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Xiaozhong Lyu *, Yu Yao, Zanjie Huang, Mingxing Jiang and Qilin Wu

School of Computer Science and Artificial Intelligence, Chaohu University, Hefei 238024, China

* Correspondence: 054097@chu.edu.cn; Tel.: +86-15205515211

Abstract

This study analyzes China's new energy vehicle patent collaboration network to explore mechanisms behind its global rise. Using data from the China National Intellectual Property Administration, we apply knowledge-graph–LLM patent classification and complex network analysis across temporal, industrial, and spatial dimensions. Results reveal a three-periods growth driven by policy and market expansion, with domestic dominance and a shift from invention to utility patents, signaling application-oriented innovation. The network shows small-world and scale-free features, forming an oligopoly led by state-owned enterprises as "innovation organizers," while private firms specialize in targeted R&D. Along the industrial chain, components act as hubs, vehicle manufacturing remains isolated, and the aftermarket clusters around battery recycling. A niche segregation between domestic and foreign actors indicates potential risks of decoupling. Findings highlight a dual-circulation innovation model combining state-led coordination with market-driven application, offering insights for sustainable industrial transformation.

Keywords: new energy vehicles; patent cooperation networks; complex network analysis; innovation ecosystem; large language model

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1. Introduction

Since the launch of China's "863 Program" major project on electric vehicles in 2001, the country has entered the new energy vehicle (NEV) R&D period and, over the past two decades, has transformed from a technology follower to a global leader. In 2023, China's NEV sales reached 9.49 million units, accounting for more than 60% of global sales (approximately 15 million units), far surpassing Europe (around 3 million units) and the United States (about 1.4 million units). The penetration rate of NEVs in China exceeded 35% in 2023, ahead of both the European Union (about 20%) and the United States (7%). Meanwhile, China exported 1.77 million NEVs in 2023, a year-on-year increase of 67%, becoming the world's largest NEV exporter with major markets in Southeast Asia, Europe, and Latin America. These remarkable achievements raise an essential question: what explains the rapid rise of China's NEV industry? This study addresses this question through the lens of patent innovation.

As the core carrier of technological innovation, patents provide a valuable window into industrial dynamics, making patent data analysis an important approach in NEV studies. However, the large volume of patents, the complexity of technical descriptions, and the abundance of specialized terminology pose significant challenges to traditional patent classification methods in terms of efficiency and accuracy [1]. Moreover, the NEV industry involves multiple layers across the industrial chain: upstream component production, midstream complete vehicle R&D and manufacturing, and downstream aftermarket services. Constructing a precise and hierarchical classification framework for such a complex industry remains an unresolved challenge. Although pre-trained language models such as BERT have improved patent classification performance, their effectiveness in the NEV domain remains limited, and the issue of model hallucinations is non-negligible [2–5].

To address these challenges, this study develops the industry-specific patent classification methodology (ISPCM, hereafter) by integrating expert knowledge with large language models (LLMs). Specifically, we first construct a detailed multi-layer classification label system—an NEV industry knowledge graph—and design rule-based matching patterns to identify patents across different industry segments. The patterns are used in the prompting of the LLMs. This method is further augmented with the reasoning and question-answering capability of large language models, which not only enhances classification efficiency but also mitigates the risk of hallucinations.

In parallel, complex network theory offers powerful tools for characterizing relationships and dynamics in large-scale systems [6,7]. By combining this theoretical framework with the ISPCM, we examine the evolution of China's NEV patent collaboration network across temporal, industrial, and spatial dimensions, thereby uncovering the underlying mechanisms behind the country's global leadership [8].

Overall, this study contributes by improving the accuracy of NEV patent identification [9–11], revealing structural features of patent collaboration, and diagnosing potential risks in the innovation network [12]. The remainder of this paper is organized as follows: Section 2 reviews related literature; Section 3 presents the research framework; Section 4 reports the results and discussion; and Section 5 concludes with implications and future research directions.

2. Related Literature

In recent years, Technology identification and patent analysis in the NEV industry has become a focal topic in both academia and industry [13,14]. Existing studies have explored various perspectives, including technological trajectories, cooperation networks, and evolutionary dynamics.

Yuan et al. [13] found that fuel cell vehicle (FCEV) technologies have experienced a gradual recovery since 2014. The United States, Japan, Germany, China, and South Korea remain the core contributors, though the sources of FCEV technologies are undergoing reconstruction. Leading firms, particularly major automakers and component suppliers, play a crucial role in advancing hydrogen fuel cell technologies. Liu et al. [14] revealed that the development of electric vehicle charging technologies is concentrated in line arrangement, batteries, safety devices, and charging station technologies. However, large institutions maintain weak collaboration, with competition primarily focusing on traction power, line arrangement, system control, and charging stations.

Complex network theory has demonstrated strong utility in analyzing international cooperation patterns and synergistic effects, often through the construction of multi-dimensional patent cooperation networks [15–17]. For instance, Wang et al. [18] employed Latent Dirichlet Allocation and patent cooperation data to construct innovation networks, identify development periods, and reveal the evolution of hotspots such as batteries, drive systems, and control technologies. Li et al. [19] examined national and regional patent networks in the Yangtze River Delta, highlighting distinct cooperation patterns across regions. Hu et al. [20] applied social network analysis to uncover the core–periphery structure and regional disparities in China's charging station patent cooperation. Chen et al. [21] integrated the S-curve model with social network analysis and time-series methods, identifying electric vehicle (EV) technology development periods and sustainable directions. Their findings suggest that EV technologies in both global and Korean contexts have reached saturation, with Korea maintaining a two-year advantage in areas such as fast charging, infrastructure, battery monitoring, and AI-based applications. Li et al. [22] argued that China's NEV industry will likely evolve toward electrification, intelligence, lightweighting, and sustainability. However, their study was limited by overly generalized directions, which may lack forward-looking guidance for national or corporate technology roadmaps.

A critical review of prior studies indicates that most analyses rely on partial datasets (e.g., specific periods or technology segments) rather than complete patent portfolios, limiting the reflection of full lifecycle dynamics. Moreover, many studies adopt keyword search and IPC classification methods for patent identification, which often lead to data noise and omissions.

Against this backdrop, this study introduces a novel patent classification framework that integrates knowledge graphs and LLMs. Building upon this, we propose a four-stage analytical framework to investigate China's NEV patents and cooperation networks across temporal, industrial, and spatial dimensions.

3. Materials and Methods

3.1. Research Framework

As illustrated in Figure 1, this study proposes a four-stage analytical framework.

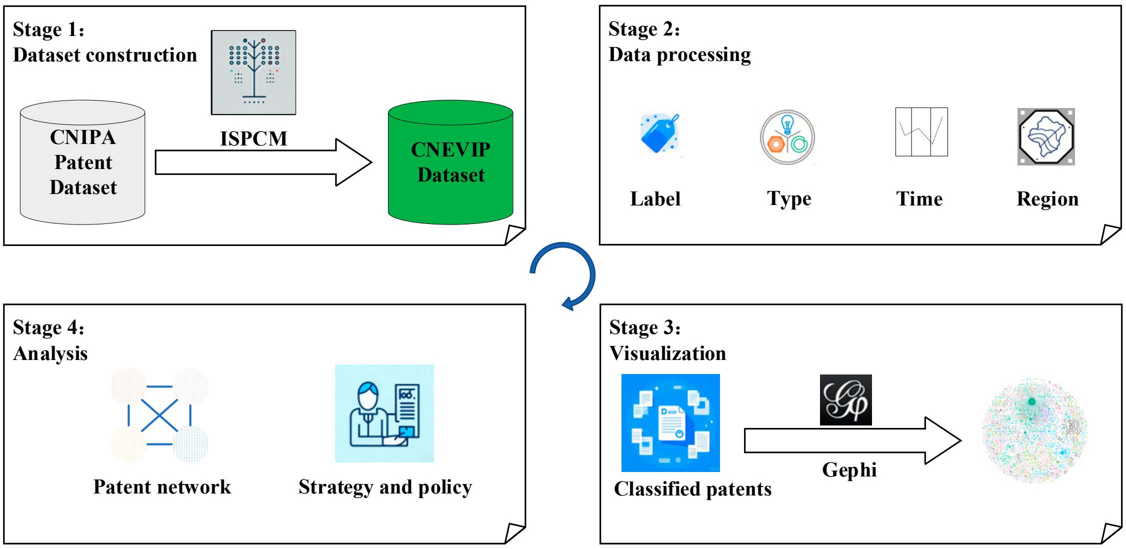

Figure 1. Research Framework.

Stage 1: Construction of the NEV patent dataset. All patent data were sourced from the China national intellectual property administration (CNIPA). CNIPA provides comprehensive patent dataset widely used in innovation and technology studies [23]. The dataset was stored and managed on an open-source Cloudera big data platform [24]. To identify NEV-related patents, the ISPCM was developed by integrating an NEV industry knowledge graph with the Qwen LLM [25], enabling hierarchical multi-label classification across the NEV industrial chain, thereby constructing the China new energy vehicle industry patent (CNEVIP) dataset.

Stage 2: Development of a multi-attribute indexing system. Each patent was indexed by classification label, patent type, applicant, grant year, and geographic location.

Stage 3: Extraction of relational data and construction of patent collaboration networks. Collaborative patents were defined as those with two or more applicants, which were further categorized as domestic or foreign. Gephi was used to construct undirected collaboration networks based on the extracted relationships.

Stage 4: Statistical and network analysis. Using both descriptive statistics and complex network analysis, the study evaluates CNEVIP landscape and derives insights for innovation policy and strategic planning.

3.2. Dataset Construction

Patents were categorized into invention patents (Type B), utility model patents (Type U), and design patents (Type S). Traditional approaches often rely on IPC codes or keyword searches to filter relevant patents; however, IPC codes and keyword searches cannot fully capture emerging NEV

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technologies, and tend to produce numerous irrelevant matches. To overcome these limitations, this study employed the ISPCM combining a domain-specific knowledge graph with a LLM. After comparing multiple open-source models, including Baichuan[26], ChatGLM[27], ChatGPT[28], and Qwen[25], Qwen was selected as the base model due to its classification performance and cost-effectiveness.

The NEV knowledge graph consists of seven hierarchical layers: three first-level categories representing upstream components, midstream complete vehicles, and downstream aftermarket, 21 second-level categories, and 75 third-level categories. The ISPCM model was parallelized on a server equipped with eight NVIDIA A40 GPUs to extract and label NEV patents from the CNIPA patent dataset to the CNEVIP dataset. Compared with conventional IPC- or keyword-based filtering, the ISPCM significantly reduces noise and enhances recall, thus providing a more reliable dataset foundation for network analysis.

3.3. Data Processing

The patent collaboration network is a core focus of this study. Patents with two or more applicants were defined as collaborative patents, and applicants were categorized as domestic or foreign. Both static and temporal analyses were conducted for patents filed from 2001 to 2022, resulting in an undirected collaboration network of the CNEVIP dataset.

Complex network analysis, a graph-theoretical tool widely used to study complex systems, was employed to characterize relationships and collaboration patterns within the network [29]. Network metrics, such as degree centrality and betweenness centrality, were used to identify key applicants, while topological properties, including small-world characteristics and community structures, revealed the distribution of innovation resources and collaboration patterns. This approach also facilitates the analysis of network evolution, technology diffusion, and potential guidance for innovation policy and corporate strategy. To systematically characterize the NEV industry patent collaboration network, we conducted structural, centrality, and cohesion analyses as follows.

3.3.1. Network Structural Analysis

Network Density (D) measures the overall connectivity among nodes and reflects how tightly nodes interact. A higher network density indicates more frequent interactions between nodes, leading to higher frequency and faster speed of knowledge dissemination [30]. Network density is defined as the ratio of the actual number of edges to the maximum possible number of edges in the network, ranging between [0, 1]. A higher value implies tighter connections between nodes.

