Hebei region, the Yangtze River Delta, and the Chengdu–Chongqing economic circle.

By 2022, the green technology transfer network had achieved nearly nationwide coverage. The eastern region exhibits "ultra-dense" connections, while the central and western

regions have attained "densified" development, ultimately forming a fully penetrated "macro-network" structure. This evolution suggests that GTT has shifted from an "east-led" to a "nationwide synergistic" development model. A possible explanation is that industrial relocation from eastern to central and western cities has driven previously GTT-active cities to seek more green technologies to support industrial upgrading, while regions that lagged in GTT have, under the dual impetus of government environmental regulations and green incentives, gradually become integrated into the green low-carbon development system.

4.2. Analysis of Node Topological Characteristics

To examine the role of individual cities in the green technology transfer network, this study quantifies node functions using three centrality indicators—betweenness centrality, closeness centrality, and degree centrality—thereby revealing the evolutionary trajectories of key cities and their influence on the overall network structure. Table 3 lists the top ten cities for each indicator, providing a basis for interpreting the shifting status of core cities.

Table 3. Top 10 Cities by Centrality in the GTT Network.

Betweenness Centrality			**Closeness Centrality**			**Degree Centrality**		
2010	**2016**	**2022**	**2010**	**2016**	**2022**	**2010**	**2016**	**2022**
Beijing (0.2185)	Beijing (0.2679)	Beijing (0.0992)	Beijing (0.2644)	Beijing (0.5697)	Shanghai (0.7367)	Beijing (0.4143)	Beijing (0.8333)	Guangzhou (1.1926)
Shanghai (0.1445)	Shenzhen (0.1294)	Shanghai (0.0858)	Shanghai (0.2424)	Shenzhen (0.5270)	Beijing (0.7130)	Shanghai (0.2709)	Shenzhen (0.6156)	Beijing (1.1892)
Shenzhen (0.0532)	Guangzhou (0.0966)	Guangzhou (0.0803)	Shenzhen (0.2352)	Guangzhou (0.5182)	Taiyuan (0.6858)	Shenzhen (0.1633)	Guangzhou (0.5918)	Shanghai (1.1655)
Guangzhou (0.0380)	Shanghai (0.0747)	Shenzhen (0.0742)	Chaoyang (0.2296)	Shanghai (0.4845)	Shenzhen (0.6762)	Guangzhou (0.1315)	Shanghai (0.5374)	Shenzhen (1.1047)
Xian (0.0323)	Wuxi (0.0495)	Wuhan (0.0369)	Suqian (0.2273)	Foshan (0.4751)	Luzhou (0.6668)	Tianjin (0.0956)	Wuxi (0.4014)	Hefei (0.8615)
Tianjin (0.0246)	Quanzhou (0.0355)	Taiyuan (0.0353)	Guangzhou (0.2249)	Dongying (0.4742)	Wuhan (0.6359)	Wuhan (0.0876)	Suzhou (0.3810)	Wuhan (0.8142)
Xiamen (0.0243)	Wuhan (0.0306)	Hefei (0.0304)	Tianjin (0.2149)	Zhongshan (0.4618)	Guangzhou (0.6345)	Shenyang (0.0757)	Quanzhou (0.3605)	Taiyuan (0.7872)
Shenyang (0.0207)	Dongguan (0.0296)	Chongqing (0.0253)	Changzhou (0.2134)	Chaoyang (0.4618)	Chaoyang (0.6235)	Hangzhou (0.0757)	Chengdu (0.3367)	Chongqing (0.7264)
Dongguan (0.0203)	Foshan (0.0294)	Tianjin (0.0237)	Haikou (0.2128)	Lishui (0.4575)	Foshan (0.6195)	Suqian (0.0717)	Dongguan (0.3197)	Tianjin (0.7162)
Dongying (0.0173)	Chengdu (0.0261)	Foshan (0.0218)	Wuhan (0.2118)	Wuxi (0.4558)	Dezhou (0.6116)	Dongguan (0.0717)	Foshan (0.3129)	Foshan (0.7095)

Note: Values in brackets denote the centrality metrics corresponding to each node city.

Betweenness centrality reflects a city's capacity to serve as an intermediary and coordinator within the network; higher values indicate a more pronounced "bridging" role in green technology flows. In 2010, the top ten cities were predominantly eastern coastal cities, with Beijing leading at 0.2185, followed by Shanghai and Shenzhen, indicating that early green technology transfer networks relied heavily on a few eastern core cities to sustain technology flows. By 2016, most cities saw increased values, and central–western cities such as Wuhan and Chengdu entered the top ten, suggesting that technological pathways within the central and western regions had gradually emerged, and these cities had begun to assume intermediary functions. In 2022, although Beijing's value declined to 0.0992, it remained first; Shanghai, Guangzhou, and others experienced slight reductions in control, indicating a shift from a "unipolar" to a "multi-polar collaborative" network. The inclusion

of cities such as Taiyuan and Hefei in the top ten suggests that they have started to connect core and peripheral cities within their regions, a change closely related to the deepening of green industrial layouts and cross-regional cooperation in central and western China.