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

where E is the actual number of edges and N is the number of nodes.

Average Degree (K) describes the average number of connections per node, reflecting the overall level of connectivity in the network. It is calculated as the arithmetic mean of the degrees of all nodes.

$$K = \frac{2E}{N}, \tag{2}$$

where E is the actual number of edges and E is the number of nodes.

Network diameter (D) indicates the expansiveness of the network, measuring the longest shortest path between any pair of nodes. It is used to analyze information propagation efficiency and network scale.

$$D = \max_{i,j \in V} d(i,j)\ , \tag{3}$$

where $d(i,j)$ is the shortest path length between nodes i and j, and V represents the set of nodes.

Average clustering coefficient (C) describes the average level of local connectivity among nodes, reflecting the modularity and community structure of the network [31]. It is the mean of the clustering coefficients of all nodes, where the clustering coefficient of a node measures the connectivity among its neighbors.

$$C = \frac{1}{N}\sum_{i=1}^{N}\frac{2E_i}{k_i(k_i-1)}, \quad (4)$$

where E_i is the number of edges among the neighbors of node i, k_i is the degree of node i, and N is the number of nodes.

Average path length (L) measures the mean shortest distance between any two nodes in the network, evaluating the overall efficiency of the network. Shorter path lengths generally indicate higher efficiency [32].

$$L = \frac{1}{N(N-1)}\sum_{i\neq j} d(i,j), \quad (5)$$

where $d(i,j)$ is the shortest path length between nodes i and j, and N is the number of nodes.

3.3.2. Network Centrality Analysis

Centrality reflects the importance of a node within the network [33,34]. Metrics include degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality.

Degree centrality (C_D) measures a node's direct influence or activity level, identifying the most active or highly connected nodes in the network. It is defined as the number of direct connections a node has to other nodes.

$$C_D(i) = \frac{k_i}{N-1}, \quad (6)$$

where k_i is the degree of node i, and N is the number of nodes.

Betweenness centrality (C_B) measures a node's role as a bridge between other nodes, identifying those that control information flow or connectivity in the network. It is defined as the fraction of shortest paths passing through a node.

$$C_B(i) = \sum_{s\neq i\neq t}\frac{\sigma_{st}(i)}{\sigma_{st}}, \quad (7)$$

where σ_{st} is the total number of shortest paths from node s to node t, and $\sigma_{st}(i)$ is the number of those paths passing through node i.

Closeness centrality (C_C) measures the average distance from a node to all other nodes, reflecting its proximity to the rest of the network. Nodes with higher closeness can disseminate information more quickly.

$$C_C(i) = \frac{N-1}{\sum_{j\neq i} d(i,j)}, \quad (8)$$

where $d(i,j)$ is the shortest path length between nodes i and j, and N is the number of nodes.

Eigenvector centrality (C_E) reflects the influence of a node based on the centrality of its neighbors. A node is considered important if it is connected to other important nodes.

$$C_E(i) = \frac{1}{\lambda}\sum_{j=1}^{N} A_{ij}\, C_E(j), \quad (9)$$

where $A_{ij} = \begin{cases} 1, & \text{if nodes } i \text{ and } j \text{ are connected} \\ 0, & \text{otherwise} \end{cases}$, A is the adjacency matrix of the graph, and λ is the largest real eigenvalue.

3.3.3. Network Cohesion Analysis

Network cohesion is generally measured through network density, average path length, and cohesiveness [35]. Higher network density implies tighter connections between nodes, enhancing the network's overall influence on individual nodes. Cohesiveness evaluates the overall tightness of connections in the network. Based on connectivity, networks can be categorized into four types: fully connected graphs, largest connected subgraphs, weakly connected graphs, and strongly connected graphs. Connected subgraphs exhibit tight internal connections and sparse external connections. The

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formation of subgraphs is influenced by collaboration types, regional preferences, and technological biases, reflecting certain connection preferences and clique phenomena.

he Materials and Methods should be described with sufficient details to allow others to replicate and build on the published results. Please note that the publication of your manuscript implicates that you must make all materials, data, computer code, and protocols associated with the publication available to readers. Please disclose at the submission stage any restrictions on the availability of materials or information. New methods and protocols should be described in detail while well-established methods can be briefly described and appropriately cited.

4. Results and Discussion

This section is divided into two parts. Section 4.1 presents the overall landscape and temporal evolution of CNEVIPs, including quantitative analyses of all patent trends, collaborative patent trends, patent-type distribution, and regional differences. Section 4.2 examines the structural characteristics of CNEVIP collaboration network, focusing on network evolution, topological properties, community structures, key actors, and linkage patterns.

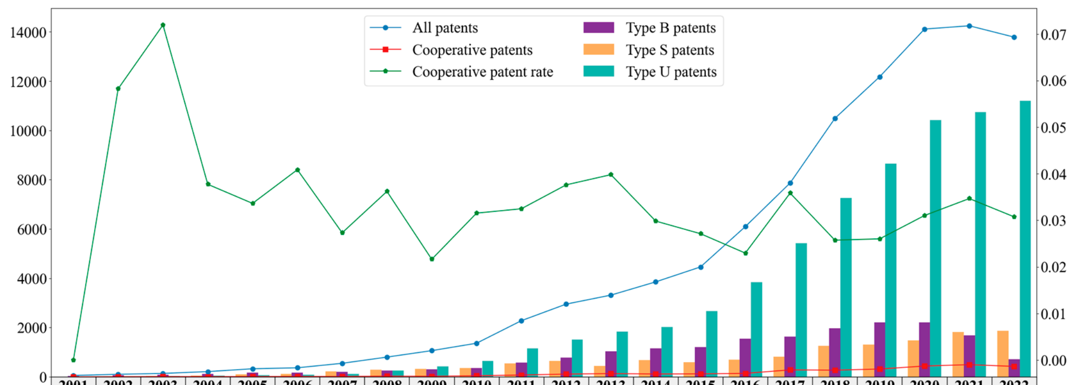
4.1. Patent Temporal Analysis

4.1.1. Overview of Patent Data

Using ISPCM, we extracted 188,989 NEV-related patents filed and granted in China between 1985 and 2022 from the CNIPA patent dataset. Since China officially entered the NEV R&D period in 2001, and the average patent authorization time is approximately 2.9 years [36], this study focuses on patents filed between 2001 and 2022 to ensure completeness and analytical validity.

4.1.2. Overall Temporal Evolution

As shown in Figure 2, a total of 100,614 authorized NEV patents were identified, including 3,078 collaborative patents, 18,517 invention patents, 13,661 design patents, and 68,436 utility model patents. Both the overall number of patents and the three major patent types demonstrate a sustained upward trajectory.



	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
All	55	103	139	212	327	367	549	801	1063	1363	2278	2951	3316	3854	4460	6096	7867	10489	12179	14113	14246	13786
Type B	40	63	83	121	169	172	211	262	308	357	582	785	1038	1152	1206	1552	1637	1964	2207	2212	1687	709
Type S	8	21	30	48	95	115	213	281	331	352	542	646	450	682	591	701	809	1262	1317	1478	1817	1872
Type U	7	19	26	43	63	80	125	258	424	654	1154	1520	1828	2020	2663	3843	5421	7263	8655	10423	10742	11205
Co. patents	0	6	10	8	11	15	15	29	23	43	74	111	132	115	121	140	282	270	317	438	494	424
Co. rate(%)	0.00	5.83	7.19	3.77	3.36	4.09	2.73	3.62	2.16	3.15	3.25	3.76	3.98	2.98	2.71	2.30	3.58	2.57	2.60	3.10	3.47	3.08

Figure 2. Statistical overview of patents in China NEV industry.

The temporal evolution of patents can be divided into three periods:

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Initial Development Period (2001–2008): Annual authorizations remained below 1,000, reflecting an exploratory phase with limited patenting activity. Invention patents accounted for a relatively high proportion, indicating reliance on fundamental research and core technology breakthroughs.

Rapid Growth Period (2009–2017): Annual authorizations rose sharply to 1,000–10,000. The launch of BYD's mass-produced NEV in December 2008 and the "Ten Cities, Thousand Vehicles" demonstration program in 2009 marked turning points for the industry. This period saw rapid expansion of application-driven innovation, reflected in a surge of utility model patents that surpassed invention patents.

Mature Development Period (2018–2022): Annual authorizations exceeded 10,000, signaling industrial maturity. China's NEV sales led the global market, underscoring the close linkage between patent growth and market expansion.

Although collaborative patents increased in absolute terms, their share remained around 3%, suggesting that innovation was still primarily firm-driven rather than based on large-scale cross-organizational collaboration.

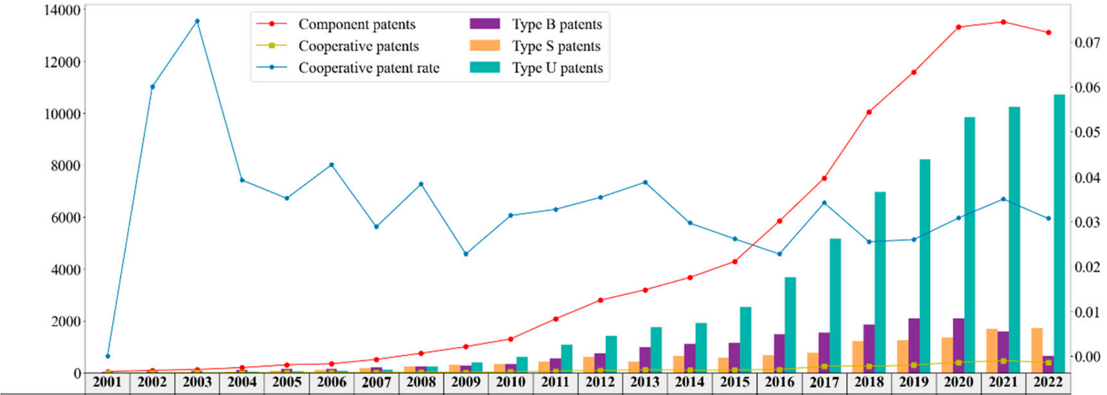
In terms of patent types, utility model patents comprised the majority, followed by invention patents, while design patents were the least numerous. This distribution pattern indicates that China's NEV industry has prioritized applied and engineering-driven innovation, while earlier phases placed greater emphasis on original inventions in core technologies.

4.1.3. Temporal Evolution of Patents in Three Industry Segments

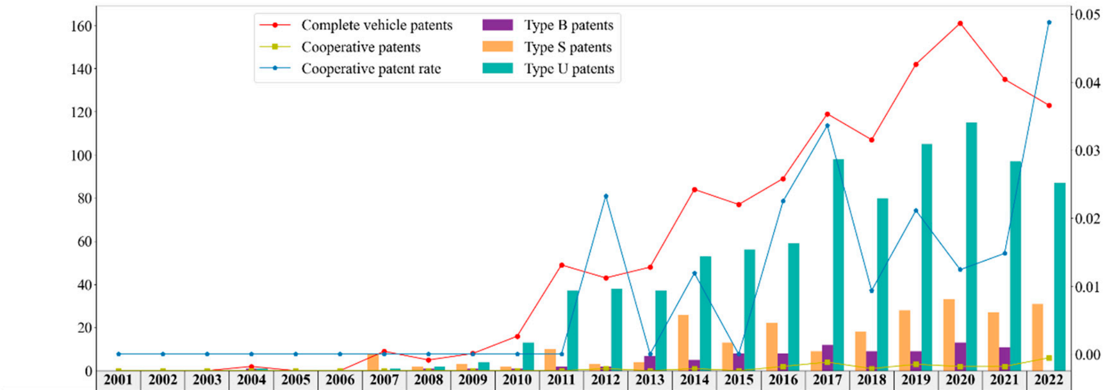
From the perspective of industry segmentation, the component segment holds the largest share of patents, with a total of 95,748, including 17,661 invention patents, 12,821 design patents, 65,266 utility model patents, and 2,901 collaborative patents (collaboration rate 3%). In contrast, the complete vehicle sector has significantly fewer patents (1,217), comprising 90 invention patents, 239 design patents, 883 utility model patents, and only 22 collaborative patents (collaboration rate 1.8%). The aftermarket sector accounts for 4,310 patents, including 851 invention patents, 733 design patents, 2,726 utility model patents, and 152 collaborative patents (collaboration rate 3.5%). Overall, China's NEV patent landscape is heavily concentrated in components, supplemented by the aftermarket, while the complete vehicle segment accounts for the smallest share. This indicates that patent activity emphasizes critical components and supporting technologies rather than complete vehicles. Notably, patent type distribution varies significantly: both components and aftermarket are dominated by utility model and invention patents, whereas the complete vehicle sector emphasizes utility model and design patents, reflecting a stronger focus on exterior protection and structural modifications.

The temporal distribution in Figure 3 shows that patent filings across all three segments have increased over time, though the share of collaborative patents remains persistently low without significant improvement. This suggests that relatively stable cooperation communities have emerged within each segment, but collaborative innovation is not the primary driver. Furthermore, the component segment started earliest and has maintained long-term dominance, while complete vehicle and aftermarket segments lagged behind. This pattern reveals an innovation trajectory of "component breakthroughs to complete vehicle integration to aftermarket." In the early period, aftermarket patents were dominated by low-barrier design patents related to decoration and customization, whereas patents for charging, battery swapping, and cascade utilization technologies—requiring higher R&D input and longer cycles—only gained momentum in the mid-to-late development period.

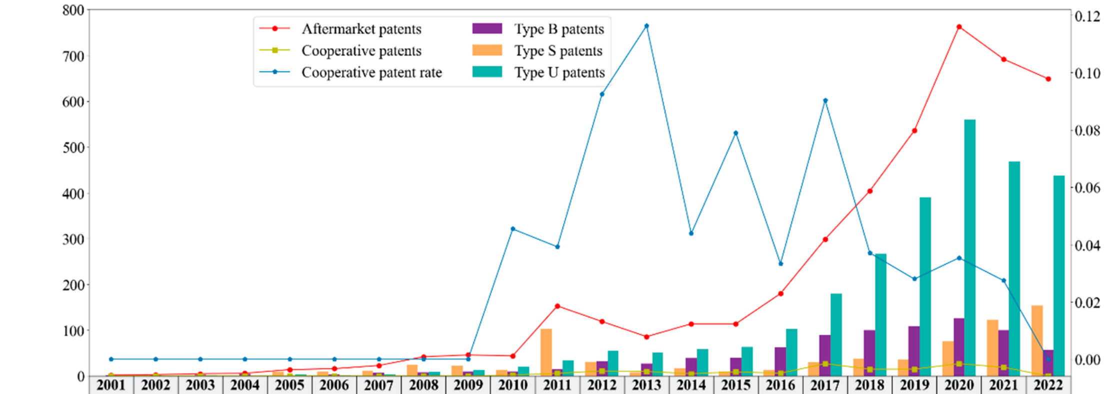
In summary, the temporal evolution and distribution of patents across NEV industry segments demonstrate that innovation initially relied on breakthroughs in components, which subsequently stimulated advances in complete vehicles and aftermarket technologies. Components and aftermarket innovation are mainly utility model–driven, reflecting an application- and engineering-oriented approach, whereas the complete vehicle segment shows greater emphasis on design protection. Moreover, aftermarket innovation has evolved from low-cost, short-term design patents in the early period to high-barrier utility models and invention patents related to charging and battery utilization in the later period, highlighting a transition from rapid, profit-oriented innovation toward high-investment, long-cycle R&D.



	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Component	53	100	134	204	313	352	521	757	1011	1309	2080	2800	3202	3678	4289	5850	7500	10054	11589	13320	13520	13112
Type B	38	61	80	115	168	168	205	253	298	346	565	753	1007	1111	1161	1485	1546	1862	2103	2093	1592	651
Type S	8	20	30	47	86	105	195	257	305	339	429	617	439	647	573	670	776	1220	1262	1378	1691	1727
Type U	7	19	24	42	59	79	121	247	408	624	1086	1430	1756	1920	2555	3695	5178	6972	8224	9849	10237	10734
Co. patents	0	6	10	8	11	15	15	29	23	41	68	99	124	109	112	133	256	256	301	410	473	402
Co. rate(%)	0.00	6.00	7.46	3.92	3.51	4.26	2.88	3.83	2.27	3.13	3.27	3.54	3.87	2.96	2.61	2.27	3.41	2.55	2.60	3.08	3.50	3.07



	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Com. vehicle	0	0	0	2	0	0	9	5	8	16	49	43	48	84	77	89	119	107	142	161	135	123
Type B	0	0	0	1	0	0	0	1	1	1	2	2	7	5	8	8	12	9	9	13	11	0
Type S	0	0	0	0	0	0	8	2	3	2	10	3	4	26	13	22	9	18	28	33	27	31
Type U	0	0	0	1	0	0	1	2	4	13	37	38	37	53	56	59	98	80	105	115	97	87
Co. patents	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	2	4	1	3	2	2	6
Co. rate(%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.33	0.00	1.19	0.00	2.25	3.36	0.93	2.11	1.24	1.48	4.88



	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Aftermarket	2	3	5	6	14	16	23	42	46	44	153	119	86	114	114	180	299	404	536	763	692	649
Type B	2	2	3	5	1	4	7	8	10	10	15	33	27	39	40	63	89	100	109	127	100	57
Type S	0	1	0	1	9	10	12	25	23	14	103	31	8	16	10	14	30	37	36	76	123	154
Type U	0	0	2	0	4	2	4	9	13	20	35	55	51	59	64	103	180	267	391	560	469	438
Co. patents	0	0	0	0	0	0	0	0	0	2	6	11	10	5	9	6	27	15	15	27	19	0
Co. rate(%)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.55	3.92	9.24	11.63	4.39	7.89	3.33	9.03	3.71	2.80	3.54	2.75	0.00

Figure 3. Patent statistics across three segments of China NEV industry.

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4.1.4. Temporal Evolution of Patents Across Domestic and Foreign Applicants

From the perspective of applicant nationality, China's NEV patents are overwhelmingly filed by domestic entities. A total of 98,518 domestic patents have been granted, including 16,980 invention patents, 13,130 design patents, 68,408 utility model patents, and 2,978 collaborative patents, with a collaboration rate of only 3%. Since 2001, domestic patent filings have grown steadily, accelerating sharply after 2015, when both overall and collaborative patents increased significantly. Notably, since 2015, China's NEV sales have remained the highest in the world. Domestic patent activity is dominated by utility model patents, underscoring a focus on engineering applicability and rapid commercialization. Their short application cycles and fast approval processes enable rapid iterations, reflecting a "large-scale, wide-coverage" innovation model that has characterized the expansion phase of China's NEV industry.

In contrast, foreign applicants account for only 2,119 patents in China, comprising 1,554 invention patents (over 70% of their total), 531 design patents, and just 34 utility model patents. Among them, 79 are collaborative patents, with a collaboration rate of 3.7%, slightly higher than domestic applicants. The temporal trend shows that foreign patents peaked in 2015 but declined steadily thereafter, forming a clear "peak-shaped" distribution. Unlike domestic entities, foreign applicants focus primarily on invention patents, underscoring original innovation and stronger technological barriers. However, their declining patent presence indicates reduced innovation investment and a shift in strategic priorities.

Overall, China's NEV patent landscape is dominated by domestic applicants, whose patents far outnumber those of foreign entities. This highlights the growing strength of indigenous innovation and the collective engagement of Chinese firms. In terms of patent types, domestic applicants emphasize utility models, whereas foreign entities focus on invention patents, suggesting divergent innovation strategies, application-driven versus originality-driven. Regarding collaboration, domestic applicants maintain a relatively stable collaboration rate (3%), while foreign entities exhibit a slightly higher but volatile rate, indicating weaker sustainability.

We attribute these differences to several factors: (1) Tesla's 2014 patent pledge, which reduced entry barriers and weakened foreign incentives to file in China; (2) rapid expansion of China's NEV market, where intense competition prompted domestic firms to secure market share through utility model patents; (3) a divergence in innovation orientation, with domestic firms pursuing application-driven protection while foreign firms emphasize original inventions; and (4) strong government support in China, including policy incentives and R&D subsidies, which fueled continuous domestic patent growth.

In summary, the NEV patent innovation landscape in China is characterized by sustained growth, domestic dominance, and a strong preference for utility model patents, while foreign applicants have shown a declining presence since 2015, reflecting their diminishing competitive advantage in the Chinese NEV market.

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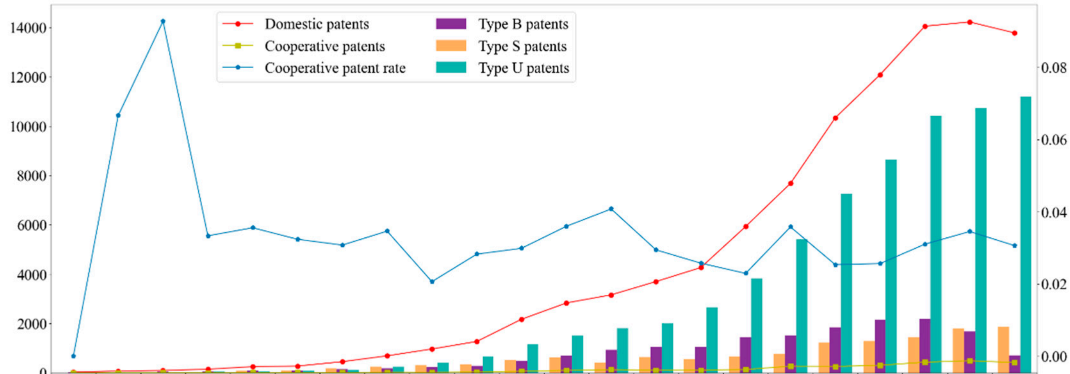
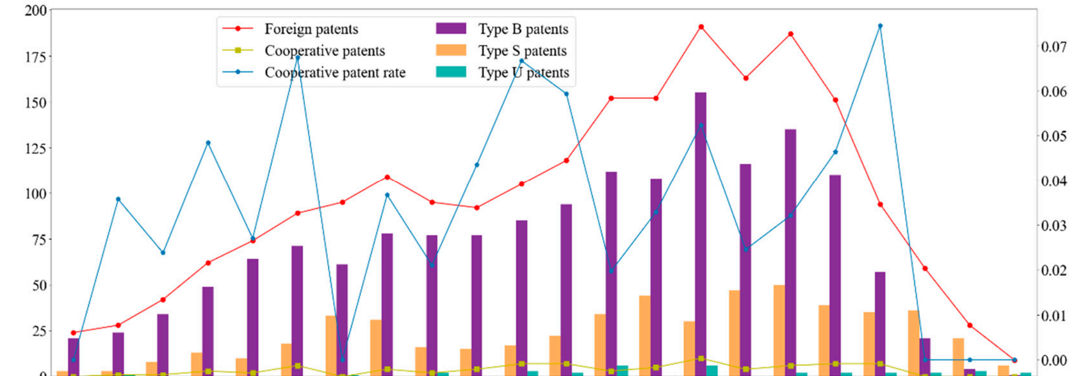


	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Domestic	31	75	97	150	253	278	455	693	969	1274	2175	2835	3164	3703	4270	5933	7682	10339	12087	14054	14221	13780
Type B	19	39	49	72	105	101	151	185	232	283	499	693	926	1045	1052	1436	1504	1855	2150	2191	1684	709
Type S	5	18	22	35	85	97	180	250	315	337	525	624	416	638	561	654	759	1223	1282	1442	1796	1866
Type U	7	18	26	43	63	80	124	258	422	654	1151	1518	1822	2020	2657	3843	5419	7261	8655	10421	10741	11205
Co. patents	0	5	9	5	9	9	14	24	20	36	65	102	129	109	110	136	275	262	310	436	491	422
Co. rate(%)	0.00	6.67	9.28	3.33	3.56	3.24	3.08	3.46	2.06	2.83	2.99	3.60	4.08	2.94	2.58	2.29	3.58	2.53	2.56	3.10	3.45	3.06



	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Foreign	24	28	42	62	74	89	95	109	95	92	105	118	152	152	191	163	187	151	94	59	28	9
Type B	21	24	34	49	64	71	61	78	77	77	85	94	112	108	155	116	135	110	57	21	4	1
Type S	3	3	8	13	10	18	33	31	16	15	17	22	34	44	30	47	50	39	35	36	21	6
Type U	0	1	0	0	0	0	1	0	2	0	3	2	6	0	6	0	2	2	2	2	3	2
Co. patents	0	1	1	3	2	6	0	4	2	4	7	7	3	5	10	4	6	7	7	0	0	0
Co. rate(%)	0.00	3.57	2.38	4.84	2.70	6.74	0.00	3.67	2.11	4.35	6.67	5.93	1.97	3.29	5.24	2.45	3.21	4.64	7.45	0.00	0.00	0.00

Figure 4. Patent statistics of NEV industry by domestic and foreign applicants.