Closeness centrality measures the average distance from a city to all other nodes in the network; higher values denote a more central position and better technological accessibility. In 2010, the overall values were low with modest intercity variation. Beijing, Shanghai, and Shenzhen ranked top three, indicating shorter and more efficient technology transfer paths between these cities and others. By 2016, closeness centrality rose across all cities, making the network more evenly connected. In 2022, values for cities such as Shanghai, Beijing, Shenzhen, and Taiyuan increased substantially, further consolidating core cities' advantage in technological accessibility. As eastern cities strengthened their technology radiation to central and western regions, the constraining effect of geographical distance on technology transfer weakened, and connection efficiency between core and peripheral cities improved significantly.

Degree centrality reflects the number of direct connections a city maintains with other cities in the network; higher values imply broader linkages and stronger influence. In 2010, overall degree centrality was low, with Beijing significantly ahead—demonstrating its role as a national hub for green technology input and output, maintaining frequent interactions with many cities. This is closely associated with Beijing's concentration of universities, research institutions, and policy resources. By 2016, the indicator generally increased, and Chengdu entered the top ten for the first time, indicating that the green technology transfer network began expanding westward. In 2022, central–western cities such as Hefei and Wuhan also appeared in the top ten, reflecting the growing activity of these innovative cities in green technology transfer—a trend underpinned by rising demand for regional industrial upgrading and stronger policy support for green technologies.

4.3. Subgroup Division and Spillover Paths

This study conducts a cohesive subgroup analysis using a sample of 48 prefecture-level and above cities from the Beijing–Tianjin–Hebei region, the Yangtze River Delta, and the Chengdu–Chongqing economic circle. These three economic circles represent the most concentrated areas of green technology innovation factors and the highest technology transfer activity in China, accounting for over 70% of the national green patent output and more than 65% of the national green patent input. A complete chain from technology supply to transmission and reception has formed within these circles, fully reflecting the functional differentiation and hierarchical spillover characteristics of a polycentric network. Moreover, the three circles cover cities at different development stages across eastern, central, and western China, encompassing various network roles such as core hubs, secondary transmission nodes, and peripheral reception points, thus offering strong representativeness and typicality. To deeply analyze the internal operational logic and technology spillover paths of this polycentric structure, this sample effectively captures the most active technology spillover pathways and block functional differentiation within the network. It should be noted that this subgroup analysis aims to reveal the block structure and multi-level transmission mechanism within the core regions; therefore, the results primarily reflect technology flow patterns among the Beijing–Tianjin–Hebei region, the Yangtze River Delta, and the Chengdu–Chongqing area, and may not be fully applicable to the technology transfer structures within non-core regions such as northwest, northeast, and southwest China. Nevertheless, since these three economic circles assume the majority of technology output and intermediary functions in the network, the findings based on this sample hold significant representativeness and reference value for understanding

the main backbone architecture and core driving logic of the national green technology transfer network.

Using the average volume of green technology transferred out by each city as the threshold, this paper assigns a value of 1 to cities above the average and 0 to those below, thereby constructing a binarized spatial association network [33]. On this basis, the CONCOR algorithm in Ucinet6.0.0 is applied with a maximum splitting depth of 2 and a convergence criterion of 0.2 to perform spatial clustering and relational spillover path analysis on the green technology transfer network of the 48 cities in the three economic circles for the year 2022. The subgroup classification results are presented in Table 4, the associations and interactions among subgroups are shown in Table 5, and the image matrix constructed using the global network density of 0.161 as the threshold is provided in Table 6.

Table 4. Cohesive subgroups in the GTT network.

Subgroup	City	Number
I	Anqing, Dazhou, Ya'an, Chengdu, Zigong, Leshan, Yibin	7
II	Baoding, Langfang, Chengde, Ma'anshan, Deyang, Guangan, Luzhou, Neijiang, Qinhuangdao, Yangzhou, Meishan, Zhangjiakou, Nanchong, Suining, Mianyang, Ziyang, Zhoushan	17
III	Beijing, Suzhou, Chongqing, Tianjin, Shanghai, Hangzhou, Nanjing	7
IV	Nantong, Huzhou, Cangzhou, Chuzhou, Jiaxing, Hefei, Wuxi, Ningbo, Jinhua, Changzhou, Shaoxing, Shijiazhuang, Zhenjiang, Wuhu, Taizhou (Zhejiang), Taizhou (Jiangsu), Tangshan	17

Table 5. Interaction among subgroups in the GTT network.

Subgroup	Reception Relationship Matrix				Spillover Block Relationship Coefficient	Recipient Block Relationship Count	Expected Internal Relationship Proportion (%)	Actual Internal Relationship Ratio (%)	Plate Attributes
	I	II	III	IV					
I	10	18	2	2	22	30	12.77	31.25	Bidirectional spillover
II	8	9	2	7	17	124	34.04	34.62	Net beneficiary
III	14	54	27	92	160	8	12.77	14.44	Net spillover
IV	8	52	4	54	64	101	34.04	45.76	Broker

Table 6. Density matrix and image matrix of subgroups in the GTT network.

Subgroup	Density Matrix				Image Matrix			
	I	II	III	IV	I	II	III	IV
I	0.244	0.153	0.041	0.017	1	0	0	0
II	0.067	0.033	0.017	0.024	0	0	0	0
III	0.286	0.454	0.643	0.773	1	1	1	1
IV	0.067	0.18	0.034	0.199	0	1	0	1

CONCOR clustering reveals distinct spatial clustering features in the green technology transfer network of the three major economic circles in 2022, identifying four cohesive subgroups with significantly different structures. Subgroup I comprises seven cities, mainly located in the Sichuan–Chongqing area and its vicinity, forming a green technology collaboration cluster in Southwest China. Subgroup II includes 17 cities scattered across the southern part of Beijing–Tianjin–Hebei, the northern flank of the Yangtze River Delta, and the eastern part of Chengdu–Chongqing, exhibiting a cross-regional, fragmented distribu-

tion. Subgroup III consists of seven core hub cities—Beijing, Suzhou, Chongqing, Tianjin, Shanghai, Hangzhou, and Nanjing—constituting the key driving block of the network. Subgroup IV contains 17 cities concentrated in the south-central Yangtze River Delta and eastern Beijing–Tianjin–Hebei, forming a secondary linkage block. Overall, Subgroups III and IV together compose an eastern technology radiation pole, while Subgroups I and II constitute a central-western technology receiving area, reflecting the spatially stratified nature of the network.

Inter-subgroup interaction further reveals the block spillover patterns of GTT. Based on functional roles, the four blocks can be classified as two-way spillover, net beneficiary, net spillover, and broker types. From the perspective of technology spillover and reception volumes, notable asymmetry exists across subgroups: Subgroups I and II spill 22 and 17 times and receive 30 and 124 times, respectively, exhibiting an overall "input-driven" pattern, indicating that the southwestern region has a high dependence on external green technologies. Subgroup III has 160 spillover relations but only 8 receptions, displaying a strong "net output" characteristic, confirming its role as an innovation hub that supplies technological resources to the entire network. Subgroup IV spills 64 times and receives 101 times, possessing attributes of both "net input" and "secondary output," reflecting its bridging function between core and peripheral areas. Regarding internal linkages, the actual internal relation ratio of Subgroup I is significantly higher than the expected value, suggesting a strong internal technology circulation. Subgroup II shows little deviation between actual and expected ratios, indicating no notable internal agglomeration effect. Subgroup III's actual internal relations slightly exceed expectations, implying that core cities are more inclined to radiate technology outward. Subgroup IV exhibits a pronounced internal synergy effect, with its actual internal relation ratio far exceeding expectations.

The density matrix and image matrix further quantify the association strength and network roles among subgroups. The density matrix shows that the internal density of Subgroup I is 0.244, much higher than its external ties, indicating an "inward-oriented" technology interaction pattern. Subgroup III has the highest density values in its relations with all other subgroups, confirming its strong radiation capacity. Subgroup IV maintains close ties with Subgroup III and within itself, and its density with Subgroup II reaches 0.180, reflecting its function as a "secondary hub." The image matrix results indicate that Subgroup I forms effective associations only internally, with weak external links, suggesting regional self-circulation. Subgroup II does not establish strong connections with any subgroup, reflecting a low degree of network integration. Subgroup III has significant associations with all subgroups, occupying a dominant position across the entire network. Subgroup IV forms effective linkages with Subgroup II and within itself, indicating that it facilitates technology diffusion within secondary regions.

Overall, the spatial spillover of GTT follows a multi-level transmission pathway: "core radiation—secondary transmission—regional integration—peripheral reception." Subgroup III, as the core driving block, exports technology intensively to the entire network. Subgroup IV acts as a secondary hub, receiving and relaying technology. Subgroup I reinforces internal technology circulation and accumulation. Subgroup II serves as the receiving terminal for technology diffusion. This structure not only reflects the leading role of core cities but also captures the spatial differentiation of GTT driven by regional disparities.

4.4. Driving Factors of the Spatial Heterogeneity in GTT

4.4.1. Selection and Description of Driving Factors

The preceding analysis indicates that while the green technology transfer network is becoming increasingly integrated overall, marked disparities persist in linkage strength among cities, reflecting a certain Matthew effect. Considerable gaps exist in GTT devel-

opment across urban agglomerations, and effective collaborative mechanisms have yet to be established. Eastern coastal cities lead the national GTT landscape, whereas western regions require additional policy support to integrate into the unified process. This spatial configuration results from the interplay of multiple factors, encompassing digital technology empowerment, spatial location constraints, infrastructure support, industrial demand pull, and institutional environment guarantees [34]. Drawing on existing theoretical and empirical research, this study selects variables from these five dimensions to systematically analyze their influence mechanisms on the GTT network structure. Before regression analysis, we calculate the average value of each variable for each city over the study period, standardize the data to eliminate dimensional differences, and then construct intercity association matrices for the drivers of GTT using a modified gravity model. The definitions and measurement methods of the variables are presented in Table 7.

Table 7. Description of parameters for core driving factors in the GTT network.

Driving Factor	Symbol	Definition
Digital economy	DIG	Synthesized from three indicators (number of internet users, number of mobile phone users, and China's Digital Financial Inclusion Index) using the entropy weight method.
Geospatial location	GEO	Assigned a value of 1 if the two cities are adjacent, otherwise 0.
High-speed rail mileage	RAI	Length of operational high-speed rail lines.
Industrial structure	IND	Proportion of secondary industry output value in GDP.
government environmental concern	GOV	Frequency of environmental protection-related keywords extracted from government work reports.