4.2. Patent Cooperation Network

4.2.1. Overall Cooperation Network

Based on the Gephi analysis of 21,347 applicants from 2001 to 2022, Figure 5 illustrates the patent cooperation network, where each node represents an applicant. Node size reflects degree centrality and relative importance, while edges indicate collaborative patent relationships, with edge thickness proportional to cooperation frequency. Different colors denote distinct cooperation communities; for clarity, the six largest communities are presented.

As shown in Table 2, the cooperation network of China's NEV industry exhibits typical features of a complex system. The network density is extremely low (0.0000087), suggesting that actual collaborations are far fewer than the potential maximum, and overall cooperation remains sparse. The network consists of 19,885 connected subgraphs, of which the largest contains only 300 nodes (1.41% of all nodes) but accounts for 25.92% of all connections and 20.21% of cooperative ties. This indicates that more than 93% of applicants exist in isolated small groups, with innovation activity highly fragmented. Most SMEs and research institutes remain outside the core network.

Despite the overall sparsity, the average clustering coefficient is high (0.711) and the average path length is relatively short (3.738), indicating a "small-world" structure [37]. Locally, dense clusters of tightly connected innovation groups exist, while a few central hub nodes serve as bridges enabling short global paths and efficient knowledge transfer across communities. This structure allows for deep knowledge sharing within clusters and rapid diffusion across clusters through hub nodes, balancing modular stability with global efficiency.

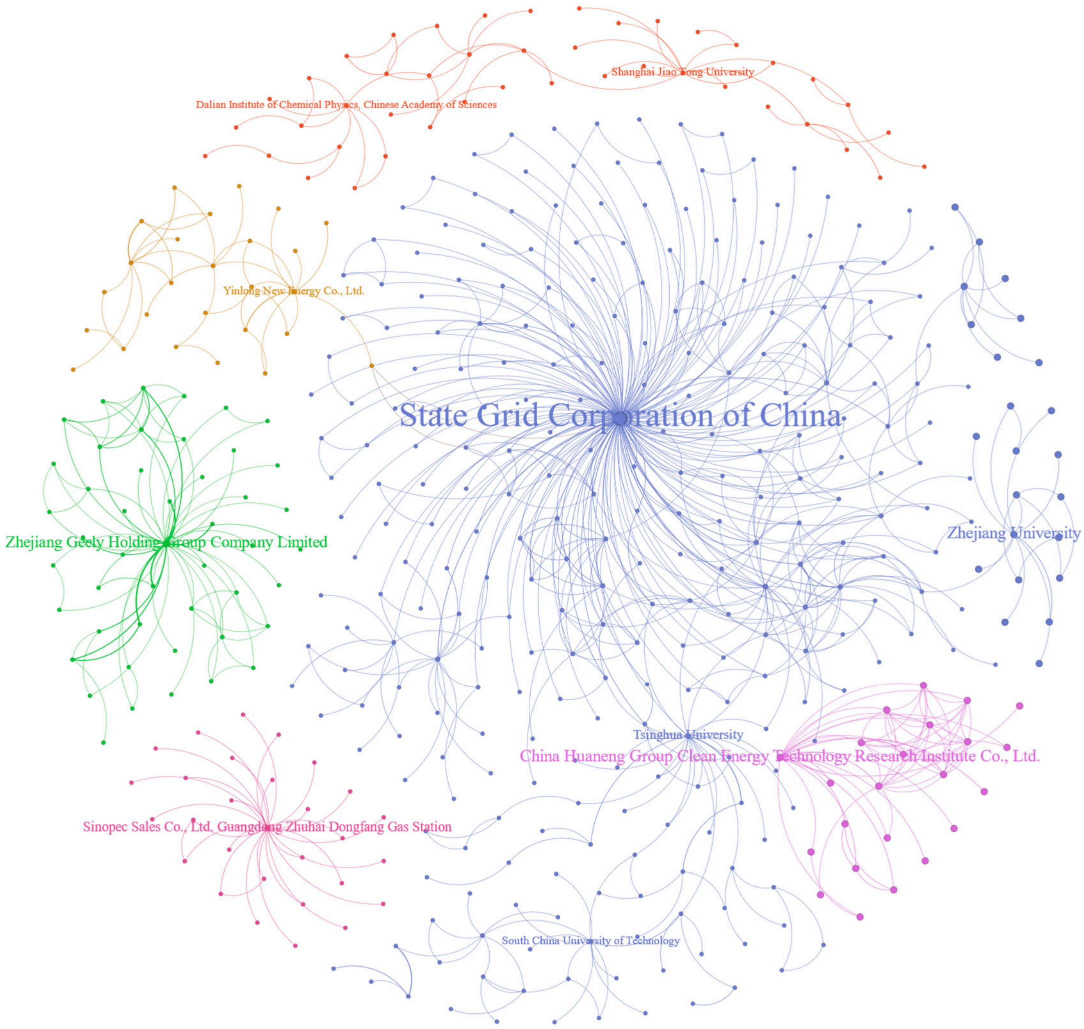


Figure 5. Major communities in the NEV patent cooperation network.

Table 1 and Figure 5 highlight the highly unequal power distribution. The State Grid Corporation of China (SGCC) ranks highest across degree, betweenness, and eigenvector centralities, underscoring its role as the dominant hub, primary bridge, and collaborator with other authoritative institutions. SGCC thus forms the only "super-hub" in the network. Combined with the analysis of Table 2, it can be concluded that the patent collaboration network exhibits characteristics of a scale-free network [38]. Other leading communities are centered on Zhejiang Geely Holding Group (private enterprise), Sinopec Zhuhai Dongfang Gas Station (SOE), Huaneng Clean Energy Research Institute (SOE), Gree Altairnano New Energy Inc (private enterprise), and Shanghai Jiao Tong University (university). Notably, four of the six hubs are SOEs, reflecting the decisive role of state-owned capital and policy support in shaping China's NEV innovation ecosystem. With the exception of SJTU, the hubs are all enterprises, confirming that firms, particularly SOEs, are the core drivers and organizers of industry–university–research collaboration. An interesting finding is that Sinopec Zhuhai Dongfang Gas Station has the highest closeness centrality, making it the most efficient information hub despite its weaker resource control compared to SGCC. This likely reflects its unique position at the market interface, linking upstream component R&D, midstream complete vehicle manufacturing, and downstream services.

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Table 1. Key nodes in the cooperation network.

Centrality	2001-2022
C_D	State Grid Corporation of China Zhejiang Geely Holding Group Company Limited Sinopec Sales Co., Ltd. Guangdong Zhuhai Dongfang Gas Station Tsinghua University
C_C	Sinopec Sales Co., Ltd. Guangdong Zhuhai Dongfang Gas Station Gree Electric Appliances,Inc.of Zhuhai BYD Company Limited Boe Technology Group Co., Ltd.
C_B	State Grid Corporation of China Tsinghua University Northern Altair Nanotechnologies Co., Ltd. GREE ALTAIRNANO NEW ENERGY INC.
C_E	State Grid Corporation of China China Electric Power Research Institute Co., Ltd. XJ Group Corporation Xj Power Co., Ltd.

Table 2. Structural characteristics of the cooperation network.

Structural characteristic	2001-2022
Network density	0.0000087
Number of network nodes	21347
Number of network connections	1983
Connecting times	6314
Average clustering coefficient	0.711
Average path length	3.738
Number of connected subgraphs	19885
Number of nodes of the maximal connected subgraphs	300(1.41%)
Number of connections of maximal connected subgraphs	514(25.92%)
Connecting times of maximal connected subgraphs	1276

Comparison of Table 1 and Table 3 reveals a mismatch between innovation productivity and network influence. Firms such as Chery, CATL, and JAC lead in patent output (over 1,000 grants each) but do not occupy central positions in the cooperation network. Conversely, SGCC, with only 658 granted patents (ranked 13th), holds unmatched influence as a network hub. This dichotomy suggests two distinct innovation models:

Technology-independent-breakthrough-driven innovation model: Firms such as Chery, China's largest vehicle exporter, and CATL, the world's leading power battery manufacturer, demonstrate substantial internal R&D capabilities, as reflected in their high patent output. However, their relatively limited engagement in external collaborations results in lower network centrality, highlighting an innovation trajectory that prioritizes technological breakthroughs over cooperative integration within the broader innovation ecosystem.

Table 3. Top 20 applicants by granted patents.

Applicant	Num.
Chery AUTOMOBILE Co., Ltd.	2101
Contemporary Amperex Technology Co., Ltd.	1865
Anhui Jianghuai Automobile Group Corp.,Ltd.	1302
Eve Power Co., Ltd.	1166
FAW Group Co., Ltd.	1153
Hefei Gotion HIGH-TECH POWER ENERGY Co., Ltd.	1109
BYD Company Limited	956
Aodong New Energy Co., Ltd.	949
Guangzhou AUTOMOBILE Group Co., Ltd.	866

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Zhejiang Geely Holding Group Company Limited	847
Honeycomb Energy Technology Co., Ltd.	790
PAN ASIA Technical AUTOMOTIVE Center Co., Ltd.	729
State Grid Corporation of China	658
Ford Global Technologies, LLC	629
OptimumNano Energy Co.,Ltd	563
Xiamen Hithium Energy Storage Technology Co., Ltd.	547
Chongqing Changan Automobile Company Limited	517
Huating (Hefei) Hybrid Technology Co., Ltd.	483
SINOTRUK Jinan Power Co., Ltd.	473
Dalian Institute of Chemical Physics, Chinese Academy of Sciences	463

Resource-integration-led innovation model: SGCC, despite moderate patent output, leverages its resource integration and infrastructural monopoly to dominate cooperation and innovation direction, demonstrating power derived from network position rather than volume of output.

In conclusion, China's NEV patent cooperation network is structurally fragmented yet locally clustered, with a "small-world" topology shaped by a few dominant hubs. State-owned capital, particularly SGCC, plays a decisive role, creating an oligopolistic structure of "only super power and multi-great power." The observed mismatch between patent output and network influence highlights that technological capacity does not automatically confer network power. Future industrial policy should therefore not only support technological breakthroughs but also address cooperation barriers, improve network connectivity, and enable broader participation of diverse innovation actors to enhance resilience and vitality of the overall innovation ecosystem.