First, digital economy (DIG). As a new production factor and technological carrier, the digital economy can break geographical constraints, reduce information asymmetry, and optimize the allocation efficiency of innovation resources, thereby shortening the matching cycle between technology supply and demand and enhancing the timeliness and coverage of knowledge spillovers [35]. This study selects three core indicators—the number of Internet users, the number of mobile phone subscribers, and the China Digital Financial Inclusion Index—and synthesizes them using the entropy weight method. These indicators cover both the penetration of digital infrastructure and the capacity of digital finance to serve technological innovation, enabling a multi-dimensional characterization of the enabling conditions for green technology transfer by the digital economy.

Second, geographic location (GEO). Based on the proximity effect theory [36], we employ a dummy variable indicating whether cities are adjacent to capture the constraining effect of geographical distance on technology transfer. Geographic proximity facilitates information transmission efficiency, enhances institutional coordination, and reduces the risk of information asymmetry in the technology transfer process [37].

Third, high-speed rail mileage (RAI). As China's primary mode of intercity passenger transport, high-speed rail offers advantages such as high speed, large capacity, and strong stability, facilitating talent exchange, contract signing, and technology demonstration. This study uses the length of high-speed rail lines in operation in each city as a proxy, which directly reflects the spatial support function for green technology transfer.

Fourth, industrial structure (IND). The share of secondary industry output in GDP is used to capture the demand for green technology. As a concentration of energy-intensive and high-emission sectors, the secondary industry is a key area for green technology

application. A higher share generally indicates more urgent demand for green technologies, which can promote technology transfer through a demand-pull mechanism [38].

Fifth, government environmental concern (GOV). As the leader of regional environmental governance and innovation development, the government's emphasis on environmental protection directly shapes the policy environment and incentive mechanisms for green technology transfer. Following the approach of Wang et al. [39], this study measures government environmental concern by the frequency of environment-related keywords extracted from government work reports. These keywords span four dimensions: air environment (e.g., haze, SO_2, CO_2, PM10, PM2.5, air, dust, exhaust, blue sky, VOCs); water environment (e.g., water ecology, chemical oxygen demand, scattered and polluted, emissions, water environment, water safety, water quality, clear water, black-odor, sewage, COD); ecological environment and sustainable development (e.g., environmental protection, green development, new energy, low-carbon, environmental quality, revegetation, ecological environment, ecological protection, ecological damage); and general environmental management (e.g., pollution, energy consumption, pollution control, emission reduction, pollutant discharge, waste residue, coal-burning environment, environmental violations, environmental crimes, environmental cases, environmental penalties, environmental governance). Government work reports are central carriers of local policy orientation, and keyword frequency objectively reflects the policy direction, priority, and implementation resolve regarding environmental protection. By setting strict environmental standards and a pollution discharge permit system, the government can increase compliance costs for high-polluting firms, thereby forcing them to intensify the introduction and application of green technologies [40].

In summary, this study takes five variables—digital economy (DIG), geographic location (GEO), high-speed rail mileage (RAI), industrial structure (IND), and government environmental concern (GOV)—as explanatory variables, and green technology transfer (GTT) as the dependent variable. Using a modified gravity model, we construct spatial association matrices for each variable to explore the formation mechanisms underlying spatial disparities in green technology transfer.

4.4.2. QAP Correlation Analysis

QAP correlation analysis is suitable for relational data and can reveal correlations between different matrices. Using Ucinet6.0.0 with 5000 random permutations, the results are presented in Table 8. They show that the correlation coefficients between green technology transfer and digital economy, geographic location, high-speed rail mileage, industrial structure, and government environmental concern are 0.009, 0.017, 0.002, 0.013, and 0.001, respectively—all significant at the 10% level. This indicates that these variables are closely associated with the network, providing a basis for subsequent regression analysis. However, correlation does not imply regression; further modeling is required to examine the causal mechanisms of each factor.

Table 8. Results of the QAP correlation analysis.

Variable	GTT	DIG	GEO	RAI	IND	GOV
GTT	1 ***	0.009 **	0.017 ***	0.002 *	0.013 **	0.001 *
DIG	0.009 **	1 ***	0.005 *	0.025 ***	0.779 ***	0.830 ***
GEO	0.017 ***	0.005 *	1 ***	−0.002	0.004	0.008 **
RAI	0.002 *	0.025 ***	−0.002	1 ***	0.014 ***	0.019 ***
IND	0.013 **	0.779 ***	0.004	0.014 ***	1 ***	0.631 ***
GOV	0.001 *	0.830 ***	0.008 **	0.019 ***	0.631 ***	1 ***

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4.4.3. QAP Regression Analysis

A QAP regression analysis of the driving-factor difference matrix is further conducted using Ucinet 6.0.0 with 5000 random permutations. The results are presented in Table 9. The coefficient of the digital economy is significantly positive at the 1% level, indicating that the digital economy facilitates green technology transfer. Geographic location yields a coefficient of 0.028 (significant at 1%), suggesting that GTT is more likely to occur between spatially proximate cities. High-speed rail mileage is positively significant at the 10% level, reflecting the fundamental support of transport networks for contract signing, talent exchange, and technology demonstration. Industrial structure has a coefficient of 0.045 (significant at 5%), underscoring the demand-driven nature of GTT—a finding well supported by Zhang et al. [41]. Government environmental concern returns a coefficient of 0.1 (significant at 1%), indicating that environmental regulations can strengthen firms' demand rigidity for green technologies.

Table 9. Results of the QAP Regression Analysis.

Variable	Unstandardized Coefficient	Standardized Coefficient	*p*-Value	Prob (A)	Prob (B)
DIG	1.831	0.121	0.000	0.000	1.000
GEO	0.113	0.028	0.000	0.000	1.000
RAI	0.015	0.013	0.091	0.091	0.909
IND	0.027	0.045	0.017	0.017	0.983
GOV	0.805	0.100	0.000	1.000	0.000
Intercept	0.130	0.000			

In summary, the digital economy and government environmental concern emerge as the most core drivers, while industrial structure and geographic location provide the foundational conditions for transfer, and high-speed rail mileage plays a supporting role through talent mobility. Together, these five factors synergistically drive the evolution of the green technology transfer network from regional agglomeration toward nationwide synergy.

4.4.4. Robustness Test

To test the robustness of the QAP regression results, this study employs two approaches: increasing the number of random permutations and excluding the four core hub cities—Beijing, Shanghai, Guangzhou, and Shenzhen. As shown in Table 10, the signs and significance levels of the standardized regression coefficients remain largely unchanged before and after these robustness checks, confirming the stability of the empirical findings on the green technology transfer network.

Table 10. Robustness Checks of QAP Regression Results.

	(1) 10,000 Random Permutations		(2) 20,000 Random Permutations		(3) Excluding Core Hub Cities	
Variable	Standardized Coefficient	*p*-Value	Standardized Coefficient	*p*-Value	Standardized Coefficient	*p*-Value
DIG	0.190	0.001	0.190	0.000	0.193	0.000
GEO	0.028	0.001	0.028	0.000	0.039	0.000
RAI	0.012	0.100	0.012	0.099	0.008	0.016
IND	0.049	0.001	0.049	0.000	0.053	0.000
GOV	0.102	0.001	0.102	0.000	0.096	0.000
Intercept	0.000		0.000		0.000	

5. Discussion

5.1. Research Conclusions

Drawing upon green patent transfer data from 297 prefecture-level cities in China spanning 2010 to 2022, this study constructs a directed weighted network and conducts a systematic analysis employing a multi-methodological framework. The core findings can be synthesized into four dimensions:

First, the overall network exhibits a pronounced trend of densification and nationwide expansion, with network coverage escalating from 83.8% to 98.3% and the number of edges surging by 14.47-fold. Its spatial structure has gradually evolved from an initially discrete configuration into a polycentric complex structure centered on the Beijing-Tianjin-Hebei region, the Yangtze River Delta, and the Chengdu-Chongqing region.

Second, node topology characteristics display dynamic evolution. The absolute dominance of eastern core cities gradually weakens, while the intermediary and control capacities of central and western cities—such as Wuhan, Chengdu, and Hefei—continue to rise. The network power structure progressively shifts toward a multi-polar, synergistic pattern.

Third, cohesive subgroup analysis identifies four major functional blocks, forming a multi-level technology spillover pathway characterized by "core radiation—secondary transmission—regional integration—peripheral reception", with distinct blocks assuming differentiated functional roles within the network.

Fourth, digital economy, geographic location, high-speed rail mileage, industrial structure, and government environmental concern collectively constitute a multi-dimensional driving system shaping the evolution of the green technology transfer network. All factors exhibit statistically significant positive effects. In terms of relative effect magnitude, digital economy and government environmental concern exert stronger influence, serving as relatively core drivers. However, the actual impact of each individual factor remains moderate to small, indicating that the evolution of the green technology transfer network results from the synergistic interaction of multiple forces.

Together, these findings systematically reveal the spatiotemporal evolution patterns and internal driving mechanisms of China's green technology transfer network, providing new empirical evidence for understanding regional green technology flows.

5.2. SWOT Analysis of China's Green Technology Transfer

To systematically assess the development trajectory of green technology transfer in China, this study applies a SWOT analysis based on the empirical findings, macro policy context, and regional realities. The evaluation examines four dimensions—strengths, weaknesses, opportunities, and threats—as summarized in Table 11.

Table 11 systematically outlines the internal and external conditions shaping China's green technology transfer. Internally, the country has established a relatively robust network foundation and a diversified driving system for green technology transfer. However, structural issues such as regional imbalances and technological dependence continue to constrain the full effectiveness of the network. Externally, the dual-carbon strategy and the development of the digital economy present historic opportunities, yet challenges persist, including carbon lock-in effects and institutional barriers. Future efforts should leverage internal strengths and seize external opportunities while addressing weaknesses and confronting challenges to steer the green technology transfer network toward a more balanced, efficient, and synergistic development path.

Table 11. SWOT Analysis Matrix for China's Green Technology Transfer.

S	W	O	T
Nationwide network coverage, with node coverage rate rising from 83.8% to 98.3% and isolated nodes virtually eliminated.	Regional development imbalance, with eastern regions dominated by technology outflow and western regions dominated by technology inflow.	The "Dual Carbon" Strategy provides substantial policy dividends, and government environmental regulation intensity continues to increase.	Severe regional barriers and siphon effects, with core cities potentially exacerbating innovation polarization.
Emergence of a polycentric structure, with enhanced collaborative radiation capacity of the Beijing-Tianjin-Hebei, Yangtze River Delta, and Chengdu-Chongqing core regions.	Core dependence risk: Beijing has long ranked first in betweenness centrality, and some cities have not integrated into the strongly connected network.	Digital economy empowerment breaks geographical constraints and optimizes the allocation of technological resources.	Industrial lock-in risk: high-carbon industrial clusters lacking absorptive capacity are prone to falling into a vicious cycle of high emissions and low transformation.
Surge in connection intensity, the number of edges increased by 14.47-fold, network density rose by 10.54-fold, and intercity interactions have become normalized.	Low integration of some subgroups, with structural bottlenecks existing in technology spillover channels.	Deepening of regional coordination strategies and accelerated construction of cross-regional technological cooperation platforms.	Inadequate undertaking capacity: inflow-dominated subgroups exhibit low internal conversion rates, with technologies remaining at the level of superficial transactions.