4.2.2. Temporal Evolution of the Patent Collaboration Network

During 2001–2008, the structural characteristics in Table 5 clearly reflect the nascent period of the industry: small scale, sparse collaboration, and simple structures. The network contained only 936 nodes, with the highest density across the three periods (0.0001577), but the absolute value remained extremely low, indicating merely sporadic cooperation. As many as 870 connected subgraphs existed, while the largest subgraph contained only six nodes (0.64%), highlighting the highly fragmented nature of innovation activities and the absence of a large-scale cooperative ecosystem. Table 4 shows that centrality was dominated by Toyota Motor Corporation and leading domestic universities (Tsinghua University, South China University of Technology, and the Dalian Institute of Chemical Physics, CAS). This indicates that the early-period patent collaboration network followed a typical pattern of *foreign technological leadership and academic research dominance*. In contrast, Table 6 reveals that domestic firms such as Chery and BYD had already started building patent portfolios (ranking first and second in granted patents), yet their activities were largely confined to independent R&D, lacking the ability to organize or lead collaborative networks—an *"island-type"* innovation model. Policy initiatives at the time, such as the "863 Program" EV projects, primarily stimulated basic research and early technology exploration, but failed to generate large-scale collaborative innovation. Overall, the patent collaboration network during this period can be characterized as a *fragmented embryonic phase* driven by foreign leadership and academic exploration.

Table 4. Key nodes of collaboration network across three periods.

Centrality	2001-2008	2009-2017	2018-2022
C_D	Toyota Motor Corporation	State Grid Corporation of China	State Grid Corporation of China
	South China University of Technology	Zhejiang Geely Holding Group Company Limited	Zhejiang Geely Holding Group Company Limited
	Tsinghua University	Sinopec Sales Co., Ltd. Guangdong Zhuhai Dongfang Gas Station	China Huaneng Group Clean Energy Technology Research Institute Co., Ltd.

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	Dalian Institute of Chemical Physics, Chinese Academy of Sciences	Xj Power Co., Ltd.	Tsinghua University
C_C	Toyota Motor Corporation	Zhejiang Geely Holding Group Company Limited	Sinopec Sales Co., Ltd. Guangdong Zhuhai Dongfang Gas Station
	South China University of Technology	Sinopec Sales Co., Ltd. Guangdong Zhuhai Dongfang Gas Station	Gree Electric Appliances,Inc.of Zhuhai
	Dalian Institute of Chemical Physics, Chinese Academy of Sciences	GEM Co., Ltd.	BYD Company Limited
	Shanghai Xinmingyuan Automotive Parts Co., Ltd.	Baotou Yunsheng STRONG MAGNET Material Co., Ltd.	State Grid Fujian Electric Power Co., Ltd.
C_B	Toyota Motor Corporation	State Grid Corporation of China	State Grid Corporation of China
	Tsinghua University	State Grid Hebei Electric Power Co., Ltd.	Tsinghua University
	South China University of Technology	Beijing Institute of Technology	Guangzhou AUTOMOBILE Group Co., Ltd.
	Foxconn Technology Group Co.,Ltd	State Grid Shandong Electric Power Company	South China University of Technology
C_E	Toyota Motor Corporation	State Grid Corporation of China	State Grid Corporation of China
	The University of Tokyo	XJ Group Corporation	State Grid Electric Power Research Institute Co., Ltd.
	KYB Corporation	Xj Power Co., Ltd.	China Electric Power Research Institute Co., Ltd.
	Helmholtz-Zentrum Berlin für Materialien und Energie GmbH	XJ Electric Co., Ltd.	Tsinghua University

Table 5. Structural characteristics of collaboration network across three periods.

Structural characteristic	2001-2008	2009-2017	2018-2022
Network density	0.0001577	0.0000208	0.0000102
Number of network nodes	936	8423	16011
Number of network connections	69	737	1309
Connecting times	104	1828	4382
Average clustering coefficient	0.496	0.701	0.761
Average path length	1.272	2.469	2.569
Number of connected subgraphs	870	7867	15041
Number of nodes of the maximal connected subgraph	6(0.64%)	86(1.02%)	188(1.17%)
Number of connections of the maximal connected subgraph	6(8.7%)	171(23.2%)	310(23.68%)
Connecting times of the maximal connected subgraph	6	393	708

Table 6. Top 20 applicants by granted patents across three periods.

2001-2008		2009-2017		2018-2022	
Applicant	**Num.**	**Applicant**	**Num.**	**Applicant**	**Num.**
Chery AUTOMOBILE Co., Ltd.	222	Anhui Jianghuai Automobile Group Corp.,Ltd.	1096	Contemporary Amperex Technology Co., Ltd.	1178
BYD Company Limited	101	Chery AUTOMOBILE Co., Ltd.	1034	Eve Power Co., Ltd.	1165
Dalian Institute of Chemical Physics, Chinese Academy of Sciences	95	Contemporary Amperex Technology Co., Ltd.	687	FAW Group Co., Ltd.	851
Zhejiang Wanfeng Auto Wheel Co., Ltd.	77	OptimumNano Energy Co.,Ltd	554	Chery AUTOMOBILE Co., Ltd.	845

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The Yokohama Rubber Co., Ltd.	66	PAN ASIA Technical AUTOMOTIVE Center Co., Ltd.	399	Aodong New Energy Co., Ltd.	839
Tsinghua University	63	Hefei Gotion HIGH-TECH POWER ENERGY Co., Ltd.	330	Honeycomb Energy Technology Co., Ltd.	785
Shanghai Sinofuelcell Co., Ltd.	58	BYD Company Limited	321	Hefei Gotion HIGH-TECH POWER ENERGY Co., Ltd.	778
Anhui Jianghuai Automobile Group Corp.,Ltd.	56	Zhejiang Geely Holding Group Company Limited	305	Guangzhou AUTOMOBILE Group Co., Ltd.	582
Key Safety Systems, Inc.	51	FAW Group Co., Ltd.	302	Xiamen Hithium Energy Storage Technology Co., Ltd.	547
Shenzhen BAK BATTERY Co., Ltd.	50	Guangzhou AUTOMOBILE Group Co., Ltd.	284	Zhejiang Geely Holding Group Company Limited	540
PAN ASIA Technical AUTOMOTIVE Center Co., Ltd.	45	Ford Global Technologies, LLC	277	BYD Company Limited	534
Suzhou Positec Power Tools (Suzhou) Co., Ltd.	42	SINOTRUK Jinan Power Co., Ltd.	260	Evergrande New Energy Technology (Shenzhen) Co., Ltd.	459
Wuhan University of Technology	42	State Grid Corporation of China	249	Hesai Technology Co., Ltd.	419
Autoliv Development AB	39	Chongqing Changan Automobile Company Limited	232	State Grid Corporation of China	409
Hitachi, Ltd.	39	Dalian Institute of Chemical Physics, Chinese Academy of Sciences	227	Suteng Innovation Technology Co., Ltd.	368
Shanghai Jiao Tong University	37	GM Global Technology Operations LLC	199	Envision Dynamics Technology(Jiangsu) Co., Ltd.	327
South China University of Technology	37	Huating (Hefei) Hybrid Technology Co., Ltd.	170	Ford Global Technologies, LLC	319
GM Global Technology Operations, LLC	36	Zhejiang Geely AUTOMOBILE Research Institute Co., Ltd.	169	Huating (Hefei) Hybrid Technology Co., Ltd.	313
Harbin Institute of Technology	34	Harbin Institute of Technology	165	Envision Ruitai Dynamics Technology (Shanghai) Co., Ltd.	303
Ford Global Technologies, LLC	33	Ningde Amperex Technology Limited	163	Jiangsu Zenergy Battery Technologies Co., Ltd.	300

From 2009–2017, the network entered a period of explosive growth and structural reshaping. The number of nodes increased nearly ninefold (to 8,423), with connections and collaboration frequency surging (737 and 1,828, respectively). However, network density sharply declined to 0.0000208, reflecting the influx of numerous new participants without proportionate deepening of cooperation, resulting in a *"large but sparse"* structure. As illustrated in Figure 6 and Table 4, a fundamental structural shift occurred. The SGCC rapidly emerged as the dominant hub, ranking first in degree, betweenness, and eigenvector centrality, thereby replacing foreign firms and becoming the sole *super-hub* of the network. Around SGCC, the largest collaboration community expanded significantly, with the largest connected subgraph containing 86 nodes (1.02%). Simultaneously, Zhejiang Geely, Sinopec's Zhuhai Dongfang Gas Station, and Shanghai Jiao Tong University rose as secondary hubs. Meanwhile, foreign enterprises such as Toyota and Hyundai witnessed a relative decline in influence. This transformation reflected the acceleration of industrialization, particularly driven by large-scale demonstration projects such as the "Ten Cities, Thousand Vehicles" initiative, where state-owned giants leveraged policy advantages and infrastructure deployment (e.g., charging stations) to reshape the collaborative ecosystem, forming an emerging *"one superpower and multiple strong players"* structure. Table 6 further confirms this trend: domestic automakers and battery

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suppliers such as JAC Motors, Chery, and CATL experienced an explosive increase in patent output, becoming the backbone of innovation. This period thus represents the formation period of an industrialization-driven, state-owned-enterprise-led *core–periphery* patent collaboration network.

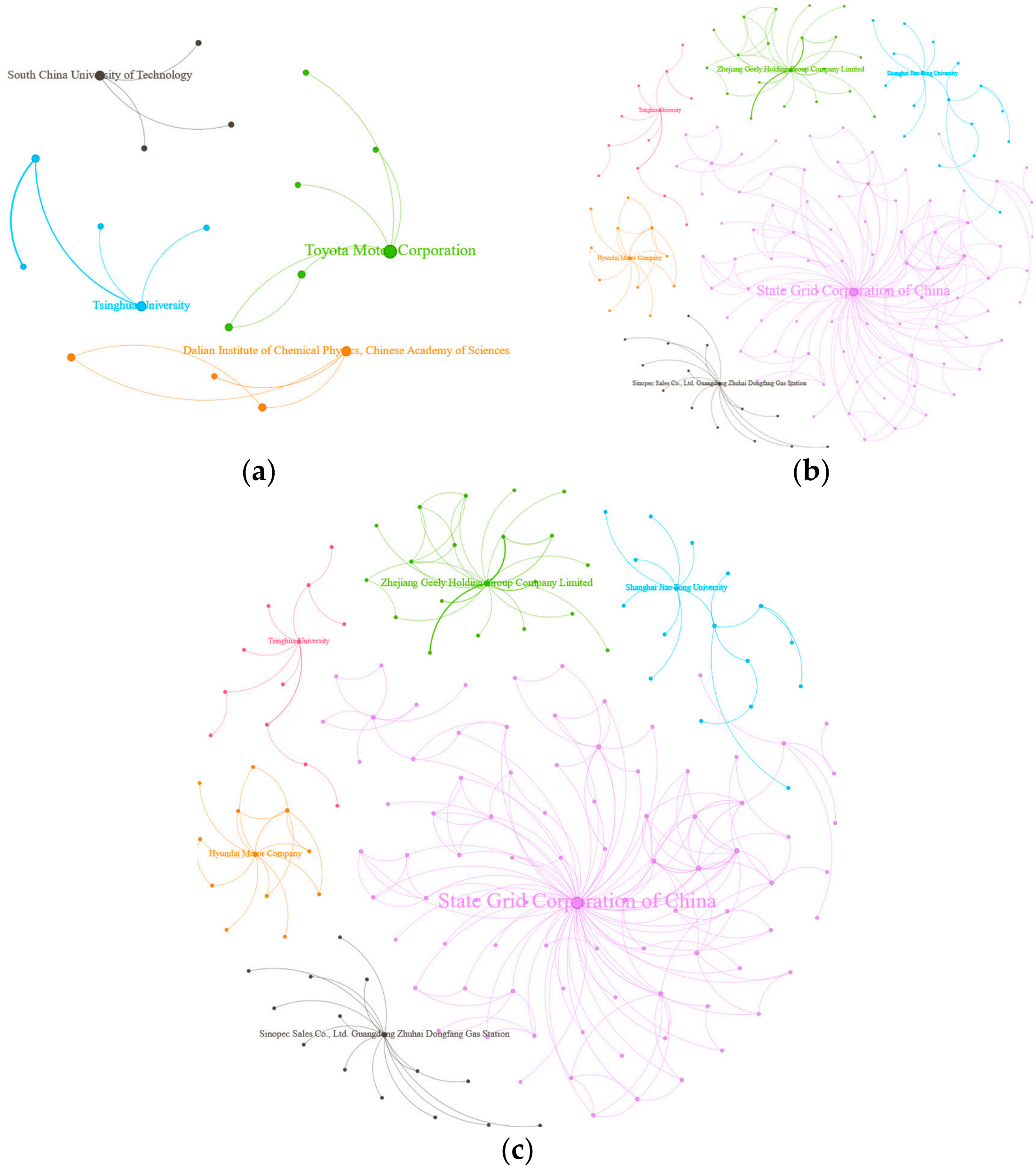


Figure 6. Patent collaboration networks across three periods: (**a**) Network from 2001 to 2008; (**b**) Network from 2009 to 2017; (**c**) Network from 2018 to 2022.