6. Policy Implications and Limitations

6.1. Policy Implications

Based on the above findings, the following policy recommendations are proposed to promote the efficient and balanced transfer of green technologies nationwide and to foster regional coordination and green low-carbon transformation.

First, optimize the structure of the green technology transfer network to alleviate regional imbalances. The technology radiation capacity of core cities such as Beijing and Shanghai should be strengthened through cross-regional technology transfer alliances and the joint construction of green technology trading platforms, thereby enhancing their driving effect on central and western regions. Meanwhile, regional hubs like Hefei, Wuhan, and Chengdu should be supported in developing green technology nodes to improve technology relay and diffusion capabilities, ultimately forming a multi-level, synergistic network pattern.

Second, adopt differentiated subgroup strategies to tailor technology transfer to local conditions. For core cities (net spillover blocks), the focus should be on original innovation and high-end technology output, promoting international technology cooperation to avoid the "siphon effect" caused by excessive agglomeration. These cities should be supported in building national-level green technology transfer platforms and international technology trading hubs, and encouraged to export high-value green patents directionally to intermediary and peripheral cities in the central and western regions. For peripheral and technology-dependent regions (net beneficiary blocks), efforts should prioritize improving technology absorption, transformation, and re-innovation capabilities, while upgrading local green industry chains to prevent technological dependence. It is recommended that the central government establish a special fund for green technology absorption capacity to support the construction of localized technology adaptation centers and enterprise

training in these regions, and incorporate their green technology introduction and usage into the local carbon peak pilot assessment system. For intermediary cities (broker blocks and bidirectional spillover blocks), the focus should be on enhancing their hub function in technology reception, transformation, and re-diffusion. These cities should be designated as regional green technology transfer sub-centers or technology incubators, strengthening their capacity to receive technology spillovers from core cities and conduct secondary diffusion to surrounding peripheral cities, thereby broadening green technology spillover channels.

Third, prioritize the five driving factors to optimize the external environment for network evolution. (1) Accelerate the deployment of digital infrastructure for green technology transfer by establishing a unified national green patent traceability and trading platform based on blockchain technology to reduce information asymmetry. (2) Strengthen the demand-pulling role of government environmental regulation by incorporating green technology introduction and utilization into the local government carbon peak pilot assessment system, forming a policy closed loop of "demand-driven technology sourcing." (3) Promote the introduction of green and clean technologies in high-carbon industry clusters. (4) Improve the spatial matching between high-speed rail networks and green technology transfer corridors, providing commuting convenience along major technology flow axes such as Beijing–Tianjin–Hebei to Chengdu–Chongqing and the Yangtze River Delta to the Central Plains, thereby reducing the cost of talent mobility. (5) Institutionalize geographic proximity advantages by encouraging neighboring cities to jointly apply for green technology innovation alliances or cross-regional green demonstration zones, transforming proximity advantages into institutionalized collaborative governance arrangements.

6.2. Limitations

This study has several limitations. First, using green patent transfers as the sole proxy for GTT excludes informal channels such as technology licensing, industry–university–research collaboration, and technical consulting. Moreover, the classification criteria of the WIPO International Patent Classification Green Inventory suffer from lags and ambiguities, potentially omitting some emerging green technologies and thus underestimating the GTT activity of certain cities. Additionally, this study distinguishes only between invention patents and utility model patents without considering patent quality differences (e.g., citation counts, number of claims, technology life cycle, or patent family size). Given that patents of varying quality differ by orders of magnitude in their technology diffusion value and industrial driving effects, relying solely on transfer quantities may mask spatial heterogeneity in the technology quality dimension.

Second, social network analysis has inherent applicability boundaries. It is primarily suited for analyzing inter-city relationships and cannot capture intra-city green technology transfer volumes. However, intra-city technology flows constitute a crucial part of green technology diffusion, particularly the collaborative transfer among universities, research institutes, and local enterprises within megacities, which plays a key supporting role in regional green development.

Third, QAP regression is essentially a correlation test based on matrix permutation and cannot rigorously distinguish causal relationships from correlations. For example, cities with a developed digital economy may be more conducive to green technology inflows, but cities with active green technology transfers may, in turn, drive further digital infrastructure development. This potential reverse causality has not been effectively identified or controlled within the framework of this study. Future research could employ panel data, instrumental variable methods, or quasi-natural experimental designs to further examine the net effects and causal directions of the driving factors.

Fourth, this study focuses primarily on the overall network structure and macro-level driving factors, with insufficient exploration of the micro-level decision-making mechanisms of technology transfer in firms. Universities and research institutes, as key suppliers of green technologies, and their industry–university–research collaboration mechanisms with enterprises have not been fully explored. Macro-level network analysis cannot reveal the interaction processes or cooperation patterns of these micro-level actors. Future research could integrate firm-level microdata for more in-depth mechanism analysis.