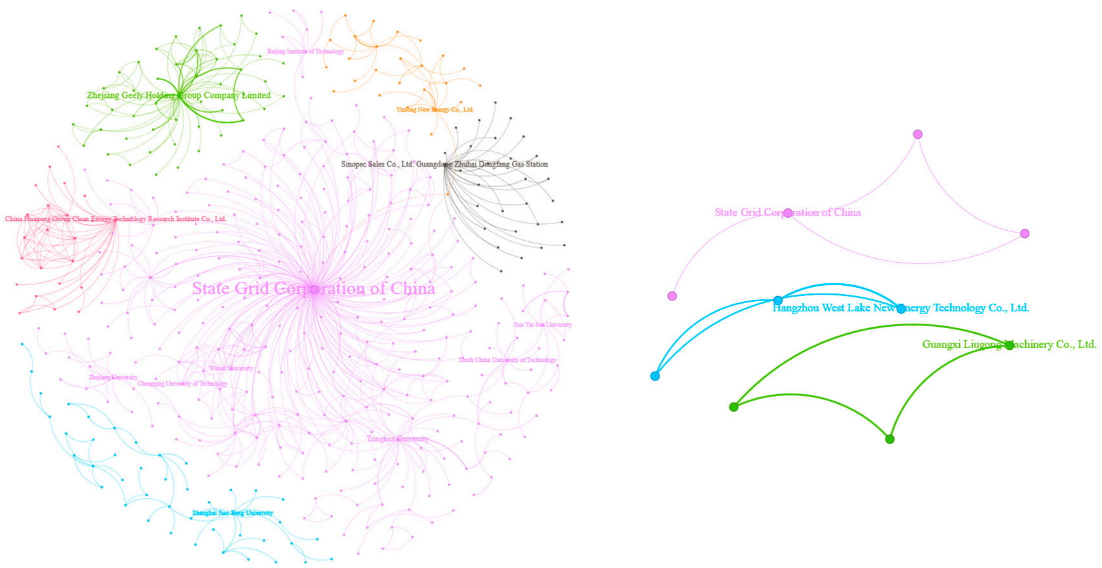
During 2018–2022, the network continued to expand (16,011 nodes) with further deepening of collaborations (4,382 connections), but density dropped to the lowest level (0.0000102), reinforcing the *"large but sparse"* pattern with a vast number of peripheral participants (15,041 subgraphs). Nevertheless, Figure 6 and Table 4 reveal that the network core underwent accelerated integration and consolidation. SGCC further strengthened its dominance, expanding its community by absorbing top academic institutions such as Tsinghua University and South China University of Technology (the largest connected subgraph grew to 188 nodes, 1.17%). This indicates a shift in industry–academia–research cooperation from loose affiliations to tighter integration, with state-owned enterprises serving as key platforms for resource integration and technology transfer. Meanwhile, the ecosystem also became more diversified: Geely retained its importance, while new actors such as China Huaneng Group and Gree Altairnano emerged as community hubs. Notably, Table 6 shows that specialized battery manufacturers, CATL and Eve Energy, monopolized the top two positions in granted patents, far surpassing automakers. This reflects a power shift within the industry chain toward upstream components (particularly batteries), with private enterprises holding core technologies becoming increasingly significant in innovation output.

However, a striking contrast emerges: despite CATL's dominant patent output, it does not rank among the top centrality nodes (Table 4). This once again illustrates that *"high patent output does not equate to high network influence."* The collaborative ecosystem remains dominated by resource-integrating SOEs such as SGCC, while technology-driven private firms emphasize internal R&D and patent generation. These two models, *resource-integration-led innovation* and *technology- independent-breakthrough-driven innovation*, coexist, jointly driving the dual engines of industry-wide innovation.

In summary, over the past two decades, China's NEV patent collaboration network has followed a clear evolutionary trajectory. Network centrality has shifted from foreign firms and academic institutions to SOEs, and subsequently to a coexistence of SOEs and private firms. Structurally, the network has evolved from complete fragmentation, to the emergence of an SOE-centered *"one superpower and multiple strong players"* core–periphery structure, and finally to partial community integration within the core layer. Innovation models have also diverged: SOEs dominate through resource integration and ecosystem orchestration, while private enterprises excel through technological breakthroughs and high patent output. Together, these dual forces form the driving engines of China's NEV patent innovation landscape.

4.2.3. Patent Collaboration Networks Across Industrial Segments

As shown in Figure 7, the State Grid Corporation of China consistently occupies the central role within all three segments of the NEV industry, underscoring its status as a key innovation orchestrator in the industrial chain. In contrast, patent collaboration in the complete vehicle segment is extremely limited. Within the aftermarket, distinct collaboration communities have emerged, led by Guangdong Brunp Recycling Technology Co., Ltd., Nanchang Cenat New Energy Co., Ltd., and Jingmen GEM Co., Ltd., while Zhejiang Geely Holding Group Co., Ltd. has also established a notable collaboration community.



(a) **(b)**

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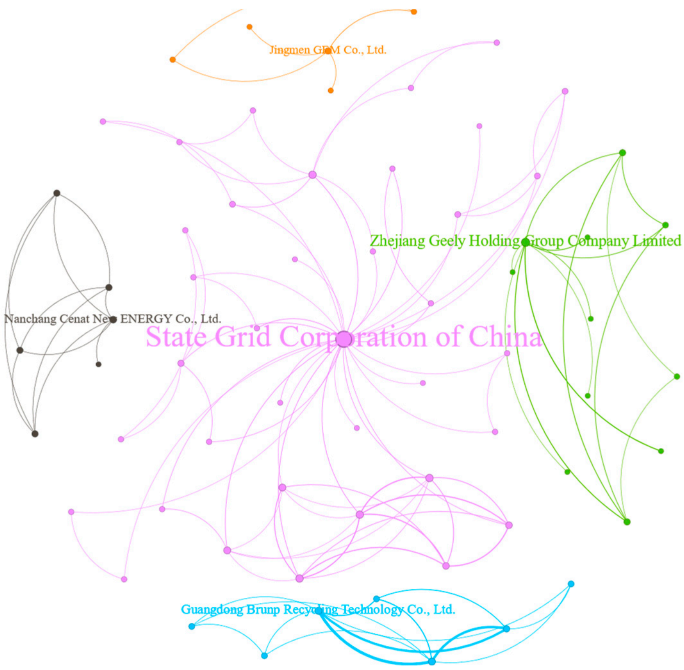

(c)

Figure 7. Patent collaboration networks across three segments: (**a**) Network of the component segment; (**b**) Network of the complete vehicle segment; (**c**) Network of the aftermarket segment.

Table 7. Key nodes of collaboration networks across three segments.

Centrality	Component	Complete vehicle	Aftermarket
C_D	State Grid Corporation of China	State Grid Corporation of China	State Grid Corporation of China
	Zhejiang Geely Holding Group Company Limited	Guangxi Liugong Machinery Co., Ltd.	Zhejiang Geely Holding Group Company Limited
	Sinopec Sales Co., Ltd. Guangdong Zhuhai Dongfang Gas Station	State Grid Sichuan Electric Power Company	XJ Electric Co., Ltd.
	Tsinghua University	Hangzhou West Lake New Energy Technology Co., Ltd.	Xj Power Co., Ltd.
C_C	Sinopec Sales Co., Ltd. Guangdong Zhuhai Dongfang Gas Station	State Grid Corporation of China	Guangdong Brunp Recycling Technology Co., Ltd.
	BYD Company Limited	Guangxi Liugong Machinery Co., Ltd.	Hunan Brunp Recycling Technology Co., Ltd.
	Gree Electric Appliances, Inc. of Zhuhai	Hangzhou West Lake New Energy Technology Co., Ltd.	Nanchang Cenat New ENERGY Co., Ltd.
	Guangdong Power Grid Corporation	Liuzhou Liugong Forklifts Co., Ltd.	Jingmen GEM Co., Ltd.
C_B	State Grid Corporation of China	State Grid Corporation of China	State Grid Corporation of China
	Tsinghua University	Guangxi Liugong Machinery Co., Ltd.	China Electric Power Research Institute Co., Ltd.
	Northern Altair Nanotechnologies Co., Ltd.	State Grid Sichuan Electric Power Company	China Networks Shanghai Electric Power Company
	GREE ALTAIRNANO NEW ENERGY INC.	Hangzhou West Lake New Energy Technology Co., Ltd.	Zhejiang Geely Holding Group Company Limited
C_E	State Grid Corporation of China	State Grid Corporation of China	State Grid Corporation of China
	China Electric Power Research Institute Co., Ltd.	State Grid Sichuan Electric Power Company	XJ Electric Co., Ltd.

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Tsinghua University	Sichuan Electric Power Vocational and Technical College	Xj Power Co., Ltd.
State Grid Electric Power Research Institute Co., Ltd.	Guangxi Liugong Machinery Co., Ltd.	XJ Group Corporation

Table 8. Structural characteristics of collaboration networks across three segments.

Structural characteristic	Component	Complete vehicle	Aftermarket
Network density	0.0000091	0.0001996	0.0000851
Number of network nodes	20484	470	1987
Number of network connections	1900	22	168
Connecting times	5871	38	358
Average clustering coefficient	0.708	0.926	0.82
Average path length	3.764	1.083	2.056
Number of connected subgraphs	19076	451	1873
Number of nodes of the maximal connected subgraph	290(1.42%)	4(0.85%)	37(1.86%)
Number of connections of the maximal connected subgraph	477(25.11%)	4(18.18%)	68(40.48%)
Connecting times of the maximal connected subgraph	1110	4	141

The component segment constitutes the largest (20,484 nodes) and most active (1,900 connections) network, yet its density is extremely low (0.0000091), reflecting a "large but fragmented" structure. The presence of 19,076 disconnected subgraphs indicates that most innovators operate in isolation or in small clusters. Nevertheless, the largest connected subgraph concentrates 25.11% of all ties, and the relatively high clustering coefficient (0.708) suggests the existence of a tightly-knit core circle. State Grid dominates degree, betweenness, and eigenvector centrality, making it the undisputed "innovation organizer" and "resource allocator" of the component segment. Its dominance is rooted in extensive patenting in charging infrastructure, smart grids, and battery swapping technologies. Tsinghua University plays a bridging role through its high betweenness centrality, while Sinopec's Zhuhai Dongfang Gas Station exhibits the highest closeness centrality, reinforcing its position as a unique information hub. Table 9 further reveals that leading patent producers, such as Chery AUTOMOBILE, CATL, Jianghuai Automobile, Gotion High-Tech, and EVE Energy, are primarily battery and NEV manufacturers. This contrasts sharply with the cooperation-centered network dominated by State Grid, indicating a structural separation between "technological output" and "ecosystem power." The component segment thus exhibits a dual structure: (i) a state-capital-driven, wide-ranging collaboration ecosystem centered on State Grid, and (ii) market-driven, R&D-intensive innovation dominated by battery and NEV firms. Together, they define the innovation dynamics of the upstream industry chain.

Table 9. Top 20 applicants by granted patents across three segments.

Component		Complete vehicle		Aftermarket	
Applicant	Num.	Applicant	Num.	Applicant	Num.
Chery AUTOMOBILE Co., Ltd.	1965	Anhui Heli Co., Ltd.	267	Aodong New Energy Co., Ltd.	552
Contemporary Amperex Technology Co., Ltd.	1855	Hangcha Group Co., Ltd.	71	Chery AUTOMOBILE Co., Ltd.	210
Anhui Jianghuai Automobile Group Corp.,Ltd.	1254	Beidou Aerospace Automotive (Beijing) Co., Ltd.	26	Anhui Xinnangang Automotive Interiors Co., Ltd.	120
Eve Power Co., Ltd.	1163	Banyitong Science & Technology Developing Co., Ltd.	23	State Grid Corporation of China	109
Hefei Gotion HIGH-TECH POWER ENERGY Co., Ltd.	1092	Anhui Airuite New Energy Special Purpose Vehicle Co., Ltd.	21	Beijing Taisheng Tiancheng Technology Co., Ltd.	93

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FAW Group Co., Ltd.	1088	China DRAGON Development HOLDINGS Limited	20	Shanghai Dianba New Energy Technology Co., Ltd.	76
BYD Company Limited	943	Luoyang Dahe New Energy Vehicle Co., Ltd.	20	Hunan Brunp Recycling Technology Co., Ltd.	66
Guangzhou AUTOMOBILE Group Co., Ltd.	841	Anhui Yufeng Equipment Co., Ltd.	18	Huawei Technologies Co.,Ltd.	64
Zhejiang Geely Holding Group Company Limited	803	FAW Group Co., Ltd.	16	Bozhon PRECISION Industry Technology Co., Ltd.	62
Honeycomb Energy Technology Co., Ltd.	790	Henan Senyuan Heavy Industry Co., Ltd.	14	Hunan Jinkai Recycling Technology Co., Ltd.	60
PAN ASIA Technical AUTOMOTIVE Center Co., Ltd.	716	Zhengzhou BAK New ENERGY AUTOMOBILE Co., Ltd.	13	FAW Group Co., Ltd.	60
Ford Global Technologies, LLC	629	Zhejiang Haoli Electric Vehicle Manufacturing Co., Ltd.	13	Guangdong Brunp Recycling Technology Co., Ltd.	58
State Grid Corporation of China	556	Anhui Jiangtian Sanitation Equipment Co., Ltd.	13	Shenzhen FINE Automation Co., Ltd.	52
OptimumNano Energy Co.,Ltd	555	Nanjing Jiayuan SPECIAL Electric Vehicles Manufacture Co., Ltd.	12	Anhui Jianghuai Automobile Group Corp.,Ltd.	50
Xiamen Hithium Energy Storage Technology Co., Ltd.	547	Hangzhou West Lake New Energy Technology Co., Ltd.	11	Zhejiang Jizhi New Energy Vehicle Technology Co., Ltd.	49
Chongqing Changan Automobile Company Limited	502	Kion Baoli (Jiangsu)Forklift Co., Ltd.	11	NIO Technology (Anhui) Co., Ltd.	48
Huating (Hefei) Hybrid Technology Co., Ltd.	483	Chongqing Bingding Electromechanical Co., Ltd.	11	Ningbo Shintai Machines Co., Ltd.	48
Dalian Institute of Chemical Physics, Chinese Academy of Sciences	463	Anhui Jianghuai Automobile Group Corp.,Ltd.	10	Zhejiang Geely Holding Group Company Limited	47
SINOTRUK Jinan Power Co., Ltd.	461	Anhui Jianghuai Heavy Construction Machinery Co., Ltd.	10	Chengdu Monolithic Power Systems Co., Ltd.	45
Evergrande New Energy Technology (Shenzhen) Co., Ltd.	459	Shanxi TianJishan Electric Vehicle and Vessel Co., Ltd.	10	Chengdu Iyasaka Technology Development Co., Ltd.	41

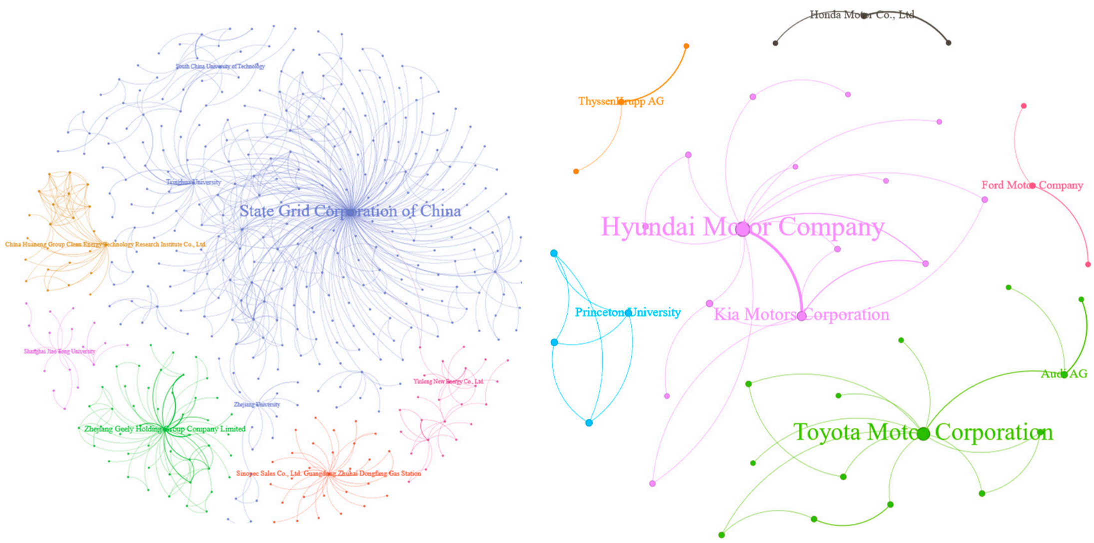
The complete vehicle segment presents the weakest network structure, with only 470 nodes and 22 connections. Despite a slightly higher density (0.0001996), its maximal connected subgraph is extremely small (4 nodes, 0.85%), and collaboration is nearly absent. Yet, its clustering coefficient reaches 0.926, indicating that the very few collaborations occur in tightly closed circles, such as intra-group subsidiaries or limited university–industry partnerships. State Grid and Guangxi Liugong appear among central actors primarily due to cross-industry activities in specialized vehicles (e.g., forklifts, sanitation vehicles) rather than mainstream passenger or commercial vehicles. The lack of a unifying collaboration hub is striking. Table 9 confirms this insularity: Anhui Heli, a forklift manufacturer, ranks first with only 267 patents, far below the thousand-level counts seen in the component segment. The overall profile is fragmented and small-scale, reflecting fierce competition, dispersed resources, and a strong preference for closed, independent R&D strategies. The complete vehicle segment exemplifies an “innovation island” model, where firms erect high technological barriers and exhibit minimal willingness to collaborate, partly due to high integration complexity, confidentiality requirements, and market pressures.

The aftermarket segment is moderate in scale (1,987 nodes) but more active in collaboration (168 connections) compared to the complete vehicle segment. Its largest connected subgraph accounts for 40.48% of ties, with a high clustering coefficient (0.82), indicating the emergence of specialized innovation communities with dense internal linkages. The power structure here has shifted significantly: while State Grid remains important, battery recycling and materials regeneration firms, such as Guangdong Brunp, GEM, and Cenat, have risen to prominence in closeness centrality rankings. Geely also appears across multiple rankings due to its diversified deployment. These findings highlight that innovation in the aftermarket segment is now centered on “battery recycling, second-life applications, and materials recovery,” with specialized circular-economy firms replacing traditional giants as key collaboration hubs. Table 9 corroborates this trend: Aodong New Energy, focusing on battery-swapping, tops the list, alongside Brunp and GEM. This suggests that with the growing stock of NEVs, end-of-life battery management has become a technology-intensive and innovation-driven new frontier, attracting substantial patent activity. The aftermarket thus exemplifies a cluster-oriented innovation model driven by emerging market demand and led by specialized firms.

Overall, innovation activities in China’s NEV industry chain are marked by pronounced “segmentation across segments”: a dual structure of cooperation and independent R&D in components, a closed and inward-looking pattern in complete vehicles, and a rapidly growing, cluster-based ecosystem in the aftermarket. Bridging these segments—particularly fostering openness among complete vehicle firms and integrating them into the broader innovation ecosystem—remains a critical challenge for future industrial policy. Although State Grid plays a central role in both the component and aftermarket segments, its influence has yet to penetrate the complete vehicle core, underscoring the complexities of achieving full-chain collaboration.

4.2.4. Patent Collaboration Networks of Domestic and Foreign Applicants

Figure 8 illustrates the patent collaboration communities of domestic and foreign applicants in China’s NEV industry. Compared with the domestic collaboration communities, the communities formed by foreign applicants are significantly smaller in scale, and their central nodes are primarily automobile manufacturers. The two largest foreign applicant communities are led by entities from South Korea and Japan, with the Japanese cluster also integrating German applicants. In contrast, the domestic collaboration communities largely mirror the structure observed in Figure 1.



(**a**) (**b**)

Figure 8. Patent collaboration networks of domestic and foreign applicants: (**a**) Network of domestic applicants; (**b**) Network of foreign applicants.

Table 10 presents the key nodes of domestic and foreign collaboration networks. Table 11 summarizes their structural characteristics. The domestic network is vast, with 20,716 nodes, yet extremely sparse (density = 0.0000088), exhibiting a typical core–periphery structure. The presence of 19,342 disconnected subgraphs indicates that over 93% of innovation actors remain isolated or at the

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periphery. However, the largest connected subgraph aggregates 27.17% of all connections, coupled with a high clustering coefficient (0.726), demonstrating the existence of a tightly integrated core power circle. Consistent with overall network analysis, SGCC dominates degree, betweenness, and eigenvector centralities, confirming its role as the absolute hub and gatekeeper of innovation resources. This core circle is composed of state-owned enterprises (e.g., State Grid, Sinopec), large private firms (e.g., Geely, Gree), and elite universities (e.g., Tsinghua University), forming a relatively closed cooperation system strongly shaped by state capital and policy influence. Sinopec Zhuhai Gas Station again emerges as a unique information hub with the highest closeness centrality.

Table 10. Key nodes of collaboration network of domestic and foreign applicants.

Centrality	Domestic	Foreign
C_D	State Grid Corporation of China	Hyundai Motor Company
	Zhejiang Geely Holding Group Company Limited	Toyota Motor Corporation
	Sinopec Sales Co., Ltd. Guangdong Zhuhai Dongfang Gas Station	Kia Motors Corporation
	Tsinghua University	Audi AG
C_C	Sinopec Sales Co., Ltd. Guangdong Zhuhai Dongfang Gas Station	Princeton University
	Gree Electric Appliances,Inc.of Zhuhai	Honda Motor Co., Ltd.
	BYD Company Limited	ThyssenKrupp AG
	Boe Technology Group Co., Ltd.	Ford Motor Company
C_B	State Grid Corporation of China	Hyundai Motor Company
	Tsinghua University	Toyota Motor Corporation
	GREE ALTAIRNANO NEW ENERGY INC.	Audi AG
	Northern Altair Nanotechnologies Co., Ltd.	Korea Advanced Institute of Science and Technology
C_E	State Grid Corporation of China	Hyundai Motor Company
	China Electric Power Research Institute Co., Ltd.	Kia Motors Corporation
	XJ Group Corporation	Toyota Motor Corporation
	Xj Power Co., Ltd.	Korea Advanced Institute of Science and Technology

Table 11. Structural characteristics of collaboration network of domestic and foreign applicants.