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References

1. Hsueh, L.; Egli, F.; Gilmore, E.; Prakash, A.; Barua, A.; Hsu, A. Confronting Challenges and Opportunities in Climate Policy and Governance. *PLoS Clim.* **2025**, *4*, e0000668. [CrossRef]
2. Liao, Z.; Hong, W.; Wang, Y.; Zhang, X. Does the Patent Value of Green Technology Affect Its Transfer? The Moderating Role of Industry Competition. *Environ. Res.* **2024**, *241*, 117620. [CrossRef] [PubMed]
3. Xu, Y.; Yao, H.; Chen, J.; Bao, H. Market-Based Environmental Regulation and Carbon Emission Reduction: Evidence from China's Carbon Emission Trading Market. *Ind. Manag. Data Syst.* **2025**, *126*, 865–887. [CrossRef]
4. Nguyen, H.T.; Hoang, T.G.; Nguyen, L.Q.T.; Le, H.P.; Mai, H.X.V. Green Technology Transfer in a Developing Country: Mainstream Practitioner Views. *Int. J. Organ. Anal.* **2021**, *30*, 699–720. [CrossRef]
5. Girgin Kalıp, N.; Erzurumlu, Y.Ö.; Gün, N.A. Qualitative and Quantitative Patent Valuation Methods: A Systematic Literature Review. *World Pat. Inf.* **2022**, *69*, 102111. [CrossRef]
6. Zhu, R.; Wei, Y.; Tan, L. Low-Carbon Technology Adoption and Diffusion with Heterogeneity in the Emissions Trading Scheme. *Appl. Energy* **2024**, *369*, 123537. [CrossRef]
7. Wu, H.; Hu, S. The Impact of Synergy Effect between Government Subsidies and Slack Resources on Green Technology Innovation. *J. Clean. Prod.* **2020**, *274*, 122682. [CrossRef]
8. Posner, M.V. International Trade and Technical Change. *Oxf. Econ. Pap.* **1961**, *13*, 323–341. [CrossRef]
9. Wang, Z.; Zhang, X.; Lu, H.; Kang, X.; Liu, B. The Effect of Industrial Agglomeration on Agricultural Green Production Efficiency: Evidence from China. *Sustainability* **2023**, *15*, 12215. [CrossRef]
10. Liang, H.; Song, J. Research on the Factors Influencing the Efficiency of Transactions between Supply and Requisitioning Parties in Green Economy Technology Transfer. *Pol. J. Environ. Stud.* **2025**, *34*, 2285–2295. [CrossRef]
11. Buenstorf, G.; Geissler, M. Not Invented Here: Technology Licensing, Knowledge Transfer and Innovation Based on Public Research. *J. Evol. Econ.* **2012**, *22*, 481–511. [CrossRef]
12. Yang, C.; Liu, Q. Driving Green Innovation Through Digital Transformation: Empirical Insights on Regional Variations. *Sustainability* **2024**, *16*, 10716. [CrossRef]
13. Jiang, H.; Sun, T. Unravelling the Impact Pathways of Green Innovation and Environmental Regulation on China's Green Development Efficiency Goals: Direct and Spillover Effects. *Ecol. Indic.* **2024**, *168*, 112713. [CrossRef]
14. Watson, J.; Byrne, R.; Ockwell, D.; Stua, M. Lessons from China: Building Technological Capabilities for Low Carbon Technology Transfer and Development. *Clim. Change* **2015**, *131*, 387–399. [CrossRef]