Structural characteristic	Domestic	Foreign
Network density	0.0000088	0.0003949
Number of network nodes	20716	629
Number of network connections	1881	78
Connecting times	6181	104
Average clustering coefficient	0.726	0.569
Average path length	3.719	1.896
Number of connected subgraphs	19342	563
Number of nodes of the maximal connected subgraph	299(1.44%)	15(2.38%)
Number of connections of the maximal connected subgraph	511(27.17%)	20(25.64%)
Connecting times of the maximal connected subgraph	1273	28

Patent output data in Table 12 highlight the domestic network's vitality. Leading firms such as Chery, CATL, and JAC each hold more than 1,000 granted patents, far surpassing any single foreign applicant. This indicates that, in terms of patent output volume, Chinese firms, supported by industrial policies and market-driven incentives, hold an overwhelming advantage. In summary, the domestic network can be characterized as a policy- and state-capital-driven mega-ecosystem: a powerful yet relatively closed core orchestrates resource flows, surrounded by a vast periphery of marginalized small and medium actors. Overall, patent quantity has experienced explosive growth.

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Table 12. Top 20 domestic and foreign applicants by granted patents.

Domestic		Foreign	
Applicant	**Num.**	**Applicant**	**Num.**
Chery AUTOMOBILE Co., Ltd.	2101	Ford Global Technologies, LLC	629
Contemporary Amperex Technology Co., Ltd.	1865	Robert Bosch GmbH	363
Anhui Jianghuai Automobile Group Corp.,Ltd.	1302	GM Global Technology Operations LLC	345
Eve Power Co., Ltd.	1166	Autoliv Development AB	335
FAW Group Co., Ltd.	1153	The Yokohama Rubber Co., Ltd.	256
Hefei Gotion HIGH-TECH POWER ENERGY Co., Ltd.	1109	LG Chem, Ltd.	110
BYD Company Limited	956	TRW Automotive Inc.	104
Aodong New Energy Co., Ltd.	949	Subaru Corporation	89
Guangzhou AUTOMOBILE Group Co., Ltd.	866	GM Global Technology Operations, LLC	87
Zhejiang Geely Holding Group Company Limited	847	Stellantis N.V.	81
Honeycomb Energy Technology Co., Ltd.	790	Mercedes-Benz Group AG	76
PAN ASIA Technical AUTOMOTIVE Center Co., Ltd.	729	Hitachi, Ltd.	71
State Grid Corporation of China	658	Volkswagen AG	65
OptimumNano Energy Co.,Ltd	563	Key Safety Systems, Inc.	63
Xiamen Hithium Energy Storage Technology Co., Ltd.	547	Audi AG	62
Chongqing Changan Automobile Company Limited	517	Infineon Technologies AG	62
Huating (Hefei) Hybrid Technology Co., Ltd.	483	Automotive Technologies Licensing, LLC	56
SINOTRUK Jinan Power Co., Ltd.	473	Bayerische Motoren Werke AG	54
Dalian Institute of Chemical Physics, Chinese Academy of Sciences	463	Hyundai Motor Company	50
Evergrande New Energy Technology (Shenzhen) Co., Ltd.	459	Toyota Motor Corporation	42

In contrast, the foreign collaboration network is much smaller (629 nodes) but considerably denser (density = 0.0003949), suggesting relatively frequent collaboration among foreign entities operating in China. Nonetheless, its largest connected subgraph includes only 15 nodes, implying that collaboration is confined to small, elite circles with limited integration into the broader domestic innovation ecosystem. As shown in Table 10, network power is highly concentrated in traditional automotive giants such as Hyundai, Toyota, Kia, and Audi. Importantly, the Korea Advanced Institute of Science and Technology (KAIST) ranks high in betweenness and eigenvector centralities, reflecting South Korea's model of close industry–university–research collaboration. The foreign network's structure follows a "firm + core supplier (e.g., ThyssenKrupp) + leading university" configuration—a tightly knit, technology- and supply-chain-based exclusive club.

Patent output comparisons in Table 12 further reinforce this contrast. The top foreign applicant, Ford (629 granted patents), holds fewer patents than China's 13th-ranked applicant, underscoring the scale gap. This may be related to the more selective patenting strategies of multinational corporations in the Chinese market. In sum, the foreign network constitutes a small, cohesive, high-barrier "elite club" that operates largely in parallel to, rather than integrated with, the domestic innovation ecosystem—an ecological separation that reflects limited embeddedness.

Notably, cross-ecosystem collaboration remains minimal. As shown by Tables 2 and 11, there are only 24 collaboration links and 29 collaboration events between domestic and foreign applicants—an extremely low level given the vast sizes of the two networks (20,716 vs. 629 nodes). This provides quantitative evidence of the community segregation observed in Figure 8.

This finding indicates that, despite active foreign patent deployment in China, their innovation activities remain largely detached from the domestically dominated ecosystem. The result is a form of parallel development, with limited effective, deep, and strategic technological exchange. Such weak connectivity highlights potential "decoupling" risks in the NEV industry's global innovation chain. For China, this suggests that while domestic firms have achieved numerical dominance in patents, future progress requires greater openness, higher-level international collaboration mechanisms, and the integration of global innovators into the core ecosystem. Strengthening such

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cross-boundary innovation loops will be essential to enhancing the global competitiveness and resilience of China's NEV industry.

5. Conclusions and Future Research

5.1. Conclusions

This study develops the ISPCM for China's NEV industry by integrating expert knowledge with the LLM. Using this classification, we systematically identify NEV patents filed between 2001 and 2022 and, for the first time, construct and analyze the patent collaboration network of China's NEV industry across three dimensions: temporal evolution, industrial chain, and applicant nationality. The analysis reveals the structural mechanisms underpinning China's global leadership in the NEV industry. The key findings are summarized as follows:

1. Explosive patent growth and sustained innovation dynamism

Patent filings in China's NEV industry exhibit rapid and continuous growth, evolving through three distinct stages: the initial development stage (2001–2008), the accelerated growth stage (2009–2017), and the maturity stage (2018–2022). Both policy interventions (e.g., the "Ten Cities, Thousand Vehicles" program) and market expansion serve as critical drivers. Domestic applicants dominate the landscape, with invention patents prevailing in the early technology accumulation stage, and utility model patents prevailing during the industrialization stage. This reflects a shift from *technology breakthroughs to application-driven innovation, and from autonomous exploration to large-scale iterative development*.

2. A "dual-circulation" innovation ecosystem dominated by state-owned capital

The Chinese NEV industry has formed a vast but sparsely connected patent collaboration network, displaying distinct *small-world* and *scale-free* properties. The network is characterized by a highly oligopolistic "one-super, many-strong" power structure, with the SGCC at its absolute core. State-owned capital dominates the network by organizing infrastructure development (e.g., charging networks) and integrating industrial, academic, and research resources, functioning as the central "innovation orchestrator." This demonstrates the decisive role of state strategy and policy in shaping innovation ecosystems—a hallmark of the Chinese model. Market-driven private independent innovation represents another core feature of the Chinese model.

3. Dynamic network evolution reveals three development stages

- *Emergence (2001–2008):* Led by foreign firms (e.g., Toyota) and universities, with fragmented collaborations.
- *Formation (2009–2017):* SOEs such as SGCC reshape the network into a "*core–periphery*" structure through policy leverage and infrastructure dominance.
- *Deepening (2018–2022):* The core continues to consolidate by absorbing top university communities, while private firms such as CATL emerge as major technology contributors. This results in a "*dual innovation model*," where SOEs orchestrate the ecosystem and private enterprises focus on specialized R&D.

4. Divergent innovation logics across the industrial chain

Component manufacturing serves as the main innovation battlefield, reflecting the above-mentioned dual structure. Complete vehicle manufacturing remains an "*innovation island*," with highly limited collaboration and insular competition. In contrast, the aftermarket (e.g., battery recycling) fosters cluster-based innovation communities led by specialized firms such as Brunp Recycling and GEM. Notably, the influence of SGCC does not effectively penetrate the vehicle-manufacturing stage, underscoring the complexity of achieving full value-chain coordination.

5. Parallel global trajectories with insufficient Sino-foreign integration

Domestic and foreign applicants exhibit an evident *"niche segregation"* in China's NEV patent ecosystem. Domestic networks, shaped by policy, represent a vast "mega-ecosystem" with

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overwhelming quantitative dominance. By contrast, foreign networks function as exclusive "elite clubs" centered on automotive giants, emphasizing high-quality patents (e.g., inventions). Cross-ecosystem collaboration is minimal (only 24 links, with 29 joint filings), revealing a lack of deep, strategic knowledge exchange and exposing potential "decoupling" risks.

In summary, China's NEV leadership does not stem from a single technological breakthrough but from the successful construction of a *dual-circulation development model*—state-owned capital orchestrates the innovation ecosystem while market forces drive application-oriented R&D. This model has enabled efficient resource integration, rapid application iteration, and large-scale market expansion. Nevertheless, challenges remain in achieving original innovation, full industrial chain coordination, and deeper international integration.

5.2. Future Research

Building on the findings and limitations of this study, future research may advance in the following directions:

1. Dynamic modeling of collaboration networks:

   This study primarily employed static and stage-wise analysis. Future work could adopt temporal network analysis or advanced approaches such as Exponential Random Graph Models to more accurately simulate the mechanisms of collaboration formation and predict future structural evolution.

2. Causal mechanisms linking network structure and innovation performance:

   While this study identified mismatches between "ecological positions" and innovation outputs, causal relationships remain underexplored. Future research may integrate panel data regressions or longitudinal case studies to quantitatively assess how network positions (e.g., centrality) affect firms' innovation outcomes, such as patent quality and new product revenues, thereby providing more targeted policy insights.

3. Expanding global comparative perspectives:

   This study focuses on China. Future work could collect patent data from the United States, Germany, Japan, and other countries to construct comparative NEV collaboration networks. Cross-national comparisons of network structures, core nodes, and evolutionary pathways would yield deeper insights into the strengths and weaknesses of different innovation systems and inform China's global NEV strategies.

4. Integrating multi-source data to enrich analysis:

   Future studies could merge patent data with information on R&D investment, government subsidies, talent mobility, and market performance to build a more comprehensive framework. For example, do subsidies effectively improve network connectivity? How does university talent output correlate with corporate innovation productivity?

5. Advancing natural language processing (NLP) in patent analysis:

   While this study applied large-model-based classification, future work could leverage NLP techniques for in-depth patent text mining to identify key technology themes, detect technological gaps, and map technological trajectories. Incorporating such content-based insights into network analysis would enhance the predictive and strategic value of research findings.

Through these directions, future research can enrich both the theoretical understanding of complex innovation networks and the practical toolkit for policy and corporate strategy. Ultimately, this will provide deeper insights and stronger decision support for optimizing innovation ecosystems, shaping technological roadmaps, and advancing international cooperation in the NEV industry.

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Abbreviations

The following abbreviations are used in this manuscript:

NEV	New energy vehicle
CNIPA	China National Intellectual Property Administration
R&D	Research and development
SOE	State-owned enterprise
ISPCM	Industry-specific patent classification methodology
CNEVIP	China new energy vehicle industry patent

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