15. Zhang, L.; Xue, L.; Zhou, Y. How Do Low-Carbon Policies Promote Green Diffusion among Alliance-Based Firms in China? An Evolutionary-Game Model of Complex Networks. *J. Clean. Prod.* **2019**, *210*, 518–529. [CrossRef]
16. Cai, H.; Wang, Z.; Zhang, Z.; Xu, X. Carbon Emission Trading Schemes Induces Technology Transfer: Evidence from China. *Energy Policy* **2023**, *178*, 113595. [CrossRef]
17. Wugan, C.; Fengru, X.; Xiaowen, L. Towards Green Development: Does Carbon Emission Trading Policy Matter? *Clean Technol. Environ. Policy* **2025**, *27*, 2173–2187. [CrossRef]
18. Battistella, C.; De Toni, A.F.; Pillon, R. Inter-Organisational Technology/Knowledge Transfer: A Framework from Critical Literature Review. *J. Technol. Transf.* **2016**, *41*, 1195–1234. [CrossRef]
19. Zhao, H.; Chen, S.; Xie, L. Influencing factors and prediction analysis of carbon emissions from the planting industry in Liaoning Province. *Chin. J. Eco-Agric.* **2024**, *32*, 1818–1828. [CrossRef]
20. Yin, F.; Tian, N.; Yan, X. Re-examining the Carbon Emission Reduction Effect of Technology Talent Clustering from the Perspective of Green Technology Transfer. *Sci. Manag. Res.* **2023**, *41*, 117–124. [CrossRef]
21. An, X.; Yang, Y.; Zhang, X.; Zeng, X. Smarter and Cleaner? The Carbon Reduction Effect of Smart Cities: A Perspective on Green Technology Progress. *Sustainability* **2024**, *16*, 8048. [CrossRef]
22. Duan, D.; Jin, H. Spatiotemporal process and driving factors of green technology diffusion in Chinese cities. *Acta Geogr. Sin.* **2023**, *78*, 2001–2018. [CrossRef]
23. Guo, R.; Lv, S.; Liao, T.; Xi, F.; Zhang, J.; Zuo, X.; Cao, X.; Feng, Z.; Zhang, Y. Classifying Green Technologies for Sustainable Innovation and Investment. *Resour. Conserv. Recycl.* **2020**, *153*, 104580. [CrossRef]
24. Li, S.; Chen, R.; Zhou, W. The Effect of Innovation Networks on Urban Energy Intensity: Evidence from China. *Energy Sources Part B Econ. Plan. Policy* **2026**, *21*, 2629841. [CrossRef]
25. Zinilli, A.; Gao, Y.; Scherngell, T. Structural Dynamics of Inter-City Innovation Networks in China: A Perspective From TERGM. *Netw. Spat. Econ.* **2024**, *24*, 707–741. [CrossRef]
26. Yu, D.; Zheng, Y.; Sun, Y.; Liao, M.; Kong, T.; Jamu, L.M. Relationship Divisive Faultlines and Subgroup Reciprocity in Technological Innovation Networks: Analysing the Sequential Mediating Role. *J. Eng. Technol. Manag.* **2025**, *78*, 101922. [CrossRef]
27. Dai, Y.; He, R. The Impact of Carbon Emissions Trading Policy on the ESG Performance of Heavy-Polluting Enterprises: The Mediating Role of Green Technological Innovation and Financing Constraints. *Sustainability* **2025**, *17*, 1365. [CrossRef]
28. Hagedoorn, J.; Cloodt, M. Measuring Innovative Performance: Is There an Advantage in Using Multiple Indicators? *Res. Policy* **2003**, *32*, 1365–1379. [CrossRef]
29. Fei, J.; Pu, Z. Green Technology Acquisition and Air Pollution—The Analysis of Efficient Market and Effective Government. *RD Manag.* **2024**, *36*, 1–13. [CrossRef]
30. Borgatti, S.P.; Mehra, A.; Brass, D.J.; Labianca, G. Network Analysis in the Social Sciences. *Science* **2009**, *323*, 892–895. [CrossRef] [PubMed]
31. Breiger, R.L.; Boorman, S.A.; Arabie, P. An Algorithm for Clustering Relational Data with Applications to Social Network Analysis and Comparison with Multidimensional Scaling. *J. Math. Psychol.* **1975**, *12*, 328–383. [CrossRef]
32. Yao, L.; Chen, W. Temporal and Spatial Evolution of Low-Carbon Transportation Efficiency and Its Influencing Factors in China. *Energy* **2025**, *315*, 134357. [CrossRef]
33. Santos Silva, L.C.; Ten Caten, C.S.; Gaia, S.; De Oliveira Souza, R. Tool for Assessment of the Green Technology Transfer Structure in Brazilian Public Universities. *Sustainability* **2023**, *15*, 6873. [CrossRef]
34. Shi, X.; Sui, F.; Huang, X. Green Technology Transfer for Firms in a Multi-Layer Network Perspective: The Dual Impact of Knowledge Resources and Regional Environment. *Environ. Technol. Innov.* **2025**, *39*, 104291. [CrossRef]
35. Luo, R.; Ullah, S.; Ali, K. Pathway towards Sustainability in Selected Asian Countries: Influence of Green Investment, Technology Innovations, and Economic Growth on CO_2 Emission. *Sustainability* **2021**, *13*, 12873. [CrossRef]
36. Sui, D.Z.; Hugill, P.J. A GIS-Based Spatial Analysis on Neighborhood Effects and Voter Turn-Out. *Political Geogr.* **2002**, *21*, 159–173. [CrossRef]
37. Hinder, S.; Cresswell, K.; Sheikh, A.; Franklin, B.D.; Krasuska, M.; Nguyen, H.T.; Lane, W.; Mozaffar, H.; Mason, K.; Eason, S.; et al. Promoting Inter-Organisational Knowledge Sharing: A Qualitative Evaluation of England's Global Digital Exemplar and Fast Follower Programme. *PLoS ONE* **2021**, *16*, e0255220. [CrossRef] [PubMed]
38. Zhao, K.; Wu, C.; Liu, J.; Liu, Y. Green Finance, Green Technology Innovation and the Upgrading of China's Industrial Structure: A Study from the Perspective of Heterogeneous Environmental Regulation. *Sustainability* **2024**, *16*, 4330. [CrossRef]
39. Shuai, W.; Jie, M.; Hui, L. The Impact of Government Environmental Concerns on the Land Resource Allocation Efficiency in Chinese Cities. *Econ. Geogr.* **2022**, *42*, 186–193. [CrossRef]

40. Jin, X.; Sun, G.; Zhang, M. Policy for Whom? The Heterogeneous Effects of Innovation Policy on Urban Economy. *Cities* **2024**, *153*, 105193. [CrossRef]
41. Zhang, B.; Tian, X.; He, B.; Xin, Q.; Yang, Z. The Impact of China's Green Technology Transfer on Energy Intensity in Countries along the Belt and Road. *J. Environ. Manag.* **2025**, *373*, 123691. [CrossRef] [PubMed]

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